Content Analysis

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Abstract

In the era of "big data," the methodological technique of content analysis can be the most powerful tool in the researcher's kit. Content analysis is versatile enough to apply to textual, visual, and audio data. Given the massive explosion in permanent, archived linguistic, photographic, video, and audio data arising from the proliferation of technology, the technique of content analysis appears to be on the verge of a renaissance. In this essay, I discuss cutting-edge examples of how content analysis is being applied or might be applied to the study of areas as diverse as education, criminology, and social intelligence.

INTRODUCTION

In the past 20 years, technology has profoundly changed the way people communicate. The widespread proliferation of email, the web, digital photography, social media, YouTube, text messaging, and cellular phones has yielded unprecedented amounts of permanent, archived data on individuals. As a result, analysts have dubbed this the era of "big data." Both private corporations and public governmental entities are actively attempting to mine this data to discover patterns of individual and group behavior. However, in order to fully leverage the power of big data, the appropriate methods for data analysis must be used. Consequently, the methodological technique of content analysis appears to be on the verge of a renaissance. Content analysis can be used with a wide variety of data sources, including textual data, visual stimuli (e.g., photographs/videos), and audio data. In addition, the technique is highly flexible in that it can be either empirically or theoretically driven. In this essay, I discuss modern examples of content analysis studies that draw on each of the aforementioned sources of data and highlight emerging trends in this area.

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Content Analysis of Textual Data

By far the most frequently used data source for content analysis is written text (Krippendorff, 2012). Perhaps one of the most prominent areas where text-based content analysis is being used is within the realm of automated essay scoring in education (Shermis & Burstein, 2013). The various approaches to content analysis in this domain range in complexity from simple keyword scoring, in which participants are given credit for including certain keywords in their essay, to more advanced approaches that use Bayesian probabilities to determine the likelihood that high-scoring essays would use a particular set of words in a particular order (Landauer & Dumais, 1997). However, what most of these programs have in common is that they are empirically driven rather than theoretically driven.

EMPIRICALLY DRIVEN CONTENT ANALYSIS MODELS

Despite the fact that scholars have been experimenting with different approaches to automatically analyzing the content of educational essays for quite some time (Page, 1966; Shermis & Burstein, 2002), efforts to score essays in a large-scale, high-stakes context have had limited success to date. Indeed, the College Board, makers of the SAT, has just announced that it will be rolling back the required writing section that was introduced as part of the SAT in 2007. Their 7-year experiment in automated content analysis of student essays was plagued by technical problems. For example, Les Perelman of MIT conducted investigations exposing several of these flaws (Weiss, 2014). He replicated the common finding in the literature that length of essay tends to be positively correlated with essay score (Page, 1966, 1994), but he also found some idiosyncrasies associated with the ETS automated scoring algorithm. For example, his research found that essays using so-called fancy words, such as "myriad," were rated more highly, even if the words themselves had no relation to the content of the essay. Furthermore, by using quotations, even when it had nothing to do with the topic, students tended to increase their scores.

Interestingly, the automated content analysis of student essays need not be so rudimentary. One of the most impressive approaches to automatically content analyzing large bodies of text that I have encountered is Latent Semantic Analysis (Landauer & Dumais, 1997; Landauer, Foltz, & Laham, 1998). This technique uses Bayesian analyses to determine the likelihood that a quality essay would contain words in a particular context. The downside of the technique is that the algorithm requires a large body of data on which to be "trained." That is to say, there needs to be a predetermined corpus of high-quality as well as marginally acceptable answers with which to train the program initially. Nevertheless, the technique shows considerable promise and represents a major advance over more simplistic scoring techniques. Given the promise of these more advanced techniques, it is somewhat surprising that ETS was so attached to their flawed e-Rater program, which operates using a far more rudimentary algorithm (Burstein, 2003).

The ability to automatically and accurately content analyze large bodies of textual responses will ultimately determine the success or failure of the latest trend in higher education—massive open online courses (MOOCs). Although MOOCs have many promising elements, not the least of which is the capacity to provide instruction to hundreds of thousands of students simultaneously, what will truly determine whether this technology is here to stay or whether it becomes just another educational fad is whether the content providers can effectively solve the problem of rapidly and automatically content analyzing textual responses to written prompts. It is worth noting, however, that even an automated approach does not completely eliminate the need for human raters. Someone still has to make judgments about the quality of responses in order to train any program on what patterns to look for and this process is, in effect, a content analysis. Once that has been accomplished, however, preliminary studies have demonstrated that various automated programs can be trained to very high consistency estimates of interrater reliability with human raters (Shermis & Burstein, 2003).

EMERGENT CODING AND GROUNDED THEORY APPROACHES TO ANALYSIS

A second approach to content analysis that is somewhere between a purely empirically derived model and a purely theoretical one is a model known as *emergent coding*. This approach is derived from the qualitative research concept of grounded theory (Glaser & Strauss, 1967). Specifically, one may approach an analysis without a particular theory in the first place, but then use the data under investigation to develop a theory. This theory is then applied to the subsequent data. One example of such approach comes from my work with Damian Bebell in which we have analyzed the mission statements of a wide variety of schools (Stemler & Bebell, 2012; Stemler, 2012). To briefly summarize our approach, which has been reported in greater detail elsewhere (Stemler, 2001), we began the process by identifying a set of school mission statements. Each of us then independently read and generated coding categories for each of the themes we encountered. We met to review the themes, revised them, and then recoded the data until we reached a consensus. We created a coding rubric and recruited new, independent raters to code a new set of mission statements according to our scheme. The independent raters reached high levels of agreement, indicating that our coding scheme was reliably detecting the derived coding categories. From this process, we developed a theoretical model about the various purposes of schools and we have subsequently analyzed thousands of school mission statements using this framework.

Using content analysis, we are able to detect the extent to which changes in educational policies or events in popular culture have impacted the mission statements of schools. For example, in one study (Bebell & Stemler, 2004) we randomly sampled a set of high schools in Massachusetts before the implementation of high-stakes graduation requirements and analyzed their mission statements. We then did a follow-up analysis of the mission statements of these same high schools 5 years later, after the implementation of high-stakes graduation requirements and found that schools that changed their mission statement tended to make more references to the cognitive purposes of schooling and had reduced or expelled their references to broader themes associated with physical development, citizenship, and social-emotional development. In another study (Stemler, Bebell, & Sonnabend, 2011), we found that the majority (62%) of a random sample of high schools in Colorado stated that providing a safe environment for children was one of their primary purposes. The presence of this theme was far more pervasive in schools in Colorado than for schools in any of the other nine states in our sample where it showed up in only 29% of all school mission statements. This result was almost certainly influenced by the Columbine school shootings. We expect that a comparison of school mission statements throughout the state of Connecticut collected before the December 2013 massacre at Sandy Hook elementary school would show systematic differences compared to the mission statements of the same schools collected after the incident. Specifically, we would predict a statistically significant increase in the emphasis on safe environment in these schools. Our approach to content analyzing school mission statements allows for the quantitative evaluation of such a hypothesis.

THEORETICALLY DRIVEN CONTENT ANALYSIS MODELS

A third area where text-based content analysis methods have been widely used is in the area of law enforcement. In the mid-2000s, the Federal Bureau of Investigation (FBI) assembled a team of content analysts to evaluate the authenticity of particular counterterrorism documents associated with Al-Qaeda in order to (i) determine whether new documents that had emerged were authored by either Osama bin Laden or the man in charge of Al-Queda at the time, al-Zawahiri, and (ii) determine whether any theoretically driven content analysis models could successfully predict future terrorist activity. The team included several content analysts, each with their own theoretically driven approach. The results were published as part of a special issue of the journal *Dynamics of Asymmetric Conflict* in 2011 and were also recently compiled into a book edited by Allison Smith (2013). Dechesne (2013) provides an excellent review of the book in which he notes that the various authors approach the analyses of the same corpus of text using different theories. For example, Winter (2011) uses McClelland's theory of needs (power, achievement, and affiliation) as a lens by which to analyze the data. By contrast, Pennebaker (2011) is focused not on the substance of the content but rather on the grammatical style. Specifically, Pennebaker used an algorithm he codeveloped called linguistic inquiry and word count (LWIC) that can be used to determine the degree to which selected texts use positive or negative emotion words, self-references, causal words, and 70 other dimensions. Other authors used other theories, sometimes relying on the same computer program to analyze the same corpus of data using a different theoretical framework. Dechesne notes that, "Across authors and methods, terrorist rhetoric is found to be of lesser complexity, to come with greater emphasis on affiliation, to stress issues of control and power, while remarkably, violent and non-violent organizations do not differ in their hostility against their adversaries, only in the methods they use to target them." (n.p.).

A subsequent series of studies by the FBI have also employed the content analysis. In one study (Adams & Harpster, 2008), the speech patterns of a sample of 911 homicide callers were systematically content analyzed. Specifically, the study used one hundred 911 homicide calls in which 50 of the callers were adjudicated to have been innocent and 50 guilty. The results were striking. Two-thirds of the innocent callers asked the dispatcher for help and focused on getting help to the victim quickly, whereas only one-third of guilty callers did. Nearly half of the callers included extraneous information in their calls, but of those who did include extraneous information, 96% were guilty of the offense and only 4% were innocent. Furthermore, the guilty callers tended to request help for themselves rather than for their victims.

In a more recent study, Woodworth *et al*. (2012) content analyzed the linguistic patterns of known psychopaths and contrasted them with the linguistic patterns of individuals who were not classified as psychopaths. They found that psychopaths tended to use more self-referent words, made more references to basic needs (food, shelter), used the past tense more frequently, and used a greater number of function words (e.g., "to" and "from"; "a" and the").

Another hot area in which content analysis is being used, particularly with regard to social media, is in attempting to link the content of Facebook status updates to dimensions of personality. One recent study used the results of a content analysis of status updates as correlates of personality factors, with the findings that narcissists tend to post more self-promotional content and deeper self-disclosure information (Winter *et al.*, 2014). Meanwhile, users with high needs for affiliation tended to disclose more personal information as well. A second study by Garcia and Sikstrom (in press) successfully used Latent Semantic Analysis to link the content of status updates to the Dark Triad of personality (i.e., psychopathy, narcissism, and Machiavellianism). Each of these studies shows the potential power of linguistic content analysis for both descriptive and predictive purposes.

FUTURE DIRECTIONS IN THE CONTENT ANALYSIS OF TEXTUAL DATA

While the range of vocabulary used varies tremendously across individuals, substantial work in the area of cognitive linguistic has demonstrated that the language we use betrays more about us than we would like to believe. The metaphors that we use to describe the world frame the way we think and communicate (Lakoff & Johnson, 1980). Automated content analytic programs could conceivably categorize people by the speech patterns associated with variables such as education level, geographic location, age, gender, ethnicity, religious affiliation, cultural values, and so on. Furthermore, it would not be impossible to conceive of an algorithm that uses latent class analysis to identify categories of individuals based on the types of words they use in different contexts. From there, algorithms may be developed that examine whether changes in tone, verb tense, usage of adjectives, particular metaphors predict particular behaviors. Developing algorithms to predict the likelihood that an individual may commit an act of violence could be immensely useful and represents one future direction for the field. The major challenge is that such an approach requires a large number of data points on which to validate the model. However, this is what the big data movement is all about. Facebook posts and Twitter feeds are two readily accessible, pervasive, and relatively permanent archives that are ripe for this type of analysis.

A second interesting direction for text-based linguistic content analysis comes from the world of artificial intelligence (AI). The AI community is engaged in text-based content analysis as well in its efforts to create realistic "bots." There are annual competitions in which programmers attempt to develop AI bots that can pass as human (the so-called Turing Test). One of the best recent examples is "Evie" based on "Cleverbot" (http://www.existor.com/ai-overview). Some of the more recent iterations of these bots are programmed to adaptively learn correct answers to questions based on feedback from hundreds of thousands of Internet users. The procedure is both quite simple and clever. The bot begins with a basic repertoire of inquiries built into the program (e.g., "How are you"). On the basis of the responses received from an actual individual every time the bot asks this question, the bot adaptively catalogs the most and least frequent responses and associates a probability of then invoking such a response for itself the next time a new user asks the bot the same question. Thus, the bot learns the appropriate way to respond to each question by reflecting the response it has received. From there, the algorithm develops a likelihood of what is a good/correct answer.

One interesting implication of this work is that one could conceive of personalized bots (e.g., Apple iPhone's Siri) developed for individuals using this same learning algorithm. Each bot could invoke an automated content analytic program that can detect deviations from "normal" speech patterns of its primary user with regard to the use of emotionally charged words, sentence/grammatical construction, length of entry, and so on and could conceivably begin to identify emotion within the individual user. Related to this, AI bots are currently being used within the world of online therapy. Content analytic algorithms could use information provided by the user to generate AI intervention that would guide the user to a different set of emotions (e.g., emotional intelligence via AI). For example, if the user/client reports feeling nervous about an impending visit to the new girlfriend's house to meet her parents, the bot could generate certain sets of questions that guide the individual into a less anxious state. What is more, the bot would be able to use content analysis to determine whether the bot's interventions were working as intended (e.g., making the client more relaxed). The possibilities for text-based content analysis are staggering. I expect that the era of big data will yield rapid advances in the analysis of linguistic data.

Content Analysis of Visual Data

As exciting as the future looks for text-based content analyses, I believe that the future promise of the technique lies with visually based data. Indeed, it is in that context that we may truly see the power of the methodology.

Some very interesting work in this area comes from Sarah Carney's (2013) content analysis of cartoon depictions of criminals. She and her team have analyzed thousands of episodes of children's cartoons across several decades and have found some fascinating results. For example, they find that criminals are typically depicted as being incapable of change. Once someone is bad, the person is bad forever. Efforts at redemption and change tend to be presented in a comedic light rather than as a real possibility for the character. Carney has argued that such framing has important implications for future voters' attitudes toward topics such as parole. From a visual perspective, she and her team have found that the physical nature of criminals have remained relatively static over time. Criminals are typically male, they are large, have exaggerated facial features (eyebrows, chins, facial hair, noses, scars, and/or bodies that are oddly shaped/disproportionate). They tend to speak with foreign accents. And perhaps most disturbingly, her work has found that scientists are typically portrayed as villains. The trope of the mad scientist is regularly invoked and the messaging is that science and scientists are not trustworthy. Such visual analyses may present some clues as to how and when stereotypes are formed.

Within the field of personality theory, recent research has focused on content analyzing the presentations of self on social media, such as Facebook. A common critique of the literature in personality is that the typical self-report personality questionnaire is highly susceptible to faking. Thus, over time, alternative indicators of personality have been sought in an effort to circumvent this problem. Historically speaking, concerns about faking led to the development of projective personality measures such as the Rorschach and the Thematic Apperception Test; however, the scoring of those instruments has been criticized on psychometric grounds. Recently, however, a new trend has emerged that involves content analyzing the data posted to social media websites. In particular, this data can take the form of text, but also of visual information such as pictures and videos. Although most research associated with social media has focused on the content analysis of linguistic content of Facebook status updates and Twitter feeds (Chew & Eysenbach, 2010), researchers could conceivably content analyze the pictures that individuals post onto their site to examine features that correlated highly with traditional measures of personality or other characteristics. Thus, visual content analysis of new media, such as digital photography, YouTube videos, and the arrangement of personal websites, has the potential to advance our theoretical understanding and empirical assessment of personality in a way that overcomes some of the limitations of typical self-report indicators. Interestingly, most personality studies that draw on social network data are still focusing on text-based linguistic analyses rather than capitalizing on the rich set of visual stimuli available for analysis. A shift in focus from linguistic to visually based content analysis seems to be one potential emerging trend.

FUTURE DIRECTIONS IN THE CONTENT ANALYSIS OF VISUAL DATA

In the current era, survey methodology is a ubiquitous approach to studying human subjects. Surveys are given to assess personalities, intelligence, happiness, learning styles, and so on. It is entirely conceivable, however, that rather than filling out a questionnaire on a dating website, for example, it may be possible to instead post a set of photographs that one thinks best represents one's personality. In that way, an algorithm could be used to detect the subtle features that a person may not even be aware of. A person may choose to submit a photograph (or a set of photographs) that show them interacting as part of a group, alone in portrait mode, or as part of some activity. Such a choice would reveal something about personality in and of itself. Then, within these categories, one may be able to match up certain qualities (e.g., personal interactions). One can imagine a program element that detects and estimates ages of each person involved, gender of those involved, and so on. Then, on the basis of such information, the algorithm attempts to match the person with another who has a similar profile. Ideally, one could submit multiple pictures (e.g., via Facebook) and the program could detect what types of pictures are usually submitted (e.g., drinking, hiking, posing with grandparents, attending a child's birthday party, etc.) and make a match to someone who posts pictures with similar qualities.

Another promising direction for visually based content analysis is that the technique may become useful in reviving the search for social intelligence. Social intelligence fell out of favor as a field of study in the late 1990s (Kihlstrom & Cantor, 2000), mainly due to technical constraints. The pioneering theories of J.P. Guilford and his group (O'Sullivan, Guilford, & deMille, 1965) in this area are truly outstanding. I believe that the tremendous access to new media, particularly digital photographs and videos, will prove extremely fruitful in the advancement of theories of social intelligence and cultural competence. At the most basic level, updates can be made to prior research (Archer, 1980). With video data comes the opportunity to analyze interpersonal interactions. This can take the form of eye contact, social distance, and so on to discern patterns of behaviors that people currently do not even see. Nearly everyone has a camera built into their phone these days and the proliferation of videos posted to social media sites is astounding. Content analyses of this footage could contribute a tremendous amount to our understanding of the dynamics of interpersonal interactions that occur in a native context (i.e., outside of the research laboratory).

Content Analysis of Audio Data

A third medium that can be content analyzed is audio data. Perhaps one of the most interesting examples of this in recent times is the musical application, Pandora. The concept behind the app is that there is an algorithm that attempts to match a user's musical preferences by learning what the user "likes" and "does not like." The result is an adaptive algorithm that is suited to the user's particular taste. Behind the scenes, the musical quality of each song is what is subject to the content analysis. Each song in the database must first be categorized and rated according to the content analytic coding rubric. This rubric presumably classifies songs according to timing, melody, harmony, genre (e.g., acoustic, big band), and so on. Once the scoring rubric is developed, it is a fairly easy matter to write an algorithm to detect a match. However, the success of the algorithm, from a user perspective, depends on the extent to which the relevant dimensions associated with musical preference are correctly categorized and coded. Just as textual data can be coded for a variety of different elements (e.g., content, grammar) so too can audio information. My opinion is that Pandora is a reasonably good starting point; however, I believe the algorithm needs refinement and/or that a competitor could easily come up with a different content analytic rubric that would show superior market value.

Another recent study that is taking audio data as a source and subjecting it to content analysis comes from an undergraduate thesis at Wesleyan that I am reading, which aims to examine the speech patterns of criminals as portrayed by the media. The concept behind this project is that it attempts to content analyze the pitch, tone, cadence, and so on of speech patterns of individuals identified as "criminals" within the context of popular media and compare their patterns to the speech patterns of "heroes."

Similar types of audio analyses could easily be conducted for presidential speeches. While there has been past research analyzing the linguistic content of presidential state of the union addresses (e.g., Lim, 2008), none of these analyses that I have encountered have systematically analyzed the particular speech patterns of the speakers with regard to the wide variety of audio information on which they could be classified. I see this as another emerging area for the field.

EMERGING TRENDS AND FUTURE DIRECTIONS IN CONTENT ANALYSIS

Analysts in the era of big data can make tremendous advances to our theoretical understanding of a vast array of topics by embracing the techniques of content analysis. There are myriad research questions on a dizzying array of topics that can be investigated using this technique. For example, do transformational leaders speak differently, use different audio patterns, use different visual patterns than do mediocre/nontransformational leaders? The relevant units of analysis may be technical data (e.g., grammatical usage of active/passive voice) or they could be more substantive (e.g., appeal to affiliation, power, achievement) or any of a variety of theoretical possibilities (e.g., appeal to different levels of moral development). As a second example, in the United States, we seem locked in perpetual conversations surrounding gun violence prevention and counterterrorism. The methodology of content analysis has a large role to play in advancing our understanding of how to prevent violence. Thanks to the proliferation of big data, algorithms that content analyze textual, visual, and audio data may ultimately be able to help predict, and therefore prevent, such incidences in the future.

However, with this nearly unlimited source of newfound data comes a second important element: the need for a guiding theory. In order to find some relationships, we typically have to have some idea of what it is we are looking for, and these ideas generally come from strong theories. The versatility of the method of content analysis to handle textual, visual, and auditory data makes it extremely powerful. The technique can use theory to analyze data, but it can also use data to help generate theory. The flexibility of the technique, coupled with the massive amounts of newly generated archival data resulting from advanced technology suggest that we will soon be reading many more studies that rely on content analysis.

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