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Comparing Grounded Theory and Topic Modeling: Extreme Divergence or Unlikely Convergence?

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Abstract

Researchers in information science and related areas have developed various methods for analyzing textual data, such as survey responses. This article describes the application of analysis methods from two distinct fields, one method from interpretive social science and one method from statistical machine learning, to the same survey data. The results show that the two analyses produce some similar and some complementary insights about the phenomenon of interest, in this case, nonuse of social media. We compare both the processes of conducting these analyses and the results they produce to derive insights about each method's unique advantages and drawbacks, as well as the broader roles that these methods play in the respective fields where they are often used. These insights allow us to make more informed decisions about the tradeoffs in choosing different methods for analyzing textual data. Furthermore, this comparison suggests ways that such methods might be combined in novel and compelling ways.

A Tale of Two Methods

Text plays an important role in research, but analyzing textual data poses unique challenges. In the case of surveys, free-text responses allow participants to report their experiences in detailed ways that might not be anticipated by researchers. However, this flexibility also creates challenges in synthesizing insights from the specificity of individual responses. This article compares two approaches to this problem, a qualitative approach from interpretive social science (Glaser & Strauss, 1967) and a quantitative approach from natural language processing (Blei, Ng, & Jordan, 2003). We demonstrate, through a running example relating to social media use and nonuse, that these methods involve surprisingly similar processes and produce surprisingly similar results.

Surveys that include open-ended, free-text responses are often analyzed using qualitative methods (e.g., Baumer et al., 2013; Rader, Wash, & Brooks, 2012; Wang et al., 2011). Analytic methods from, e.g., grounded theory (Charmaz, 2006; Glaser & Strauss, 1967) can generate rich, thick descriptions (Geertz, 1973). Coming from interpretivist (cf. Ma, 2012; Orlikowski & Baroudi, 1991) analysis of empirical social phenomena, these approaches emphasize how a social group co-constructs both their reality and its meaning. However, such methods are time-consuming and difficult to apply to massive datasets. Furthermore, concerns can emerge about the particular subject position(s), and concomitant bias(es), of the researcher (Clifford & Marcus, 1986).

Methods from machine learning provide an alternative approach. Roberts, Stewart, and Tingley (2014a) analyzed open-ended survey responses using topic models (Blei et al., 2003), which find statistical regularities in word co-occurrence that often correspond to recognizable themes, events, or discourses (Jockers & Mimno, 2013). This method scales to billion-word datasets and can arguably provide an analysis driven more by the documents than by human preconceptions. However, algorithmically defined “topics” run the risk of misleading researchers. Not only does properly making sense of the results require detailed technical knowledge, but these techniques forgo a certain degree of human contextual interpretive ability (Rost, Barkhuus, Cramer, & Brown, 2013). Moreover, an appeal to computational objectivity may embody fundamentally different epistemic commitments than those at work in interpretivist approaches (Ma, 2012; Orlikowski & Baroudi, 1991).

Each method thus carries its own strengths and weaknesses. We can algorithmically identify latent patterns in complex datasets with relative speed and ease, but in a way that potentially forfeits an appreciation for context, subtlety, and an interpretive approach to social reality. Alternatively, we can conduct detailed analyses of particular sociotechnical practices, but the effort involved precludes analyzing data collected from larger pools of respondents. These tensions arise not only in the analysis of surveys but also for a wide variety of data sources, from usage logs and scraped data (Backstrom, Boldi, Rosa, Ugander, & Vigna, 2012; Schoenebeck, 2014) to popular media coverage (Harmon & Mazmanian, 2013; Lind & Salo, 2002; Portwood-Stacer, 2013) to policy documents (Epstein, Roth, & Baumer, 2014).

However, we have relatively little understanding of how these differences play out in practice. Mixed methods research combines different methods (e.g., Baumer et al., 2013; Schoenebeck, 2014), but such work rarely examines similarities and differences in the methods themselves. To the authors' knowledge, no empirical comparative analysis has examined how approaches from the interpretive social sciences and computational analysis techniques either converge, diverge, or both when applied to the same data.

To conduct such a comparison, we consider a case study in social media reversion (Baumer, Guha, Quan, Mimno, & Gay, 2015), that is, when a social media user leaves a site to become a nonuser (Satchell & Dourish, 2009; Wyatt, 2003) but then subsequently returns to become a user again. Social media reversion represents a phenomenon that has been identified as important in prior work on technology nonuse (Baumer et al., 2013; Brubaker, Ananny, & Crawford, 2014; Schoenebeck, 2014) but has not yet received significant attention (Wyatt, 2003). To study this nascent phenomenon, we leverage data from an online campaign by the Dutch advertising firm Just that encouraged users to stay off of the social networking site Facebook for 99 days (http://99daysoffreedom.com/). Participants were then surveyed by Just after 33, 66, and 99 days. Of the more than 5,000 survey responses collected, 1,095 reported returning to Facebook before 99 days had passed. We analyzed these participants' descriptions of their experiences in returning to the site.

These data provide a prime opportunity to compare qualitative and computational methods. The dataset is large enough that a computational text analysis will provide meaningful results, but it is small enough to ensure that an interpretive social scientific approach remains tractable. These data are analyzed using two separate approaches—grounded theory (Glaser & Strauss, 1967) and statistical topic modeling (Blei et al., 2003)—which were conducted independently by separate authors. We chose these particular methods due to their respective popularity among interpretive and computational approaches, their roughly analogous goals of identifying thematic patterns in unstructured text data, and their popularity among information science researchers.

However, conducting a comparison of these methods purely as abstract analytic techniques would be nearly impossible. Neither topic modeling nor grounded theory are applied purely by rote. Rather, each requires nonnegligible amounts of researchers' subjective judgment, both in the application process and in interpreting results. Indeed, if two researchers conducted independent analyses following the principles of grounded theory, one would expect different results from each. Comparing these results would highlight where each analysis confirms, or perhaps discredits, the other's findings. This article takes a similar approach, but instead it compares results from a grounded theory analysis and from a topic modeling analysis. This comparison provides a better understanding of both where and how these methods for textual analysis might either converge or diverge.

Our findings show both numerous areas of resonance and some key divergences. First, the authors identified several correspondences between the grounded theory themes and the algorithmically generated topics. These correspondences did not strictly map either set of results onto the other but suggest a many-to-many, or in most cases a “two-to-two,” mapping. Second, the authors found several alignments in analysis processes. Both methods begin with a provisional model or theory that is iteratively refined based on the data. Thus, the theory or model arises primarily from the data themselves. However, what is meant in each approach by the terms “model,” “theory,” “iteration,” and even “data” differ, perhaps dramatically. Third, grounded theory and topic modeling each serve important discursive functions in terms of legitimating particular analytic practices to a broader disciplinary audience. Both approaches attempt to shift the perception of particular methods on a spectrum from impressionistic to computational (Ramsay, 2003, 2011), each moving toward a potential center but from opposite directions.

Thus, this article makes a primarily methodological contribution. It advances our understanding of how approaches from the interpretive social sciences and from computer science both resemble and differ from one another, both in terms of substantive results and in terms of analytic process. It also argues that these methods should be considered in the context of the broader theoretical and methodological shifts they represent in their respective fields. The article concludes by suggesting directions to orient future work that explores mixed computational-interpretive methods.

Related Work

The Development of Grounded Theory

Grounded theory (Glaser & Strauss, 1967) offers an orientation toward developing theories to explain phenomena observed in qualitative data. It is not a research method per se but rather includes a family of methodologies (Babchuk, 2011; Charmaz, 2006; Clarke, 2005; Corbin & Strauss, 2008; Glaser, 1978, 1992) that share common characteristics. Grounded theory is also *not* a theory per se, hence sometimes being referred to as grounded theory method (Muller, 2014).

Grounded theory also performs important discursive functions by making qualitative and interpretive methods more codified, legible to, and legitimated to a broad, diverse sociological community. As a discipline, sociology comprises a diverse set of methodological practices and disciplinary traditions (Collins, 1994; Ritzer, 1975). These approaches variously emphasize social facts (Durkheim, 1895), the social definition of social structures (Weber, 1947), social behavior (Skinner, 1971), conflict and struggle (Marx & Engels, 1848), rational or utilitarian actors (Newell & Simon, 1972), poststructuralism (Foucault, 1969), feminism (Haraway, 1991), or other traditions. Grounded theory, in addition to providing concrete guidance, makes a certain type of work comprehensible across these diverse sociological orientations.

Some orientations, such as social behavior or rational actors, emphasize theory testing, which Glaser and Strauss (1967) describe as having the following four mostly linear steps: (a) postulate a theory, (b) collect relevant data, (c) analyze that data to test the theory, and (d) interpret the analysis as either supporting or discrediting the theory. In contrast, they suggest grounded theory as an alternative wherein the processes of theorization, data collection, analysis, and interpretation can, and perhaps should, interleave with one another. Data are analyzed as they are collected, and provisional theories drive further data collection. New data are constantly compared both with previously collected data and with the theory currently under development (Glaser, 1965). In this way, “theory [is] an ever-developing entity, not a perfect product” (Glaser & Strauss, 1967, p. 31).[1]

Conceptually, this orientation aligns most closely with what Ritzer (1975) calls the social definition paradigm. It also spans what Collins (1994) calls the Durkheimian tradition and the micro-interactionist tradition. Methodologically, grounded theory suggests alternative means of establishing rigor. For instance, rather than objectivity, it emphasizes confirmation of findings, either from informants or from other researchers (Muller, 2014). Although approaches to grounded theory differ in their particulars (Corbin & Strauss, 2008; Glaser, 1978, 1992), they share in common this interleaving of data collection, analysis, and theorization.

Grounded theory and related approaches have been critiqued, both for the significant amount of human time and energy required, and because concerns emerge about bias and verifiability. For instance, many of Mead's findings about adolescent sexuality in Samoa (Mead, 1928) were later challenged as based more on her own political agenda than on empirical data (Freeman, 1983). Recently, Goffman (2014) intentionally obscured factual details to anonymize more fully her informants, since they were engaged in potentially illegal activities, thereby limiting verifiability.

Such critiques can be answered in at least two ways. First, a key strength in grounded theory and related approaches comes from intersubjectivity. Differences in researchers' conclusions can raise debates, which can then be arbitrated by a broader community of scholars (e.g., Shankman, 2009). Similarly, despite Goffman's efforts, at least one investigative reporter identified her informants and was able to fact-check aspects of her account (Singal, 2015). In some ways, this emphasis on intersubjectivity resembles the importance of replication in more traditional scientific research. Second, interpretivist analyses do not attempt a veridical representation of reality. Rather, they seek to construct a situated understanding and interpretation of human and social affairs. Goffman (2014), for instance, offers not a generalized depiction of life for certain groups but rather a detailed account of one specific social group's experiences in one particular neighborhood. This point draws attention to important epistemological distinctions between positivist and interpretivist research, which are addressed further below in the Discussion section.

Topic Modeling in Social Science and the Humanities

Computational text analysis has garnered significant attention in the humanistic and social science disciplines. Much of it centers around one method, statistical topic modeling (Grimmer & Stewart, 2013; Jockers, 2013; Mohr & Bogdanov, 2013; Rhody, 2012), which can be traced to work in the early 1990s on latent semantic analysis (Deerwester, Dumais, Furnas, Landauer, & Harshman, 1990). This unsupervised process takes only a corpus of documents as input and transforms each document into an unordered sequence of words. Documents and words are then mapped to a low-dimensional latent space wherein geometric proximity matches human notions of semantic similarity. However, the dimensions are not by themselves meaningful. Later work added probabilistic constraints (Blei et al., 2003; Hofmann, 1999), which result in a latent space consisting of probability distributions over a vocabulary. The high probability words in each distribution can be readily interpreted as recognizable themes, and are thus referred to as “topics.” For example, a topic that reflects feelings of guilt about returning to Facebook might weight heavily such words as *felt, days, myself, guilty,* *disappointed*, and *bad*. Each document is in turn modeled as a combination of these topics in different proportions.

Although many algorithms estimate topic models, most include progressive refinement of an arbitrary or random initialization. The specific algorithm employed in this article, Gibbs sampling (Griffiths & Steyvers, 2004), provides an approximate solution, since finding an optimal solution is computationally intractable. This algorithm uses thousands of iterations through the documents, considering the topic proportion of each word token in turn. Words that frequently occur together in documents are likely to be placed into the same topic, so that each document contains relatively few topics. The resulting topic allocation can be used as an overview of the contents of a corpus and as a guide to documents that exhibit a particular topic.

This method was quickly adopted in historical and literary analysis, such as collections of early American newspapers (Newman & Block, 2006). Recently, topic modeling has become especially popular in social science and humanities, with applications in areas as varied as 19th century novels (Jockers, 2013), political press releases (Grimmer, 2010), articles in literary journals (Goldstone & Underwood, 2014), and Danish folktales (Tangherlini & Leonard, 2013). Humanists and social scientists have found this kind of model useful because it takes a corpus of unmanageable size and maps that corpus down to a manageable set of dimensions that can be interpreted as themes or concepts (Jockers, 2013). The advantage of topic modeling is that it is purely data-driven, requiring no human supervision to identify and define "topics," but this power is also the source of some limitations. Not all learned topics can be mapped to recognizable themes (Chang, Gerrish, Wang, & Blei, 2009; Newman, Lau, Grieser, & Baldwin, 2010). The results are sensitive to document representation choices, such as the use of "stopword" lists (Leskovec, Rajamaran, & Ullman, 2014), which remove frequent words, as well as how data are partitioned into "documents," which may be subsections of longer works (Jockers, 2013). Finally, although the appeal of topic models is often in their perceived objectivity and data-driven rigor, topic models assist but do not replace human interpretation (Grimmer & Stewart, 2013).

Grounded Theory and Topic Modeling in Information Science

Both of these methods have seen significant uptake among information science researchers. For instance, topic modeling has been used to uncover the temporal evolution of topics in documents (Song et al., 2015), to compare between the popularity of scientific themes in open and closed access publications (Hu et al., 2015), and to detect communities of taggers in social recommendation systems (Li et al., 2011). Some preliminary work has compared machine classification with existing categorization schemes (Suominen & Toivanen, 2015).

Similarly, grounded theory has been deployed in diverse ways, such as to uncover the thematic influences behind how teenagers use social networks (Agosto, Abbas, & Naughton, 2012), to understand the practices of organizing online information within the context of large organizations (Burford, 2014), and to analyze information-seeking behaviors on Twitter (Elsweiler & Harvey, 2015). Again, some work has sought to blend qualitative and quantitative methods to generate novel approaches, for example, "group informatics" (Goggins, Mascaro, &

Valetto, 2013). Such mixed methods approaches raise numerous challenges, both in terms of technical logistics and in terms of epistemic commitments (Ma, 2012). The comparison provided in this article helps address such challenges, contributing to the growing body of work on the adoption and blending of diverse methodologies.

Methods

After describing the data and their means of collection, this section describes both the process of applying grounded theory and the process of applying topic modeling. To reiterate, these methods were applied and interpreted separately by mutually exclusive subsets of the authors. Only after each analysis was completed did the authors confer to compare their results.

Data

Information about 99 Days of Freedom was disseminated by Just via an online ad campaign.[2] The effort was also covered by several major news media outlets, including *USA Today*, *The Huffington Post*, *Time*, *Sydney Morning Herald*, *Business Insider*, *ReadWrite*, and Examiner.com. These venues were not chosen by the authors of the article but were those news media organizations who chose to cover the story.

Individuals who chose to sign up were encouraged to change their profile picture to the project's logo (Figure 1), post a status update indicating their absence, and then provide Just's staff with their email address. At 33, 66, and 99 days, Just sent participants surveys, which included a mix of Likert-style responses (e.g., “How would you rate your mood for the past 33 days?” with five responses from *very unhappy* to *very happy*) and open-ended free-text responses (e.g., “How did your friends react [to you leaving Facebook]?”). At the end of the survey, participants were given the option to share their data with university researchers. In total, 5,245 participants opted to share their data.

Figure 1 Logo used by 99 Days of Freedom organizers. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

The surveys also asked whether the participant had returned to Facebook and, if so, it asked "How did you feel about returning?" and "How did your friends react?" Across the three surveys, 1,095 (20.9%) of respondents indicated that they had returned to Facebook. These responses comprise the dataset analyzed in this article.

These free-text responses provide an optimal dataset for comparing grounded theory and topic modeling. They provide enough data that computational methods can produce meaningful results but not so much data that an iterative qualitative analysis becomes intractable.

Grounded Theory

Analysis in grounded theory involves "the discovery of theory from data" (Glaser & Strauss, 1967, p. 1). It uses an iterative process, constantly comparing (Glaser, 1965) different incidents in the data to develop conceptual categories and theoretical themes that describe or explain what is going on. Categories are revised through repeatedly finding counter-examples until themes sufficiently account for what is observed in the data. In most formulations of grounded theory, this iteration also involves repeated data collection. Because we analyze a static set of surveys, our approach may be more accurately described as using an analytic method that follows the principles of grounded theory.

We manually removed responses in non-English languages because our research team was only proficient in English. Two researchers (one in a primary role and one in a support role) then read through the remaining dataset iteratively to develop conceptual categories. For each category, the researchers noted patterns and common ideas. During this iterative process, categories were created, altered, combined, or removed to best fit the responses. As the analysis progressed, initial categories were grouped into broader, more abstract themes. For each theme, researchers wrote memos (Lofland & Lofland, 1995) that noted the constituent categories and the ideas they represented, described relationships among categories within each theme, and identified connections among the various themes. Writing the memos was also iterative, and initial drafts fed back into further revision of the themes themselves and of their component categories.

Topic Modeling

Statistical topic modeling (Blei et al., 2003) seeks to represent a set of documents as combinations of themes, where each theme consists of a probability distribution over a vocabulary (i.e., a set of words). Each of these themes can be described both in terms of the words that appear most frequently in those documents and in terms of the documents that are most representative of that theme. We use iterative algorithms that identify such probability distributions (which we refer to as “topics”) without human supervision. The only input to the model is a set of documents and a number of topics, which we set to 10 based both on the overall size of the corpus and on testing different numbers of topics between 5 and 30.

The response to each survey question is treated as a single document, yielding two documents per respondent (2,190 total documents). We split each document into a sequence of tokens (words separated by punctuation or whitespace), and changed all words to lowercase. We also removed stopwords (Leskovec et al., 2014; Wilbur & Sirotkin, 1992), a small set of high-frequency determiners, conjunctions, and prepositions (e.g., “the,” “and,” “for”). We used Mallet (McCallum, 2002) to train Latent Dirichlet Allocation (LDA) topic models. As LDA is an approximate algorithm that produces different results based on different initializations, we ran 10 independent random initializations and verified that the same topics repeated with small variations in every case. For simplicity, we used a consistent number of topics and observed variability across random initializations. Future work could explore the effects of using more or fewer topics.

Results

This section first presents the grounded theory results in terms of high-level themes. It then presents the topic modeling results, which consist primarily of the 10 topics and the various experiences described in responses representative of each topic. We then identify alignments and disconnects by comparing the two sets of results. The ramifications of this comparison are considered further in the subsequent discussion section.

Throughout the results, quotes from participant numbers are denoted with the format XX.YYY, where XX is either 33, 66, or 99 for the survey from which the quote is taken and YYY is a participant ID number. For legibility, we have omitted [sic]; all quotes are verbatim.

Grounded Theory Results

The grounded theory analysis yielded five high-level themes that organize the conceptual categories identified during the analysis. Together, they speak to the ways that a sense of agency mediate technology (non)use. Respondents experience tensions between, on the one hand, striving for a sense of control over their own technology use and, on the other hand, the desire, or in some cases the need, for social communication and (re)connection.

Triggers for returning

Many respondents describe returning to Facebook in response to a specific trigger event, Triggers included, for example, work or school obligations, for example, “I hated returning to Facebook. I ONLY did it because of work” (33.3607). Individuals reported experiencing negative emotions such as disappointment since they intended to stay off for the entire 99 days but returned prematurely.

Triggers also included major life events such as engagements, births, or deaths. For instance, one individual returned after news broke reporting that Robin Williams had passed away, and she “felt the need to be a part of a shared mourning experience” (33.9112). For many individuals, Facebook served as a platform to broadcast personal milestones, support connections, and share experiences; for instance, “My daughter was born and I wanted to tell everyone, where else to spread the news?” (33.25218). Collectively, triggers denote an abdication of agency. Participants did not want to return, but they “had” to for reasons beyond their control. Many of these reasons dealt with social connection.

Social (re)connection and communicative necessity.

Connecting or reconnecting with friends and family represented both a frequent trigger to return and an action taken upon return. Many people report returning primarily to view the lives of their Facebook friends. “I don't want to post anything anymore” said one respondent, “I prefer to just check in to see what others are doing” (99.51149). Others described “lurking in messenger” or using the social network now to just “check in” on others, that is, what Marwick (2012) calls social surveillance. Interestingly, some respondents report turning to Facebook to help boost their mood when they feel down. For example, one respondent returned to Facebook because she expected “something hilarious [to] come up to make [her] laugh” (99.48121).

In some cases, Facebook offered the only platform available for certain kinds of communication. Although many attest to Facebook providing genuine value, respondents report becoming dependent on the social networking site and feel a strong sense of “disconnection” when they leave for a period of time. One respondent likened returning to

Facebook as “return[ing] from being stranded on a desert island” (66.31001). Although some individuals report positively on regaining the social connection with their network, others report being conflicted about their decision.

These conflicted individuals report feelings of frustration and guilt for the act of returning early, which they perceive as indicating decreased self-agency. Although the early return can create feelings of disappointment, being reconnected to family and friends often outweighed the negativity. For example, one respondent felt “frustrated that [he] could not complete the task. But all right about the fact that [he is] connected” (33.27282). For these individuals, return serves as a revitalizing experience of reconnecting with Facebook friends.

Morality

Regardless of a respondent's level of remorse, moral overtones characterized many descriptions of reversion. The inability to curb one's own urges was seen as a sign of weakness, a personal moral failing that led them to feeling ashamed and “sorry for [them]selves.” Even the minimal task of “logging in” or a “quick read” can make individuals feel guilty, as though one has “…cheated on a spouse or something” (33.11610). In some cases, respondents justified their actions by qualifying them. For example, one respondent “only logged in… [and] didn't stay connected for more than 10 mins” (99.55329). Another respondent said, “I have not posted or commented or checked out news feed” (66.34938). These lesser evils suggest a hierarchy of perceived intensity (cf. Ellison, Steinfield, & Lampe, 2007) for actions on Facebook (e.g., is posting a photo worse than checking the news feed?). They also imply normative, moral judgments (cf. Dourish & Satchell, 2011) dictating how one should (or should not) be using social media.

Renegotiating use

Many who returned to Facebook described attempts to reign in their Facebook habits. These respondents used 99 Days to kick start a process of reducing and/or renegotiating their engagement with and through the site. Some approaches leveraged affordances of Facebook itself, such as friend count reduction (cf. Gershon, 2011) or “no longer us[ing] Facebook Mobile” (33.9278). Other respondents described a self-regulation process in which they engaged with the site differently. One respondent said, “I didn't just randomly check everything I saw anymore, because I knew that led me to feeling lost and purposeless” (66.39761).

On the other hand, some individuals describe reversion as a complete lack of control. Often, this experience is described in terms of feeling “addicted” Facebook, “like it was a drug calling me back” (33.3505) or “when smokers see an ex-smoker go back to smoking” (33.714). One respondent said, “I only [came back] for my job. At first i thought i will only use it for work purposes only, but by today i am totally addicted again” (33.26864). These respondents returned not because they had more control but because (they felt) they had lost control.

Friends' reactions

When respondents returned to Facebook, their friends' reactions ranged from oblivion, to concern, to accusations. In some cases, respondents noted that they received no reaction from their friends, which could have many causes. The respondent might not have been back long enough for anyone to respond, the respondent's absence may have gone unnoticed in the first place, or the newsfeed curation algorithm could have limited which of the respondent's posts that friends saw. Those who did not notify their Facebook friends about joining the experiment more often described that, for example,, “[My friends] were worried that something bad happened to me since i rarely visited FB” (66.39062).

On the other hand, those who did notify their Facebook friends evaluated reactions by the amount of Facebook activity, such as “likes,” comments, or posts. Some respondents reported that their friends responded to their return in a joking, amicable fashion. Some participants reported being questioned by friends regarding their commitment to stay true to the experiment, for example, “Has it been 99 days?” (66.31859). However, other participants' friends respond to the return in a disagreeable manner. One respondent said, “My friends didn't like my return, because they think I could have broken the ‘promise' I've made” (66.41326). That is, from these friends' perspective, the act of returning early exposed a lack of self control, a character flaw that might carry over into other arenas.

Synthesis

Each theme reflects different facets of experiences related to respondents' individual sense of agency and self control. The various triggers that prompted reversion, such as needing Facebook to communicate or the strong desire for social (re)connection, suggest limits to one's own control over social media use. Respondents' renegotiation of their Facebook use offers an instance in which reversion can demonstrate an increased sense of agency. Both respondents' and their friends' reactions demonstrate how reversion is often perceived as a character flaw or moral failing, because it exposes the individual's lack of control over her or his own impulses and desires.

Topic Modeling Results

We analyzed the results of a topic model trained on the same data. We describe results in terms of each topic through two criteria. First, a topic is defined by its probability distribution over words, so we show the top 25 most probable words and describe patterns in these words. Second, after describing the words, we sort responses by their concentration in each topic and analyze the top 50 responses. This provides the 50 most representative responses for each topic, from which we provide a selection of quotes, along with each quote's rank for that topic in brackets. Based on these criteria, we manually assign a high-level descriptor for each topic. We do not analyze three topics. One (topic 6) consists of non-English words (mostly Spanish, Portuguese, and Dutch). The second (topic 9) consists of metadiscourse relating to a confusing survey instruction and a grammatical error. The third (topic 10) showed drastic variations across the 10 different random initializations and thus does not capture any robust statistical regularity. Because the use of topic modeling is not as developed a method, we do not synthesize across the topics as in the grounded theory analysis above.

1 Positive response from friends

Top 25 words: *back, happy, i'm, off, see, still, very, nothing, some, said, you, days, i've, would, friends, knew, when, got, make, missed, glad, changed, surprised, made, again*

The topic contains many emotion words, as well as past-tense verbs: missed, changed, surprised, made. When we sort responses, the top-ranked statements pertain to friends' responses. Friends are usually described as either happy or not surprised, for example,, they “knew” the respondent would be back.

> [1] “I changed my profile picture and I had a lot of likes but nothing special” (99.51850).
> [4] “Theyre happy that Im back … Hahaha made fun of me! Hahah” (33.28230).
> [6] “They said they knew I'd be back” (33.2575).

2 Necessary for communication

Top 25 words: *with, friends, people, contact, because, way, only, other, family, some, keep, touch, needed, talk, could, who, need, really, also, phone, all, communicate, felt, miss, certain*

The topic contains words about contact and connections (talk, family, friends, communicate, touch), as well as words relating to exclusivity and constraint (“only way” and need). Example responses describe Facebook as the only connection with friends and therefore a necessity. Responses include examples of tragedies, where communication becomes a need. Distance also emerges as important in terms of contacting overseas friends or distant relatives. A few respondents treat this negatively—they found they did not need to contact people, or they had other ways to contact important friends.

> [1] “mixed, but it's an easy way to keep connected with some of my friends - facebook is our main connection because we live far apart.” (33.30393).
> [5] “I felt good because I needed to talk to people who only keep in touch through Facebook.” (33.7904).
> [6] “I was annoyed that I couldn't hold out, but I also needed to have conversations with people who I only have contact with on Facebook” (33.3625).

3 No reaction

Top 25 words: *don't, know, about, care, really, one, think, some, people, friends, even, what, notice, noticed, just, most, did, haven't, anything, want, reaction, many, miss, return, there*

Words in this topic pertain to relationships (friends, people) and reactions (care, notice, reaction, miss). Negative words frequently occur (don't, haven't). Many words relate to degrees (one, some, even, just, most, many). Almost all representative responses deal with friends (or sometimes the respondent) not caring about or not noticing the respondent's absence.

> [1] “Not many seem to know about it. A few have asked me how it is to not be on Facebook and have asked me if I miss it.”
> [2] “I don't even think they noticed that I left, but plenty of people ‘liked' my return” (33.6417).
> [4] “I don't know. Either they didn't notice or they didn't care.”

4 Brief, focused, guilty return

Top 25 words: *only, just, check, messages, returned, because, did, logged, get, out, there, off, back, minutes, once, day, log, page, went, news, times, information, work, account, post*

The words relate to access (logged, check, log, account), time (minutes, day, times), and small quantification (just, only, once). Representative responses relate to brief relapses, almost always for a specific reason (check messages, show a picture, work). Respondents always emphasize brevity and the fact that they immediately left and have not returned. Respondents often report feelings of guilt or distaste.

> [1] “I only occasionally returned for the business/work related pages I run […]. However I have not looked on my personal account” (33.27058).
> [3] “Got sucked in. But i quickly went back to staying off and just checked it once a week for responses to messages” (33.6472).
> [4] “A little defeated….I wanted to show a picture to someone and logged on to show it but did not check notifications or feeds or anything” (33.2239).

5 Negative emotions (guilt, disappointment, addiction)

Top 25 words: *like, felt, because, stay, days, myself, after, returned, feel, away, off, time, guilty, again, good, disappointed, when, used, first, bad, wanted, returning, being, little, wasn't*

Here words relate to emotion (felt, feel, guilty, disappointed, wanted) and time/distance (away, off, time, when, first, again). “Myself” is prominent. Responses convey mostly negative emotion on returning, usually inwardly directed such as disappointment and guilt. Responses include frequent references to smoking, dieting, and cheating. Returning is described as a defeat or a failure. In contrast, some respondents feel negative about the time spent away and are happy to return.

> [1] “I felt guilty for not being able to stay off for as simple has 33days” (33.1718).
> [4] “I felt guilty and like I was breaking my word” (33.8568).
> [5] “Like I said. I peeked on two occasions. Like I took two sneaky puffs of a cigarette. A bit guilty, but all the more motivated to stay away!” (33.167).
> [9] “I felt I lost precious time being outside, and when I returned I felt pretty good” (33.30926).

6 Stories, obliged return, immediate reaction

Top 25 words: *she, her, friend, our, one, wanted, death, photos, best, about, his, book, saw, always, else, since, same, wedding, hold, place, signed, immediately, got, shared, everyone*

The topic contains numerous pronouns (she, her, our, his) and temporal terms (always, else, since, immediately). There are some references to events (death, wedding). This topic is less interpretable from the word list than other topics. The responses tend to be much longer than other topics, usually providing small stories. These are occasionally positive, such as a wedding, but usually they are bad, often someone dying or becoming seriously ill. Sometimes this is phrased negatively, for example, "I haven't missed a birth or death.…" A few times people mention friends who immediately contact them when they return, often after specifically waiting for them in order to "catch them." Other respondents report friends who do the opposite, telling them to sign out immediately to maintain their pledge.

> [1] "I don't really classify it as returing to facebook as a woman in her 80's called to ask me to verify an address for a book signing that was only listed on a persons facebook page. […] the book signing [was] over an hour away and she would need to secure a ride and have an accurate time. So, I did log into my husbands facebook, went directly to that persons page, got the information and signed back out immediately" (33.30075).
> [2] "I'm adding this response despite the fact I'm off Facebook. I have one friend I've known since childhood (over 44 years). We have gone through the deaths of our parents, siblings and our divorces. I'd thought we would always be there for one and other. I'm sad to say, that's no longer the case. She lives on Facebook and has her smart phone on all day long. She […] appears to live for the numerous posts she follows. By and large she has stopped connecting in the real world. She no longer visits for birthdays or holidays and posts about her life online. She was somewhat upset I'd quit Facebook, and wondered how she could keep in touch with her 'best friend'. I cried when she asked me that question, because the answer seemed obvious to me."

7 Positive emotions, changed use

Top 25 words: *time, feel, now, will, more, use, less, much, return, like, don't, think, good, it's, than, before, with, want, experiment, all, using, life, bad, can, when*

The topic contains many short words. Many are present tense verbs (feel, will, use) or relate to quantification or comparison (now, more, less, much). Responses are usually short. Almost all are positive, reporting less engagement with FB. Some are happy to disconnect completely, others report that their use pattern has changed, saying, e.g., they will be more selective about friends or modes of use. Attitude towards return is usually positive, with greater control and less compulsion, although some describe mixed feelings, slight guilt, or other nonintense emotions.

> [2] "I think without it life will be smoother. So dont think I need it. yes if it necessary later I ll decide that time." (33.25489).

[3] “I think i feel less tied to it. i definitely don't go on it as much even with the short break. i kind of use it more like a news app now instead of a social app.” (33.12481).
[4] “Little Guilty, feeling less addicted because I spent less time on facebook and using it for over purpose than stalking” (33.981).

Comparison of Results

The topic modeling results captured to a surprising degree many of the themes identified in grounded theory, and vice versa. Table 1 summarizes these correspondences. Each topic aligned with some aspect of at least one, in most cases two or three, themes. For instance, topic 4 described utilitarian needs to look up information (e.g., email address or event location) as a particular type of Trigger. Respondents expressed guilt (i.e., Morality) about these returns, but qualified that guilt with the brevity of their return.

Table 1. Similarities between topics identified in topic modeling (left) and themes identified in grounded theory (top).

	Triggers for returning	**Communicative necessity**	**Morality**	**Renegotiated**	**Social reconnection**	**Friends' reactions**
1. Positive response from friends						Friends had positive reactions
2. Necessary for communication (distance, tragedy, etc.)	Need to communicate as a type of trigger	Reasons for communicative necessity				
3. No reaction						Friends showed no reaction
4. Brief, focused, guilty return	Utilitarian (e.g., info seeking)		Qualified guilt			
5. Negative emotions (guilt, disappointment, addiction)			Guilt, let myself down	Addiction implies limited control		
7. Stories, obliged return, immediate reaction	Major life events as triggers				Welcomed back	Mixed reactions
8. Positive emotions, changed use				Increased self control	Positive about reconnecting	

- *Note*. Cells describe how each topic resonates with one or more themes.

Similarly, most themes resonated with at least one, usually two or three, topics. For instance, for the Renegotiated theme, responses from topic 5 highlighted instances where respondents felt a loss of control, while responses from topic 8 described increased feelings of self control.

None of the grounded theory themes were completely unaccounted for in the topic modeling results. The only topics that found no resonance among the grounded theory themes were those excluded from the analysis (see Topic Modeling Results, above).

Despite their strong correspondences, these two results are not the same. The many-to-many, often "two-to-two," mapping in Table 1 shows that neither topics nor themes are interchangeable, nor is one simply a refinement of the other. In several instances, both the topic model and the analysis based on grounded theory identify the same excerpts from the data as emblematic of a certain theme. However, because there is no simple one-to-one correspondence between topics and themes, quantitative measures of intercoder agreement would not be meaningful. Because no theme–topic pair describes the exact same phenomenon, we would not expect those responses coded for a given theme to align exactly with those identified as having a high proportion of a related topic. Even when grounded theory analysis is conducted by multiple researchers, agreement is rarely, if ever, quantified at the level of individual coding units (Glaser & Strauss, 1967). Instead, researchers look for alignment at the level of basic themes (Armstrong, Gosling, Weinman, & Marteau, 1997). Similarly, the key point here is the degree of resonance in the higher-level findings from the two analyses.

That said, the topics appear to describe patterns at a slightly lower level of abstraction. Topics captured constituent components of the themes. For example, several topics identified different types of triggers for returning to Facebook, but no single topic aligned with the higher-level theme of triggers. In applying LDA (Blei et al., 2003) to Finnish scientific papers, Suominen and Toivanen (2015) similarly found that, in most cases, the topic model included finer distinctions than existing classification schemes. For instance, the Organization for Economic Cooperation and Development classification for medical research includes 10 subfields, but documents in that classification came from over 26 different topics (Suominen & Toivanen, 2015, p. 7). In our work, we see topics as more analogous to Glaser and Strauss's (1967) categories, groups of responses that have some conceptual property in common, which then are (or need to be) organized into higher-level coherent themes.

To summarize, the degree of similarity between the topic modeling and grounded theory results represents a major finding and contribution to our understanding of both these methods.

Discussion

Our results provide important insights about both topic modeling and grounded theory as analytic methods. Furthermore, our experiences may usefully inform future work combining computational and interpretive approaches.

Comparison of Methods

Convergence

We identified three primary resonances between grounded theory analysis and topic modeling analysis.

First, both methods identify thematic patterns. Topic modeling does this by algorithmically seeking statistical regularities in language use. Grounded theory employs constant comparison (Glaser & Strauss, 1967, pp. 101–115; Glaser, 1965) among incidents in the data to draw out conceptual similarities. Because grounded theory involves repeatedly reading every incident in the data, it has a better chance of finding the proverbial needle in the haystack. However, both methods still focus on overarching patterns and themes.

Second, both methods are grounded in the data. In topic modeling, the probability distributions are initialized randomly, and any patterns that emerge do so directly from the data. Similarly, the conceptual categories of which themes in grounded theory are constituted also arise, in potentially varying degrees (Corbin & Strauss, 2008; Glaser, 1978, 1992), directly from the data. This grounding does not guarantee that two researchers both conducting an analysis by following principles from grounded theory will arrive at the same results. Grounded theory and similar approaches rely on comparative analyses across multiple studies to confirm, or to discredit, individual findings. However, no such guarantee exists for topic modeling, either. Not only does the random initialization mean that no two solutions will be exactly identical, but the step of interpreting the topic distributions and representative documents for each topic allows two researchers looking at the same algorithmic output to draw different conclusions.

Third, both methods involve an iterative process. In an analysis based on grounded theory, data are iteratively self-compared, grouped and regrouped, analyzed and reanalyzed, until a satisfactory explanation emerges. Analysis using topic modeling begins with a random distribution for each topic and then iteratively refines those distributions. These iterations continue, saving samples periodically, until topics averaged over multiple samples do not change with further iterations. Both these processes involve positing a provisional explanation, testing the explanation against the data, and iteratively refining the explanation until further iterations produce no significant changes in the resulting themes. Others have also noted such similarities (Muller, Shami, Geyer, & Davis, 2015), although with respect to machine learning more generally rather than topic modeling specifically. Of course, what is meant here by “explanation,” “theme,” and even “data” differs, perhaps dramatically, between the two methods in question.

Divergence

Data analysis in grounded theory leverages a researcher's complex contextual knowledge. For instance, identifying a collection of experiences as related to boundary negotiation (Palen & Dourish, 2003) or social surveillance (Marwick, 2012) requires knowing how those phenomena can manifest. In contrast, topic modeling does not use part-of-speech, grammatical relationships, or even word order, let alone higher-level constructs such as humor, irony, or figurative language. Topic modeling only incorporates statistical regularity in word usage. Our results suggest that, even with this fairly blunt approach that ignores much contextual information, statistical topic models identify patterns that, at some level, align with those found by human researchers. This finding echoes Rhody's (2012) result that the model does not need to understand the figurative nature of a metaphor to recognize the patterns of language that instantiate that metaphor.

Grounded theory and topic modeling analyses also require different amounts of time. The grounded theory analysis took two researchers several hours of work per week over roughly 2½ months. In contrast, a single researcher conducted and wrote up the topic modeling results within a few hours over 2 days. The primary difference was the time spent reading. With grounded theory, every single response was read and reread multiple times. With topic modeling, only a selection of the responses was read and reread, still iteratively, but requiring far less reading time than the grounded theory analysis.

Finally, the methodological underpinnings of grounded theory and topic modeling make differing epistemic commitments. Grounded theory draws on an interpretivist tradition, which "asserts that reality, as well as our knowledge thereof, are social products and hence incapable of being understood independent of the social actors (including the researchers) that construct (cf. Charmaz, 2006) and make sense of that reality" (Orlikowski & Baroudi, 1991, p. 13). In contrast, most computational techniques come from a positivist tradition, which assumes "an objective physical and social world that exists independent of humans, and whose nature can be relatively unproblematically apprehended, characterized, and measured" (Orlikowski & Baroudi, 1991, p. 9). We must acknowledge the complexities inherent in combining methods that originate in different epistemological traditions (cf. Boehner, Vertesi, Sengers, & Dourish, 2007; Ma, 2012). Indeed, epistemic tensions repeatedly emerged during the authors' discussions, and elements of these tensions remain to be resolved in future work. However, both this article and other examples (Jockers, 2013; Leahu & Sengers, 2014; Mohr & Bogdanov, 2013; Rhody, 2012) suggest that, equipped with a critical awareness for these issues, researchers can combine diverse methods in meaningful, compelling ways.

Implications

These results carry significant implications for the broader use of both topic modeling and grounded theory. Topic modeling is based on a rich underlying mathematical framework. However, that framework provides little reason to expect that the word distributions in topic models would align in any meaningful way with human interpretations. Indeed, not every similar computational model has such interpretable dimensions (Deerwester et al., 1990). Despite the fact that this interpretability is essentially an unintended artifact, researchers have been using topic in this interpretive fashion (Jockers, 2013; Mohr & Bogdanov, 2013; Rhody, 2012) without clear evidence that doing so was reasonable. Our results suggest that, yes, topic modeling results can align with results from human-only interpretivist analyses. However, our results come from a single study. Future research should conduct similar comparisons to identify the circumstances under which such alignments do and do not occur (see A Conjecture, below).

Similar questions could be raised about analytic methods following the principles of grounded theory. When a researcher notices a “conceptual similarity,” what aspects are actually being seen as similar? Our results suggest at least two possible interpretations. First, it is possible that the human researcher subconsciously notices subtle linguistic regularities, and that these are the same regularities drawn out by topic modeling. That is, at some level, grounded theory and topic modeling may be doing essentially the same thing. However, this possibility seems not only unlikely but also de-emphasizes the crucial contextual knowledge that a human researcher brings to bear. As a second and perhaps more likely possibility, these more abstract constructs may be instantiated through algorithmically identifiable statistical regularities in lexical choice. That is, topic modeling and grounded theory do distinctly different things, such that one does not provide an interchangeable stand-in for the other.

Moreover, we do not believe that this comparison represents a contrast between a “positivist” and an “interpretivist” perspective3 (Ma, 2012; Orlikowski & Baroudi, 1991; Palen, 2015). Epistemological commitments are revealed not via particular data collection and analysis methods but in the overall research design and orientation. Qualitative approaches can be used in a manner that attempts to uncover an objective reality (Myers, 1997), and machine learning has been incorporated into interpretivist work (Leahu & Sengers, 2014).

Instead, a continuum of approaches spans from “computational” to “impressionistic” (Ramsay, 2003, 2011). Within sociology, grounded theory moves qualitative work slightly away from the impressionistic end of the spectrum and toward the computational end, making qualitative work both legible by and legitimated to a broader community of sociologists (Star, 2007). Conversely, recent use of topic modeling by social scientists and humanists (Grimmer & Stewart, 2013; Jockers, 2013; Mohr & Bogdanov, 2013; Rhody, 2012) shifts that method away from the computational end and toward the impressionistic. The topic model is not a direct representation of observations. Rather, the model is a text to be read and interpreted (cf. Leahu & Sengers, 2014; Underwood, 2014). Probability distributions of words can be suggestive, especially in retrospect. However, the most valuable insights from the topic modeling analysis presented here came from reading (and rereading) the responses with the highest proportion of each topic. Indeed, “the question these methods propose is not, ‘What does the text mean?' but [how] can we ensure that our engagement with the text is deep, multifaceted, and prolonged?” (Ramsay, 2003, p. 170). Thus, we should not think of topic modeling as replacing human reading (Grimmer & Stewart, 2013); a statistical model of word co-occurrence cannot provide even remotely actionable meanings for those co-occurrences. Rather, topic modeling provides a method for selecting what to read and organizing documents into groups that are likely to be thematically coherent. The question of whether other computational approaches to text, such as sentiment analysis (Pang & Lee, 2008), always require human interpretation should be explored in future research.

Suggestions for Future Work

The comparison in this article between grounded theory and topic modeling suggests some deep, potentially surprising resonances between human and computational content analysis. From these findings, we distill two sets of suggestions, one for those who use grounded theory (and related analytic methods), and one for those developing topic modeling algorithms (and similar computational techniques).

First, practitioners of grounded theory can benefit from incorporating computational techniques into their work. Algorithmic approaches may be able to operationalize at latent variables the patterns, themes, or concepts identified by qualitative researchers. As noted elsewhere in this article, such algorithmic approaches complement rather than replace existing researcher practices. First, they can scale to much larger quantities of text and process that text more quickly than a human can read. Second, they can provide researchers with an alternative lens through which to observe their data. In our work, we find that algorithmically generated topics match closely to human generated themes. However, the two views are rarely exactly aligned, and the algorithm does not capture the high-level conceptual patterns identified by humans. Computational models thus offer one kind of empirical evidence that can be used in conjunction with other kinds of empirical evidence (transcripts of interviews, field notes, archival documents, etc.) to support an argument. Such models-as-evidence do not necessarily provide the researcher with something more than would be available with traditional methods. Rather, they provide something different, an alternative lens for interpretation.

Second, developers of topic models and associated algorithms may benefit from considering how those models are used and interpreted. Much computational work on evaluating topic modeling is based on optimizing specific metrics, such as log probability or topic coherence (Chang et al., 2009). The metrics used to assess performance at such tasks do not necessarily map well onto the emerging practices of researchers who are using topic modeling (e.g., Mohr & Bogdanov, 2013; Rhody, 2012; Roberts et al., 2014b). Rather than providing definitive answers, the results of topic modeling could instead be seen as providing a scaffolding for human interpretation. For example, recent work suggests that topics can be valuable as a means to help define categories (Poursabzi-Sangdeh, Boyd-Graber, Findlater, & Seppi, 2016). It may be possible to develop performance metrics that focus not on simply finding coherent groups of words (Chang et al., 2009) but rather on detecting concepts, themes, or constructs grounded in text. Indeed, topic models may actually be more valuable if they provide some uncertainty and interpretive flexibility (Pinch & Bijker, 1987) in their results.

Conclusion

This article provides a methodological comparison of grounded theory and topic modeling. Separate researchers used each approach to analyze the same dataset. The results show a surprising degree of alignment in the findings arising from the two methods. This article provides two primarily methodological implications.

First, the comparative analysis presented here reveals both striking similarities and key differences between grounded theory (Glaser & Strauss, 1967) and topic modeling (Blei et al., 2003), both in terms of their respective processes and products. Not only does this comparison enable more informed methodological choices, it also advances our understanding of the relationships between interpretive approaches and computational analysis techniques. Second, these results suggest compelling possibilities for future work on mixed methods approaches that blend computational analysis and impressionistic criticism (Ramsay, 2003, 2011). While the examples here use free-response survey data, similar approaches could be applied to interview transcripts, diary entries, or other semi- or unstructured texts. This article articulates several important tensions that should be addressed as researchers leverage computational methods to grapple with massive quantities of data while simultaneously maintaining the linguistic, contextual, and interpretive insights that can only come from human reading.

- 1 A parallel can be drawn here to developments in statistics contrasting exploratory data analysis (Tukey, 1977) with traditional hypothesis-testing methodologies.
- 2 Official press release available at http://99daysoffreedom.com/press-release.pdf
- 3 We see parallels with the tension among statisticians between frequentists, who describe events in terms of underlying probability distributions, and Bayesians, who focus on observers' beliefs about the likelihood of different events. Full explication of this parallel, however, exceeds the scope of this article.

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