Content Analysis for Values Elicitation

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Abstract
To design for users' values, one must first elicit those values. This paper describes research on detection of values in texts and describes applications to design. Expert, crowdsourced, and automatic content analysis offer non-intrusive ways of learning about users' values that can serve as accompaniments or alternatives to interrogative methods such as surveys, interviews, and focus groups.

Keywords
Values, content analysis, computational social science.

ACM Classification Keywords
K.4.1 [**Computers and Society**]: Public Policy Issues – *ethics.*

General Terms
Design, Human Factors.

Introduction: Discovering Users' Values
Understanding what users value is a critical prerequisite for designing for users' values. The simplest approach to determine what users value is to ask them; however, this approach is imperfect, as there is the potential for social desirability bias, where participants answer questions to please the interviewer or to match social norms. There is also significant cost to both the researcher and the participant in the collection of such data, including time spent designing and completing survey and interview instruments. Another option is

direct observation. However this approach also has limitations of cost, thoroughness, and social desirability bias. Thus, while each of these approaches has merit and is useful for understanding human values, there is room for additional approaches that can be less intrusive and more scalable while reducing the potential for social desirability bias.

Content analysis may be able to address some of the shortcomings of interrogative and observational approaches to discovering users' values [3, 4]. Given the volume of text that individuals create in the digital age, especially through social media such as Facebook and Twitter, there is already a significant amount of information about what people value that can be analyzed. This paper describes our efforts to develop and apply content analysis approaches to study users' values within several domains, including corporate e-mail archives, ongoing information technology (IT) policy debates, media interpretations of current events, and use of social media by individuals from marginalized groups.

Approaches to Content Analysis of Values

Traditional content analysis first involves the development of classification categories with which units of analysis can be labeled, then the validation of these categories through independent annotation (measured through inter-annotator agreement), and finally the application of these categories to large amounts of data sufficient to test quantitative hypotheses (using statistical tests). Traditional content analysis has several advantages, including the expert annotator's insights and tacit knowledge of the domain. However, this approach is costly and time-consuming, and does not scale up easily. Thus, scalable approaches to content analysis, such as crowdsourcing and unsupervised, semi-supervised, and supervised machine learning are worth exploring.

The first step in any content analysis approach is to determine the classification categories. One approach is to use an existing instrument, such as the Schwartz Value Inventory (SVI) [15], a validated survey instrument used to measure human values, as an annotation scheme [2], in some cases augmented [7, 8, 9] with additional values from the value sensitive design literature [10]. In prior work, we found that this approach has some limitations, as instruments developed for surveys do not necessarily yield the best results for content analysis due to overlapping value categories (as demonstrated through inter-annotator agreement scores [2]). We also found that using a single value instrument was limiting. Therefore, we developed a meta-inventory of human values (MIHV) [1] using twelve existing value inventories from human-computer interaction, anthropology, sociology, psychology, and business. We then modified the MIHV to study tweets, developing the meta-inventory of human values for informal communication (MIHV-IC) [12, 13]. Through the development of the MIHV and the MIHV-IC, we have improved our inter-annotator agreement scores compared to our results using the SVI.

After achieving success in training expert annotators, next we set out to determine if we could classify values in texts using crowdsourcing. Crowdsourcing involves breaking down complex tasks into simple tasks that can be completed by individuals distributed around the world. Specifically, we used Amazon's Mechanical Turk platform. We found that through a combination of asking people to complete a value survey and to rate their attitudes toward particular paragraphs, we could identify relationships between values and attitudes which could be used to determine the values that are activated by particular paragraphs [5, 16, 17].

Finally, we have also investigated the potential to automate the classification of values in texts. First, we employed a thesaurus-based approach using the SVI [19]. Next, we moved to machine learning, using both expert annotation [11] and crowdsourced annotation [18] as training data. We have achieved preliminary success in automatically classifying values in texts, although this is certainly a hard problem to solve. One interesting aspect of this work is how it differs from traditional content analysis such as sentiment analysis [14]. Our approach trains classifiers to take on different perspectives (based on individuals' values) rather than simulating a generic, undifferentiated reader [5].

Application Domains

We have applied expert, crowdsourced, and automatic content analysis approaches to a wide range of domains. Specifically, one of our studies focused on corporate e-mail, using the Enron e-mail dataset. In that study, we found a relationship between values and communication patterns [19]. Another study focused on the role of values in the design and use of computational models at corporate, academic, and government research laboratories. We found that values such as *equality* are correlated with modelers' attitudes toward codes of ethics [7], the number of value conflicts that arise with other stakeholder groups [6, 9], and the organization within which they work [8]. Another study focused on the role of values in the Net neutrality debate, finding *innovation* to be correlated with the pro position and *wealth* to be correlated with the con position [2]. Another study focused on the relationship between values and attitudes toward current events, specifically the Park51 Project (the 'Ground Zero Mosque'). We found that *universalism* was correlated with a pro-Park51 position and *security* was correlated with an anti-Park51 position [16, 17]. Finally, another study focused on the relationship between values and homelessness using Twitter data. We found that several values were reflected more frequently in the tweets of individuals who self-identified as homeless than of those who did not [13]. Thus, we have already demonstrated the applicability of this approach to a variety of research problems, all of which have direct or indirect applications to design.

Values Content Analysis as a Tool for Design

Designers need to consider the values of their users when designing new IT. However, getting access to users is often difficult or expensive. However, in the age of social media, getting access to texts written by users can be easier to achieve. The challenge is thus to determine the values embedded within those texts, so that we can then design for those values. To achieve this goal, in our future work we hope to further improve our crowdsourced and automatic approaches, so that we'll be able to create a tool that designers can use to elicit users' values from their texts. Once we know what users value, the next step is to determine how the design should be modified to ensure compatibility with users' values. Ideally, our future tool will recommend specific design approaches that can be taken to address these values. These evaluations and recommendations can be based on individual-level or organizational-level data. Thus, our approach can change how designers incorporate values in IT.

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