Cultural Influences on the Measurement of Personal Values through Words

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Abstract

Texts posted on the web by users from diverse cultures provide a nearly endless source of data that researchers can use to study human thoughts and language patterns. However, unless care is taken to avoid it, models may be developed in one cultural setting and deployed in another, leading to unforeseen consequences. We explore the effects of using models built from a corpus of texts from multiple cultures in order to learn about each represented people group separately. To do this, we employ a topic modeling approach to quantify open-ended writing responses describing personal values and everyday behaviors in two distinct cultures. We show that some topics are more prominent in one culture compared to the other, while other topics are mentioned to similar degrees. Furthermore, our results indicate that culture influences how value-behavior relationships are exhibited. While some relationships exist in both cultural groups, in most cases we see that the observed relations are dependent on the cultural background of the data set under examination.

Introduction

The ever-growing collection of publicly accessible web data continually provides new and exciting opportunities to study how people are thinking, behaving, and feeling (Lazer et al. 2009). Advances in natural language processing and information retrieval techniques have allowed researchers to better understand and model social and psychological processes such as personality (Yarkoni 2010), emotion (Strapparava and Mihalcea 2008), gender identity (Bamman, Eisenstein, and Schnoebelen 2014), and online behaviors (Zhang et al. 2011). We can now study psychological traits and their links to behaviors on a larger scale than ever before through the analysis of social media data.

However, it may be worth contemplating the effects that the cultural background of web authors will have on the results that we discover. Cultural groups differ not only in the way that they use language, but also in their personal values and everyday behaviors (Moran, Abramson, and Moran 2014). While culture can be defined many ways (Valsiner 2007) and does not necessarily adhere to international borders, for this study we use a person's geographical location as an approximation for culture. In particular, we examine cultural differences in the ways that value–behavior links are expressed by people from the United States (U.S.) and from India. However, we hope to use an approach that could be applied toward the analysis of psychological phenomena among any cultural groups that researchers are interested in.

In psychological research, the term *value* is typically defined as a network of ideas that a person views to be desirable and important (Rokeach 1973). Here we walk through a study in the use of words to computationally understand the psychological construct of values, which have long been argued by psychologists, historians, and other social scientists to influence people's behaviors (Ball-Rokeach, Rokeach, and Grube 1984; Rokeach 1968). We are interested in discovering value–behavior relationships in a data-driven manner. Furthermore, we want to look at values and related behaviors in the context of specific cultural groups. Prior work has shown that human values are captured in everyday language (Chung and Pennebaker 2014; Lepley 1957). As an example, consider the following textual expression of personal values: *"I believe in being honest. I try my best not to lie and to be forthright in my intentions and statements. I also try to help those who have helped me, especially when I was in desperate need of help. . . "*. While this person is clearly discussing values, text on the web will rarely be this focused and computational approaches will require robust models of personal values in order to be applied at scale. This remains as a long-term objective.

For the current study, we focus our efforts on texts explicitly describing values and behaviors and examine cultural differences in the writing samples. To accomplish our goals, we would like to be able to measure a person's values and real-world behaviors by using computational methods to analyze the words that they choose to write. The Meaning Extraction Method (MEM) is an approach to automatically identifying common themes among documents in a corpus and has been shown to be effective in extracting psychologically relevant topics from texts (Chung and Pennebaker 2008). This has allowed social scientists to move beyond traditional self-report survey methodology that constrains choices to a predefined set of alternatives. On the contrary, the approach enables subjects to more directly communicate their thought patterns. Among other things, the MEM has been used to explore self-concept (Chung and Pennebaker 2008), depression (Ramirez-Esparza et al. 2008), and the relationships between personal values and everyday behaviors (Boyd et al. 2015). However, these studies were either carried out exclusively within the U.S., or no location based demographic information was reported. It is unclear how the claims made can be extended to other cultural groups or how the results might change given a culturally different set of subjects.

Understanding what role culture plays in the interpretation of our models' results will inform not only values research, but should be taken into consideration whenever researchers are building models of language generated by people from different cultures. Previously, we have shown that the MEM provides a broad and comprehensive view of how values and behaviors are related (Boyd et al. 2015). We now set out to show to what extent we will arrive upon different results when applying the same models to texts whose authors differ culturally.

Data and Method

We first sought to understand the types of things people from each culture generally talk about when asked about their values and behaviors. To do this, we collected a corpus of free-response writings from U.S. and India respondents. The authors of the texts in our corpus were asked to reflect upon their own personal values for a set amount of time (at least six minutes), and they also spent some time writing about things that they had done in the past week. These data come from two sections of a social survey that was designed using Qualtrics survey software and distributed via Amazon Mechanical Turk. In order to guarantee an adequate amount of text for each user, we only retained surveys in which respondents wrote at least 50 words in each of the writing tasks and each essay was manually checked for coherence. Additionally, multiple "check" questions were placed throughout the survey to identify those people who were not paying close attention to the instructions, and we do not use any part of the survey from those who missed these questions. After this filtering process, we chose the maximum number of surveys that would still allow for an equal balance of data from each country. Since there were more valid surveys from the U.S., a random subsample was drawn from the larger set of surveys. The result is 209 surveys from each culture, or 418 surveys in total, each with both value and behavior writing components.

In the set of surveys from India, 36% of respondents are female and 55% reported being between 26 and 34 years old. All but 4% have completed some college education. For the those from USA, 63% are female and 38% were between the ages of 35 and 54 (more than any other age range). 88% have had some college education. We acknowledge that some of these other demographic differences between the two groups may also be contributing to any country-based cultural differences observed.

Each of the text samples was preprocessed using the Meaning Extraction Helper (Boyd 2014). This software lemmatizes the words in each document, and additionally removes common stopwords, rare words (those used in less than 5% of documents), and function words, as our analysis is focused on content words. Each of the documents is then converted into a binary vector indicating the presence of a given word with a value of 1 and the absence of a word with a 0. Based on the notion that word co-occurrences can lead to psychologically meaningful word groupings, we then perform principal components analysis on the correlation matrix of these document vectors, and applied the varimax rotation. The top 15 components were kept and became the set of themes, or topics, that categorize the set of content words in the corpus. The number of themes was chosen for topical interpretability and slight variations are possible while reaching the same general conclusions. Any word with a factor loading of at least .2 for a particular component is retained as part of the theme, while words with loadings of less than -.2 are also kept and used to quantify text that is opposed to the particular theme. Let $f_t(w)$ be the factor loading of the word w for the new topic t. We then define the membership relation for a word w to a theme t:

$$m(t,w) = \begin{cases} 1 & \text{if } f_t(w) > .2, \\ -1 & \text{if } f_t(w) < -.2, \\ 0 & otherwise. \end{cases}$$

To measure the degree to which a particular topic is used more by one cultural group, we use the following definition of Culture Ratio (CR) for a topic t:

$$CR_t(U,I) = \frac{\left(\sum_u^U s(t,d_u)\right)/|U|}{\left(\sum_i^I s(t,d_i)\right)/|I|}$$

where U is the set of all respondents from USA, I is the set of respondents from India, d_x is the relevant document written by respondent x, and the score function s is:

$$s(t,d) = \frac{\sum_w^d m(t,w)}{|d|},$$

assuming that a document is an iterable sequence of words. This score is essentially a normalized count of words in a document that belong to a particular theme minus any words that were found to be in opposition to that theme (those words for which $m(t,w) = -1$). Thus, the CR score simply summarizes the relative usage of words in a given topic by each of the two cultures under consideration. Values of $CR_t > 1$ indicate prevalence of that topic in the U.S., while scores less than 1 will be achieved by topics that are more commonly used by authors from India.

Results

We use the approach described in the previous section to generate themes from our corpus. Table 1 shows the themes extracted from the values writing samples from both cultures, and Table 2 shows the behavior themes. The theme names are manually assigned and are only for reference purposes; each theme is itself a collection of words with scores of either +1 or -1. For each theme, some sample words are given along with the CR_t for that theme. Note that each word can appear in more than one theme.

Even when using the same set of topics, we see cultural differences coming into play. CR scores for the value

Table 1: Themes extracted by the MEM from the values essays, along with example words and culture ratio scores.

Theme	**Example Words**	CR_t
Hard Work	job, work, hard	1.44
Financial	spend, money, time	1.31
Respect	moral, respect, person	1.24
Faith	faith, god, belief	1.23
Understanding	understand, teach, right	1.21
Honesty	honest, truth, sure	1.14
Familial Love	love, family, child	1.04
Relationships	friend, family, people	0.96
Sharing Thoughts	see, speak, mind	0.95
Caring	compassion, kind, equal	0.84
Positivity	happy, feeling, great	0.76
Rule Following	rule, follow, society	0.73
Family Support	support, provide, husband	0.72
Decision Making	decision, future, consider	0.71
Peaceful	human, peace, respect	0.60

Table 2: Themes extracted by the MEM from the behavior essays, along with examplewords and culture ratio scores.

Theme	**Example Words**	CR_t
Days	monday, tuesday, sunday	2.18
Celebration	drink, party, fun	1.62
Leisure	tv, play, online	1.41
Out Together	bought, together, trip	1.19
Chores	chore, task, phone	1.18
Relaxing	tea, snack, enjoy	1.16
Grooming	tooth, hair, shower	1.01
Meetings	meeting, busy, schedule	1.01
Family chat	chat, family, good	0.92
Child Care	child, dress, bus	0.90
Religious	temple, pray, visit	0.88
Daily Routine	breakfast, office, sleep	0.82
Work	work, drive, bill	0.77
Commuting	park, walk, daily	0.67
Household	laundry, wash, cook	0.60

themes show that Hard work, Faith, and Financial are predominately talked about by Americans. Indian authors tend to use words from the Peaceful, Rule Following, and Decision Making themes. Both cultures mention Familial Love roughly the same amount of the time. Looking to the behavior themes, we see that authors from the U.S. mention specific days of the week (Days) more than twice as often as authors from India. Respondents from U.S. also talk more about their Leisure time when asked about their past week. People from India, on the other hand, mentioned taking care of their Household and Commuting much more than their American counterparts. Both cultures shared equally about experiences with Meetings and time spent Grooming.

Next we explore how culture affects discovered value–behavior relationships. In order to take a look at the relationships between values and everyday behaviors as expressed in text, we use the previously defined s function to assign a score to each writing sample for each topic so that the document can now be represented as a vector of topic scores. Transposing the matrix made up of these vectors provides easy access to a vector for each topic that contains a series of scores, one for each writing sample. We use these vectors to compute the Pearson correlation coefficient between any two themes. In order to ensure that correlations are not inflated by the presence of the same word in both themes, we first remove words that appear in any values writing theme from all behavior writing themes. Then, for each culture, we compute the relationship between every value theme and every behavior theme (Table 3, next page). All reported results are significant at $\alpha = .05$ (two-tailed). Multiple hypothesis testing was addressed by using a series of 10,000 Monte Carlo simulations of the generation of the correlation matrix.

Analysis of these results shows both cultural similarities and differences. Interestingly, two of the value-behavior relationships are common across the two cultures: the value of Hard Work is positively related to behavior Family Chat, and people who use words indicating a value of Decision Making also commonly use words from the behavior topic Work. On the other hand, there are many relationships that are unique to one of the cultures. In India, for example, the Peaceful value theme is negatively correlated with Child Care, but in the U.S., this same value theme is positively correlated with Meetings. In the U.S., the value of Caring is negatively related to behavior words in the Work category, yet the same value in India is negatively correlated with the Grooming theme.

Conclusions

We have shown how topic models can be used to explore cultural differences both qualitatively and quantitatively. A quick glance at Tables 1 and 2 provides a high level descriptive summary of hundreds of writing samples. We were able to take a set of themes and compute the degree to which a particular theme is being used in different cultural settings. The same approach could also be used to understand differences in topic usage between members of any groups that we defined, such as males and females. Other analyses, such as the degree of overlap between culture-specific themes, would also provide a unique look at cultural language differences and similarities. In the future, we also hope to explore how well these culture-specific themes are able to describe texts from various cultures in comparison with themes that were generated using texts from many cultures.

Additionally, we have briefly explored how culture influences the interpretation of topic modeling results. Using the same set of topics, vastly different results were obtained when examining data from different cultural domains. In particular, value–behavior relationships are not consistent between the U.S. and India. This result suggests that cultural biases are at play whenever text from different geographic locations is being analyzed. Though perhaps intuitive, this should be remembered when performing large scale studies of user generated text from social media or other online sources. While this study only focused on small linguistic samples from two countries, further work should explore a greater number of cultural backgrounds with even larger data sets.

	Days	Daily Routine	Leisure	Household	Chores	Work	Celebration	Out Together	Commuting	Grooming	Family Chat	Meetings	Relaxing	Religious	Child Care
Hard Work	○										●■				
Family Support		□					□								
Familial Love															
Caring	●		●			○				□		○			
Decision Making			○			●■		■				●			
Peaceful												●			□
Positivity										■		□			
Faith										●					
Honesty						○					●	○			
Relationships											●				
Understanding						○		●				○			
Rule Following							●		○				□		
Sharing Thoughts										□					
Respect		■													
Financial		□	□			●									

Table 3: Coverage of behavior MEM themes by value MEM themes for two different cultures.
USA: Positive relationship: ●. Negative relationship: ○. **India**: Positive relationship: ■. Negative relationship: □.

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