# Analyzing Conservative and Liberal Blogs Related to the Construction of the 'Ground Zero Mosque'


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## Abstract

The issue of the 'Ground Zero Mosque' has been one of the most controversial political issues in US politics in the last several years. Using two different statistical text-analysis techniques, we analyze conservative and liberal blog posts, related to the construction of this Muslim community center and the debates surrounding the issue. In the first experiment, we use a machine learning technique to automatically classify the blogs according to which group wrote them. We also examine the distinctive features that make these blogs liberal or conservative. In the second experiment, by examining posts in consecutive time blocks, we show that there was a significant increase over time in affective processing, and in anger, especially for conservatives. Overall, our results show that there are significant differences in the use of various linguistic features between liberals and conservatives, highlighting the differences between the ideologies and the moral frameworks of the two groups.



**Keywords:** blog analysis; text classification; sacred rhetoric; LIWC; machine learning; SVM; Ground Zero mosque


## Introduction

There is evidence that striking differences in the very definitions of morality are at the root of many social-ideological differences within a country. Haidt and Graham (2007) propose that liberals and conservatives in the US have very different ways of seeing the social environment around them, and rely on distinct moral structures and ideologies. Consequently, several important differences have been noted in the political rhetoric employed by these groups (Lakoff 2002, 2008; Marietta 2008, 2009). Lakoff (2008) argues that the type of language used in political discussions is of utmost importance because it "is far more than a means of expression and communication… It organizes and provides access to the system of concepts used in thinking" (p. 231). In other words, the language in these discussions often conveys the value systems adhered to by liberal and conservative groups**.** A linguistic study of presidential debates from 1976-2007 (Marietta, 2009) reveals that Republicans employed sacred rhetoric, which is grounded in "transcendent authority and moral outrage", more frequently and on a broader range of issues, while Democrats relied more on quantitative facts such as plans and projected numbers.

The issue of the Cordoba Muslim Community Center, known as Park51 or 'the Ground Zero Mosque' as it came to be called, has been one of the most contentious political issues in the United States in the past five years or so. It served to highlight the ideological differences between liberal and conservative moral frameworks and to a certain extent, exposed the deep prejudices that still remain toward the Muslim community. This paper focuses on the differences in the use of linguistic features in over 3000 conservative and liberal blog posts related to the construction of Park51.

We first explore whether the differences in the choice of words used by conservative and liberal bloggers with regard to this issue is significant enough that classifiers can be trained to automatically categorize posts as conservative or liberal. If such classifiers can be trained, we can use feature analysis to explore the most indicative features of the groups, exploring what makes the posts liberal or conservative, and gaining insight into the ideologies of the groups. Examining further differences in language use, we use the Linguistic Inquiry and Word Count tool (Tausczik & Pennebaker, 2010) to track linguistic changes associated with affect, religiosity and sociality in the two groups over a period of seven months. Our hypothesis is that if there is a greater use of sacred rhetoric by conservatives, it should be accompanied by an increase in the use of religious and affective words, especially words related to anger.

We begin by discussing the timeline of events that took place in response to the construction of Park51. Next, we describe our data collection method. Then, we discuss experiments, and close with conclusions and implications.

## Timeline of Events

On December 8, 2009, the *New York Times* published an article on plans to build an Islamic cultural center at a building two blocks from Ground Zero (Blumenthal & Mowjood, 2009). In response to this article, a conservative blogger criticized the project dubbing it as the "Ground Zero mosque" (Geller, 2009) and started a national controversy about the issue that lasted about six months (Elliott, 2010). The story did not receive much media attention until May 6, 2010, when the building of the mosque was approved by a committee, and in response, some of the 9/11 victims' families expressed anger that the center was being built so close to where their relatives were killed (Salazar, 2010). Following this news, the story was brought back to public attention by a series of posts by conservative bloggers which relied heavily on the use of sacred rhetoric, framing the issue as a religious/historical event, threatening the American identity (e.g. "This is Islamic domination and expansionism. The location is no accident. Just as Al-Aqsa was built on top of the Temple in Jerusalem", Geller 2010a). Rallies were organized by bloggers on May 29 (marking "May 29, 1453, [when] the Ottoman forces led by the Sultan Mehmet II broke through the Byzantine defenses against the Muslim siege of Constantinople.") (Geller, 2010b) and June 6 (marking D-Day, June 6 1944) (Peyser, 2010). By this time the controversy was not only widespread through conservative blogs, but mainstream media and liberal blogs were also giving considerable attention to the issue (Elliott 2010). On July 21, in response to plans to build Park51, a Florida Church announced "plans to host an 'International Burn A Quran Day,' on the ninth anniversary of the Sept. 11 attacks this year" (Hyde, 2010), which lead to much expressed anger from both sides. On August 13, President Obama gave a speech in which he defended freedom of religion and stated that Muslims are entitled to build the center. This resulted in a heated response from the right ("Right-wing media blast President", 2010). Another rally was held on August 22 in NYC by the opponents and supporters of the mosque in which there was prevalent use of sacred rhetoric by both sides, clashing the sacred American value of religious freedom against the moral decadence of contamination of the "hallowed ground" (Davis & Dover, 2010) of Ground Zero. In September, in conjunction to other events related to Park51, much media attention was given to the issue of burning Qurans in Florida, where two different American sacred values clashed again: "the constitutional right" to burn a Quran versus the sacred value of religious tolerance. Beginning in October, the coverage of the issue started disappearing from the media as quickly as it had initially started.

One of the most interesting aspects of the controversy regarding Park51 is the fact that it initially started on the blogosphere by a single blogger (Elliott, 2010), and most of the discussions regarding this issue took place on various different political blogs. This provided us the ability to track responses to events as they naturally unfolded, allowing longitudinal analysis of changes in different linguistic and psychological factors.

## Data Collection

In order to compile a representative sample of the blog posts of each group, we first identified five top popular conservative and liberal news blogs, each rated by the website blogs.com[1]. Next, we performed a Google search to find all posts within each of these blogs that include the word "mosque" and were posted between March 1, 2010 and October 6, 2010. We then automatically downloaded the HTML files for all the links returned by the search queries. This included a total of 3140 blog posts, consisting of 1473 posts from the conservative blogs and 1667 from liberal blogs. Finally, we used customized scripts for each blog to remove HTML tags, headers, tables, etc. and extracted only the blog post itself and the comments on the post, ignoring all the other fields such as advertisement, blogrolls, name of the authors, dates, etc.

## Experiment 1

As we argued in the introduction, one of the important differences between liberals and conservatives is the type of language and rhetoric they employ in political discussions -- reflecting disparities in the ideologies and value systems of the two groups. The aim of the first experiment is to see if the differences in language use and choice of words are great enough that blog posts can be automatically classified as conservative or liberal using a machine learning technique. If we are able to classify these blog posts, then we will be able to determine the indicative features of each group using feature analysis and gain insight into what makes the blogs conservative or liberal.

In a similar line of work, using machine learning to examine political differences, Diermeier and colleagues (in press) classify transcribed Senate speeches by first training a classifier on the speeches of the 25 most liberal and 25 most conservative senators from the 101st through 107th Congresses. Then, their classifier is tested on the speeches of the 25 most liberal and 25 most conservative senators of the 108th Congress, achieving an accuracy of 92%. Also, they use a similar technique to classify Senate speeches by training on the House speeches of the same year (Yu, Diermeier & Kaufmann, 2008). Performing a feature analysis, they report that the most important features for Democrats included company names and words related to environmental and economic interests (e.g. Enron, ethanol, hydrogen, lakes), and for conservatives included words with cultural significance (e.g. cloning, unborn, abortion, marriage and homosexual).

Our approach was to use supervised machine learning, in which training data for each predefined category is needed to build a classifier. This classifier is then used to predict for each new data point which category it belongs to. Support Vector Machines (SVMs), first introduced by Vapnik (1995), is a general learning algorithm used for binary classification. SVMs represent features, or data points, as points in space and try to find a hyperplane that is maximally distant from nearest training data points of each of the categories. Also, in SVMs, words with the highest absolute coefficients (i.e. most positive for one group, and

[1] The conservative blogs we chose for this experiment are: hotair.com, reason.com, redstate.com, rightwingnews.com and townhall.com, and the liberal blogs are: crooksandliars.com, dailykos.com, huffingtonpost.com, thinkprogress.com and wonkette.com.

Conservative: obama, leftist, rino, islam, obamacar, koran, pelosi, allah, suicid, illeg, jihadi, infidel, socialist, shariah, bloomberg, hussein, hamas, islamist, saddam, communist

Liberal: center, republican, gingrich, teabagg, beck, religi, corpor, muslin, filibust, wingnut, fear, jeer, hate, glenn, cheer, stewart, right-w, anti-muslim, sarah, geller

Figure 1: 20 of the top 50 feature words with the highest weight for each group within a classifier which achieved 86% accuracy. Words are listed in decreasing weight order. All words were converted into lower case, and in order to reduce vocabulary size, word stems were used in classification.

most negative for the other group) are considered the most informative features, and are the most indicative, or discriminative, of each category.

We used SVM^light (Joachims, 1999) with its default settings in this experiment. Prior to generating features vectors for classification, the documents were subjected to several pre-processing procedures. We first used a tokenizer[2] to separate text into individual words. Next, in order to reduce vocabulary size, word stems were derived[3] and different forms of each word were mapped in to the same word stem. Finally, we removed stop words, which are common words not useful for classification (e.g. "the", "a", "is"), and several other categories of words such as name of the blogs and names of frequently referred to websites such as twitter.com and youtube.com. For training, we used "term frequency–inverse document frequency" (*tf*idf*) word weighting scheme to convert documents and words in the documents to numerical document vectors. However, in the prediction step, given that the total number of documents is assumed to be unknown to the classifier, only word frequencies were used to represent test documents.

We also examined blog posts according to the date that they were posted. In order to get consistent number of posts per time period for both groups, we grouped blog posts into seven consecutive time blocks (3/01-7/16, 7/17-8/09, 8/10-8/17, 8/18-8/24, 8/25-9/04, 9/05-9/13, 9/14-10/06)[4]. The time blocks were chosen so that there would be at least 200 blog posts for each of the groups per time block. The large time blocks were necessary in order to compensate for the amount of noise existing in the files retrieved from the websites, especially the noise in the comments sections.

## Results

Classification accuracy was calculated using a 10-fold cross validation, where in each run our program randomly chose a subset of the blogs from each group as the training set, and 25 other blog posts from each group as the testing sample. This process was repeated ten times and the overall accuracy of the classification was obtained by averaging over the accuracy of each of the tests. Overall, with a training set consisting of 750 blogs per group, our system achieved average prediction accuracy of 85.6% ($p < 0.001$).

We coded the top 100 feature words with the highest absolute coefficients for each group within a classifier that achieved an accuracy of 86% for in-group and out-group membership. This coding was done relative to each subculture, for example "pelosi", "leftist" and "socialist" were coded as out-group for conservatives, and "republican", "right-w" and "beck" as out-group for liberals (Figure 1). The results show that for both conservative and liberals, the most important words for distinguishing them were words which referenced out-group members (conservatives: 31% out-group, 14% in-group, $\chi^2 = 7.3405$, $p = 0.0067$; liberals: 25% out-group, 3% in-group, $\chi^2 = 18.314$, $p < 0.001$) (Figure 2).

We performed the same analysis for each of the time blocks. Specifically, for each time block, our program randomly chose 175 blog posts from each group for training and another 25 posts per group for testing. Similar to the previous analysis, this process was repeated 10 times for each of the time blocks and the overall accuracy of the classifier was calculated by averaging over the 10 tests. The classification results, averaged over the 7 time periods, was 75.54% ($p < 0.001$). The accuracy of the classifier did not significantly differ between any of the time blocks. Coding the words with the highest feature weights, in classifiers which achieved accuracy most close to the mean accuracy rate of each block for in-group and out-group membership, resulted in a similar pattern as above. That is, within each time block, the most indicative words for each group, were references to out-group members and negative portrayals of out-group members (all $p$'s $< 0.05$).

## Discussion

Choice of words used by these two ideological groups were distinct enough that our system was able to classify their blog posts as conservative or liberal with an accuracy of 85.6%. Even though we expected that this difference would diminish for posts within each time block, as the topics of discussion would be more similar, we were able to classify blog posts within each block with an average accuracy of 75.54%. Also, feature analysis revealed that the most distinctive aspect of either liberal or conservative blogs is not the description, or the ideology, of the in-group, but

[2] For tokenization, we used the Word Splitter tool, available at http://cogcomp.cs.illinois.edu/page/tools_view/8

[3] To derive word stems, we used the lisp implementation of the Porter stemmer, available at http://tartarus.org/~martin/PorterStemmer/

[4] There was no significant difference in word count of blog posts between the liberal and conservative groups and in any of the time periods.

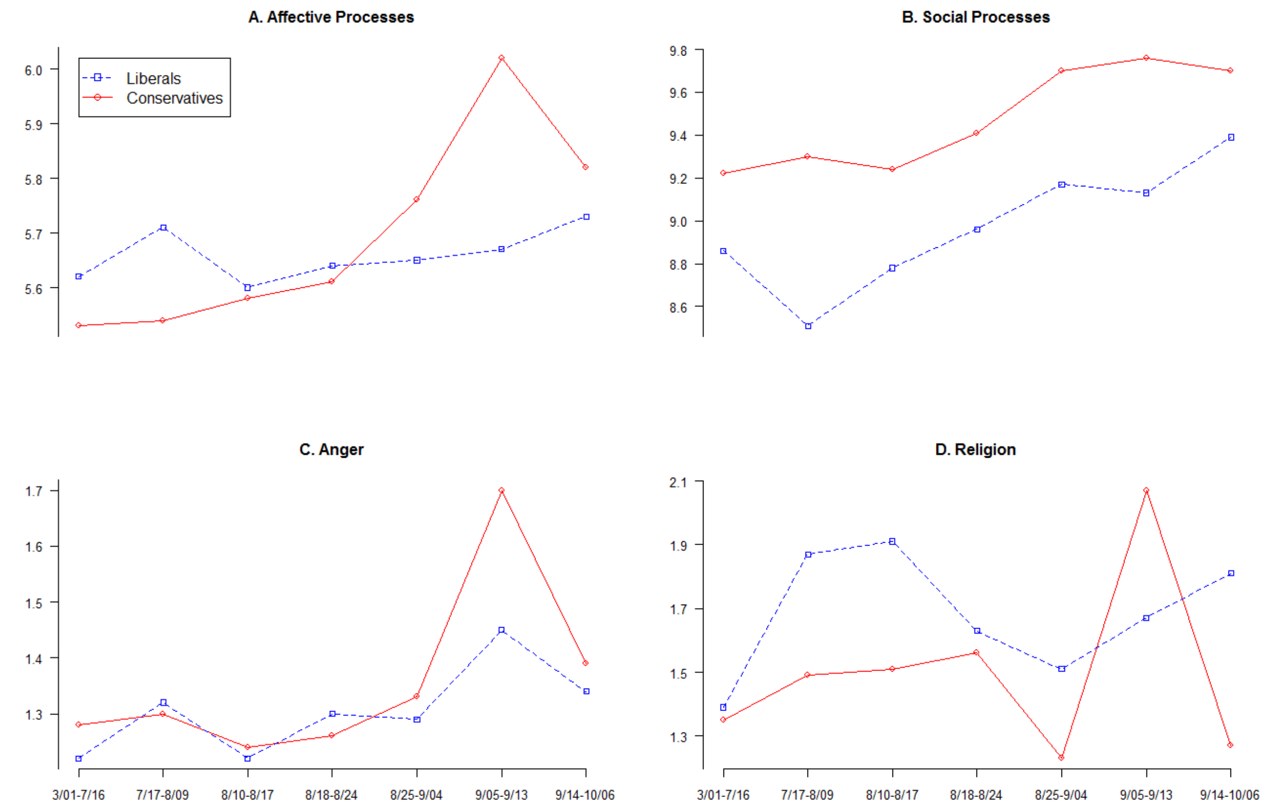


Figure 2: Changes in different psychological processes captured by LIWC

rather the use of words related to the negative portrayal of the out-group.

## Experiment 2

In Experiment 1, we demonstrated that the use of language, and choice of words, between liberal and conservative are different enough that classifiers can be trained to predict with high accuracy which group wrote a particular post. In Experiment 2, we use the Linguistic Inquiry and Word Count (LIWC) tool (Tausczik & Pennebaker, 2010) to both further investigate differences in language use between the two groups and to track linguistic changes associated with affective and social processes within a seven months time period. LIWC is one of the most widely used tools for automatic text analysis in psychology, and has provided evidence for the psychological and social implications of word use in various studies (Pennebaker, Mehl & Niederhoffer, 2003). LIWC has also been used as a tool for tracking changes in linguistic features over time. For instance, Back, Küfner and Egloff (2010) examine the immediate negative emotional reactions on September 11, 2001 expressed in messages sent to text pagers within the US using LIWC. In a similar study, Cohn, Mehl and Pennebaker (2004) track psychological changes in response to the 9/11 attacks using daily writings of 1,084 bloggers for two months prior to and after the attacks using LIWC.

LIWC performs word counts and catalogs words in to psychologically meaningful categories (Tausczik & Pennebaker, 2010). The default LIWC2007 dictionary includes 4,500 words and word stems which define its 76 different language categories. LIWC assigns each word to specific linguistic categories, and it reports the total number of words in each category normalized by the total number of words in the document. The LIWC categories examined in this study are: social processes (e.g. talk, share, friends), affective processes (e.g. happy, cried, abandon), anger (a subcategory of affective processes) (e.g. hate, kill, annoyed) and religion (e.g. Altar, church, mosque). We also created a custom Islam category which included all words in the religion category related to Islam.

### Results

First, we examined how linguistic features for affective processes changed over time for the two groups by correlating the percentage of affective words reported by LIWC for each of the groups with time. There was a positive correlation between time and use affective words for conservatives ($r$ = 0.85, $p$ = 0.014), however this correlation did not reach significant for liberals ($r$ = 0.49, $p$ = 0.26)[5]. For conservatives, there was a significant increase

[5] Examining this correlation within the first 6 time periods, revealed the same trend (conservatives: $r$ = 0.86; liberals $r$ = 0.15).

in affective words between the first time block and the 9/05-9/13 time block ($t(8) = 3.6949$, $p = 0.006$). At the 9/05-9/13 block, the differences in this category between the two groups approached significance ($t(8)=2.2023$, $p = 0.0587$). Overall, the amount of affective words used by conservative websites was higher than liberal websites ($t(68) = 1.9342$, $p = 0.0573$).

A repeated measures ANOVA with a Greenhouse-Geisser correction, where the first factor was time and the second factor group, determined an overall main effect of time for anger ($F(2.470,48) = 5.894$, $p = 0.007$). The same test revealed that the interaction between time and groups approached significance for anger ($F(2.470,48) = 2.988$, $p = 0.064$). Even though the overall difference in the use of words related to anger between the two groups did not reach significance ($t(68) = 0.9329$, $p = 0.35$), this difference became significant at the 9/05-9/13 time block ($t(8) = 5.3128$, $p < 0.001$).

We also ran LIWC on the top 5000 words with the highest absolute coefficients for each of the groups in each time block, from SVM classifiers that achieved average predication accuracy. The results show that in words that are most indicative of conservative blogs, there was an increase in the use of words related to anger within the first six time periods ($r = 0.7843$, $p = 0.064$).

As shown in the graphs, there was a sharp decrease in the use of affective words and anger in the last time block, especially for conservatives, which is an indication of these processes returning to baseline rates (there is no significant difference between the first and last time blocks in any of the emotion categories mentioned above for either of the two groups).

Another repeated measures ANOVA was ran for the religion category. There was a main effect of time ($F(6,48) = 4.333$, $p = 0.001$), and the interaction between time and group approached significance ($F(6,48) = 1.959$, $p = 0.090$). There was a positive correlation between anger and religion ($r = 0.7447$, $p = 0.0548$). Correlating the Islam sub-category with anger indicated that the correlation between anger and religion was not due to use of words related to Islam ($r = 0.0171$, $p = 0.9708$).

For both groups, there was increase in social orientation over time (conservatives: $r = 0.92$, $p = 0.004$; liberals: $r = 0.86$, $p = 0.0133$) which unlike other factors did not return to baseline. Also the use of words related to social processes was higher for conservatives than for liberals ($t(68) = 3.9122$, $p < 0.001$).

## Discussion

Overall, there were significant differences in the use of words related to affective and social processing between conservatives and liberals. As our results show, for conservatives there was a significant increase in the use of words related to affect, and anger, in periods leading to the anniversary of 9/11. These changes in the choice of words used in the posts reflect underlying differences in the type of rhetoric employed, and subsequent changes in emotional responses.

Also, for conservatives the rise in the use of words related to anger was positively correlated with the use of religious words, which is an indication of an increase in reliance on sacred rhetoric. The use of sacred rhetoric has been linked to the emergence of sacred values (Marietta, 2008; Dehghani et al., 2009; Dehghani et al., 2010), as values that get tied to religion more easily achieve a sacred status (Marietta, 2009). As previous work shows violations of sacred values result in anger and moral outrage (e.g. Tetlock, 2003; Ginges et al., 2007).

The number of words related to anger in feature words (words with the highest absolute coefficients in SVM classifiers) increased in the first six time blocks for conservatives. In other words, echoing the increase in anger words, the proportion of anger words, useful in distinguishing conservative posts, increased with time.

Traumatic and upsetting events are generally followed by an increase in social processes such as seeking of social support, increase in collective orientation and social sharing (Mehl & Pennebaker, 2003). Our results indicate that there were increases in the use of words related to social processing by both conservatives and liberals over time, which may be due to attempts to validate their threatened cultural worldview (Pyszczynski et al., 2004), and to facilitate social sharing (Rimé et al., 1998).

## Conclusions

In this paper, we analyzed conservative and liberal blogs posts, and their corresponding comments, related to the construction of a Muslim community center close to Ground Zero. Most of the controversy and debates surrounding the issue took place online and thus this methodology seemed quite apropos. Using two different statistical text analysis techniques, we showed that there are significant differences in the use of various linguistic features, and in choice of words, between liberals and conservatives.

In the first experiment, we used a machine learning technique to both automatically classify the blogs based on the group they were written by, and to examine the indicative features which make these blogs liberal or conservative. Our results indicate that words which reference out-group members and are used for out-group derogation are most characteristic of the ideology of a group (whether liberal or conservative). Similar to Haidt and Graham (2007), Lakoff (2002) argues that the ideologies of conservatives and liberals embody their value systems and personal conceptions of morality. Instead, our results show that at least in political debates, the ideas that make these groups liberal or conservative, are stereotypes of the out-group.

In the second experiment, by examining posts in different time blocks, we showed that there was an increase in words related to affective processes and anger over time, especially for conservatives. We argued that this increase is potentially related to the use of sacred rhetoric, as there was a significant correlation between anger and the use of religious words.

In conclusion, by analyzing over 3000 conservative and liberal blog posts related to the constructions of Park51, our results confirm significant differences in the use of language, and its resultant emotions, between the two groups. Language use in these blogs reflects ideological differences between liberals and conservatives. We believe the ability to perform this type of mass text analysis and to track changes of different psychological processes over different periods of time, as they naturally unfold among diverse cultural groups, can provide new insights which arguably cannot be achieved in an experimental setting inside the lab.

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