# Values and Argumentation in the Living Voters Guide

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## ABSTRACT
This paper explores argumentation in the Living Voters Guide, focusing on the Same-Sex Marriage debate. It decomposes the values used in the debate and use latent semantic analysis to group points by values. Values are predicted using support vector machines - with minimal results. Next, this paper examines metrics of discourse quality and measures the correlations between these metrics and values at stake. There are strong correlations between the diverse appeal of points and their discussion as well as between similar value groups. Notably, points framed in terms of achievement, self-direction, and personal harms or concerns were used by both sides of the debate, as opposed to the polarized universalism/fairness frames or tradition/purity frames.

### Author Keywords
online deliberation; personal values; semantic analysis.

## INTRODUCTION
Two individuals with the same set of facts may have very different conclusions, based on their experiences, desires and personal values. Virtual forums often lack in supporting characteristics of human discussion: emotion and personality. Without these, it's easier for debates to go sour and we've seen a steady increase in polarization in line with the increase in virtual interaction and the expansion and redefinition of our social networks. This work seeks to identify the personal values at play within online arguments in order to help users find common ground and combat online polarization.

We once thought that the Internet would become this great engine of democracy. While it gives almost unlimited access to information, most people just seek out like-minded friends and the capacity of the Internet to become a wide expanse of thought is reduced to become echo-chambers [9]. Social media exacerbates homophily and users often push away or terminate weak friendships during political disagreements [12]. It is my hypothesis that by identifying the values at play in online arguments, we can help users identify value tensions and address appropriately to find common ground and maintain cross-partisan relationships.

### Research Questions
1. Can we build computational models to reliably determine the personal values at play in online discourse?
2. How do personal values affect the outcomes of online discourse?

## RELATED WORK

### Values in Discourse
Social psychologists and human computer interaction researchers have examined the roles that values and other factors come into play in online conversation. There are many models for argument flow, combinations of discrete pieces of arguments such as predicates, beliefs, and conclusions. Some models explicitly pivot on personal values [1]. Examining the way that the media frames debates, researchers have found that framing along particular values activate values held by individuals and changes the way they respond to new content [2]. Thereby, if we observe the values as they are present in a debate, we can nudge a debate between two individuals to pivot on the values they present to reflect their personal beliefs more appropriately.

In order to measure values, researchers in the HCI community have often grouped words into LWIC semantic categories [16] and correlated them with observed values. Examples of this are correlating semantic categories to personal of values of users to reddit and twitter posts [3] and observing aggregates of morals and sentiment in relation to party affiliation and policy change [11, 22]. The only robust dataset that has labeled values to deliberation is a human annotated set on hearings about net neutrality [4]. Kenneth Fleischmann, An-Shou Cheng, and Yasuhiro Takayama have iterated on this dataset, revising human coding schemes and eventually arriving at a 5-value scale tailored to the debate, predicting values with SVMs and LVMs [20].

### Discourse Quality
There are a catalogue of measures that relate to quality discussion. Many of these metrics require participant feedback: reaching consensus [7], becoming more informed [21], and respect [19, 21]. Human annotation may suffice for: the level and content of justifications, and rating something as constructive politics [19]. Some metrics have been developed to work alongside automatic analysis. Relevance compares the Bag of Words similarity of new material to either past material or the original post [6]. Schematic coherence, schematic integration, and schematic differentiation all relate to how self-consist an argument in and if it draws upon a small set

of values or a wide breadth [10]. Lastly, attitude certainty can indicate the quality of an argument [10].

## DATA

For this mini-project, I used data from the Living Voters Guide. This system was developed by Travis Kriplean and others at the University of Washington in the period 2010-2014 [14, 8]. This system is a website in which users discuss current measures on the general election's ballot. In viewing a ballot measure, users can select on a slide how much they agree with the resolution. Users are invited to contribute points which will appear on the right side of the page (in favor of the resolution) and on the left side of the page (against the resolution). Users can see the points that they and previous users have written and can drag them into the center of the page to indicate how much they agree with a particular measure to form an argumentation portfolio. Having a broad understanding of one's political environment has been demonstrated to positively effect outcomes in democratic society [21].

### Same Sex Marriage Debate

For the purposes of this analysis, I choose to focus on the Same-Sex Marriage debate in 2012. After the legislature passed a bill affirm Same-Sex Marriage, the issue was subject to a public vote, Referendum 74. The summary on the official ballot is as follows:

> This bill allows same-sex couples to marry, applies marriage laws without regard to gender, and specifies that laws using gender-specific terms like husband and wife include same-sex spouses. After 2014, existing domestic partnerships are converted to marriages, except for seniors. It preserves the right of clergy or religious organizations to refuse to perform or recognize any marriage or accommodate wedding ceremonies. The bill does not affect licensing of religious organizations providing adoption, foster-care, or child-placement.

3.2 million Washingtonians submitted their ballots in 2012, with a narrow majority of 1.67 of voters voting to accept this measure. It marked a milestone moment in the same-sex marriage debate, the first time voters approved of marriage equality.

The same-sex marriage debate was quite contentious and there are good reasons to choose this example as well as a few concerns. This issue has strong moral and value framings, which increases the salience of values, making them easier to label and confirm, but will make human annotator neutrality difficult. This debate was the 4th most discussed issue on the living voters guide and the 2nd most rated issue. Although there is user representation across the board, the number of participants is very skewed towards for gay marriage. 13 participants who choose a stance on the issue choose the strongest value against the referendum, 81 participants choose the highest value on the scale for the referendum and other participants choose stance values of participants choose partial opinions or to be neutral. See Figure 1, illustrating the self-reported stances of users.

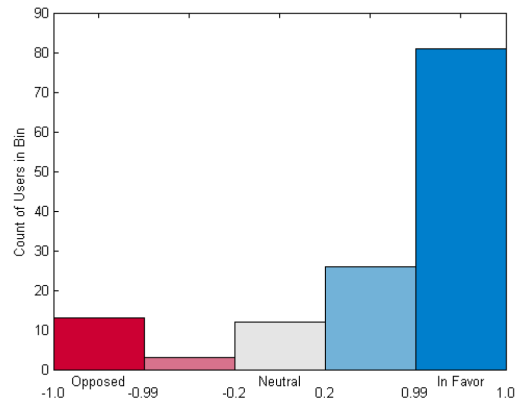


**Figure 1. User stance on Referendum 74. Numbers represent the raw values between the bins**

In total, 498 Living Voters Guide users viewed the Same-Sex Marriage ballot page and took action by writing a point, choosing a stance on the issue, and/or choosing points that they agreed with. In total, they wrote 134 points for this debate, 92 in favor of the resolution and 42 against. Users wrote 49 comments on these points, 35 for, 10 against, and 4 neutral to the issue. In total, there are 5684 words (1045 unique) in points and comments. Figure 2 shows the distribution of each user bin of the proportion of points that were chosen against and for the issue.

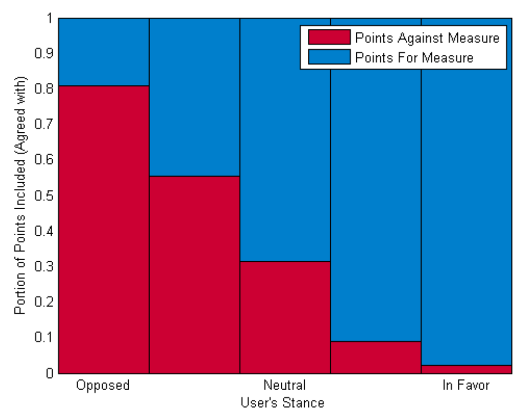


**Figure 2. Amount of pro and con points included for users by stance.**

## VALUES & MORALS

### Choosing the right Set

Values and morals are very personal and there is no gold standard without asking the individuals who composed the statements immediately after. However, we can approximate the values at play using human annotation [13, 5], bag of words correlations [3, 11], and more sophisticated NLP techniques [20]. Human annotation faces incredibly low inter-coder reliability for such a subjective subject, and even the most robust human coding frameworks often fail to achieve sufficient agreement [13]. Thereby, without interviewing the individuals at hand, we need to rely on a combination of human

| Schwartz's Value Types | Graham's Moral Foundations |
|---|---|
| Benevolence | Harm/Care |
| Universalism | Fairness/Reciprocity |
| Self-Direction | In-Group/Loyalty |
| Stimulation | Authority/Respect |
| Hedonism | Purity/Sanctity |
| Achievement | |
| Power | |
| Security | |
| Conformity/Tradition | |

**Table 1. Values and Moral Foundations used in this Analysis**

annotations and computational models to approximate their values, taking this analysis with a grain of salt.

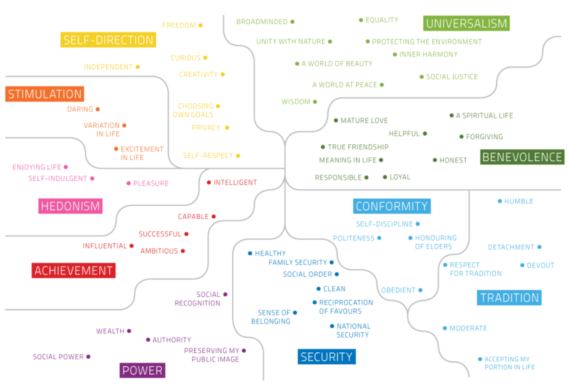


**Figure 3. Schwartz's Value Inventory**[1]

The first task is to choose the set of values that best work for the data. Shalom Schwartz's Value Theory is the seminal work exploring personal values in a cross-cultural context [18]. Schwartz enumerated 56 common, basic human values as shown in the figure above[1]. 56 labels is far too much for reliable analysis and in each of the studies mentioned above, the researchers compressed values from the original list to between 4 and 12. For this experiment, we'll use Schwartz's 10 Value Types to classify personal values. For most analysis we will combine Conformity and Tradition since most researchers, even Schwartz, groups them together in large scale analysis, yielding 9 Value Types.

To provide an alternative model, the analysis and labeling was also done with Graham's 5 Moral Foundations [11]. While investigating differences in the morals of liberals and conservatives, Graham catalogued 5 primary moral foundations. The values in each category are listed in Table 1.

## Labeling

The data was labeled in two ways: Human annotation and Word dictionary counts. Since time and money were a factor for the mini-project, only the original investigator labelled sentences by whether or not each value was present. For a real study, participants should be recruited to label the sentences. Low levels of inter-coder reliability will be expected as demonstrated in [13], but they can be adjusted for by collecting many samples and accepting labels only above a certain agreement threshold. The large set of Schwartz Values, the reduced set of 10 Value Types, and the set of Morals were manually coded for every point and comment in the Same-Sex Marriage debate.

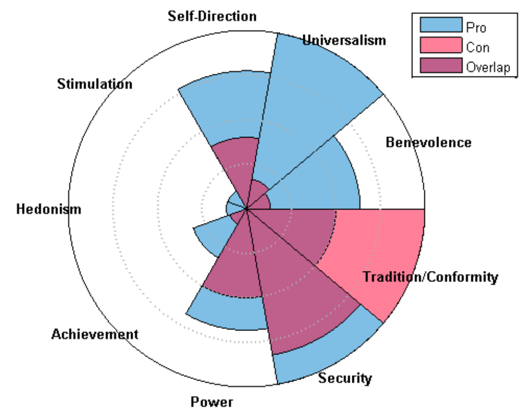


**Figure 4. Distribution of manually annotated Values**

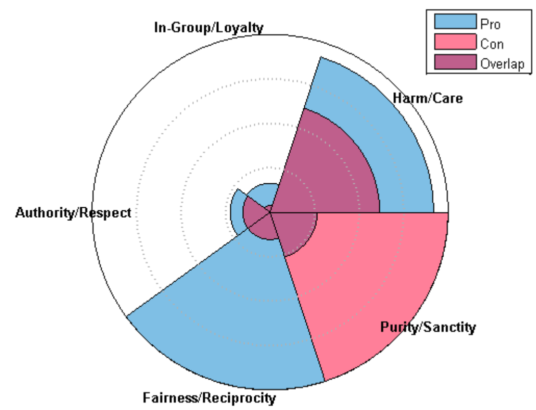


**Figure 5. Distribution of manually annotated Morals**

Figure 4 shows the distribution of values between the Pro arguments and Con arguments for Same Sex Marriage. The rose chart shows the distribution of values for these posts by value category. The most frequent value is scaled to 1. Rose charts do carry a visual bias, effects of larger values are more pronounced, but this illustrates the contrast of the frequency of items such as how the Con arguments generally rely on Tradition/Conformity (top constituent value: Respect for Tradition) while the Pro arguments use Universalism value frames often (top constituent value: Equality).

Figure 5 illustrates the differences in moral frames between both sides. Using human annotation, there is little usage of Authority and In-Group moral foundations, and a strong overlap of Harm/Care moral frames. However, there is a stark different between the usage of Purity/Sanctity frames and Fairness/Reciprocity frames.

[1] `http://valuesandframes.org/handbook/2-how-values-work/`

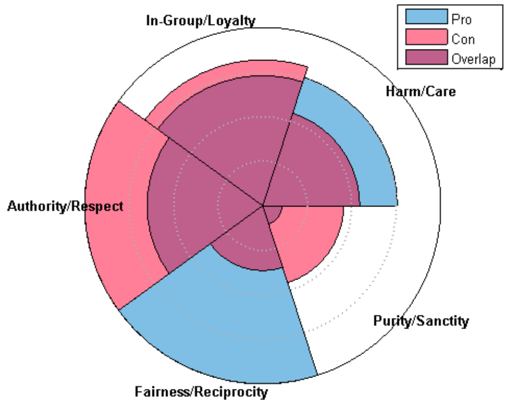


**Figure 6. Distribution of Morals derived from a word dictionary**

In additional to human annotation, morals were also labeled by counting the number of words in a dictionary of related words [11]. Since words in these dictionaries were sparse in the sample data, inclusion of any word of the moral category was considering using that moral. Unfortunately, this model did not agree well with the human annotation, creating almost opposite results. This could be caused by limitations in Bag of Words models but also bias in human annotation. In the Future Work section see a discussion of improvements to this model.

Using the same bins to categorize Living Voters Guide users by stance, we can see the distribution of values across user groups. Since each user indicates the points that they agree with or have affinity to, we can aggregate the values included for each group of users. Figure 7 and 8 show the prevalence of value and moral frames in the points that users of each bin choose.

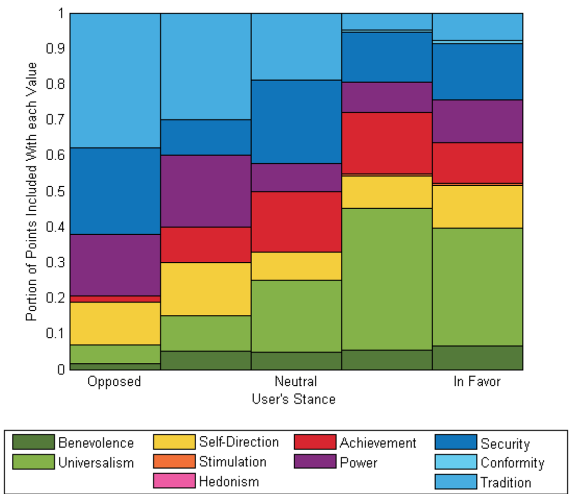


**Figure 7. Frequency of values in included points for users by stance.**

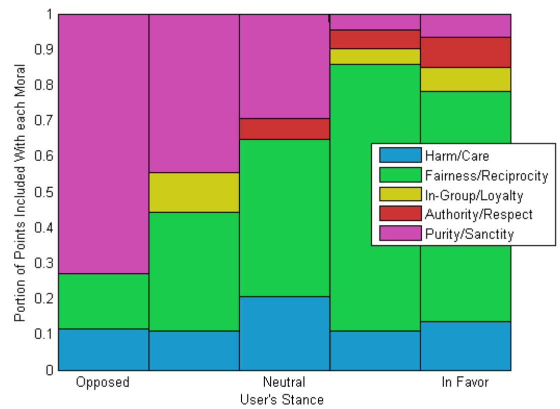


**Figure 8. Frequency of values in included points for users by stance.**

## DISCOURSE

We will explore the relationship between metrics of discourse in the living voters guide debate for Same-Sex Marriage. There are a few sets of features to start out with:
$\mathbb{U}$ = Set of all Users
$\mathbb{P}$ = Set of all Points
Every $p \in \mathbb{P}$ is a set of words, $[w_1, \ldots, w_n]$
$\mathbb{I}$ = Set of all Inclusions
Every inclusion $i$ is a pair of a user $u$ and a point $p$, such that $u$ has included $p$ on the list of arguments that they agree with or have affinity to. $i = (u, p)$

### Measures

We will observe the discourse quality of each point using 9 measures: Inclusions, Stance, Diverse Appeal, Arousal, Valence, Relevance, Novelty, Certainty, and Comments.

For each point $p$, I will measure it's contribution towards discourse quality using select metrics discussed in the related work as well as features specific to the living voters guide. These measures illustrate the position of be used to predict whether or not users included the posts.

**Inclusions** ($\mathcal{IN}$): First, we will just count straight-up how many times a user included a point in their argumentative repertoire relative to the total number of inclusions.

$$\mathcal{IN}(p \in \mathbb{P}) = \frac{|\{i \in \mathbb{I} : i = (*, p)\}|}{|\mathbb{I}|}$$

**Stance** ($\mathcal{S}$): Generally, we expect people to agree with posts that align with their stance. Users voluntarily choose a stance for each ballot measure. I will compute the stance of a point by taking the mean of the distribution of stances that people had who choose to include a particular point.

$$s(u \in \mathbb{U}) = \text{stance of a user}, -1 \leq s \leq 1$$

$$\mathcal{S}(p \in \mathbb{P}) = mean\{s(u) | u \in \mathbb{U}, (u, p) \in \mathbb{I}\}$$

**Diverse Appeal** ($\mathcal{DA}$): In the original design of the living voters guide, they intended to use the diversity of appeal to rank posts. They did this to encourage people to find points that crossed party lines. It isn't certain if this factor had an effect so I will reuse this feature. Diverse Appeal is computed by taking the standard deviation of the distribution of user stances for a particular post.

$$\mathcal{DA}(p \in \mathbb{P}) = stdev\{s(u)|u \in \mathbb{U}, (u,p) \in \mathbb{I}\}$$

**Arousal, Valence** ($\mathcal{AR}$, $\mathcal{EMO}$): Sentiment will be computed using counts of the LWIC dictionary. For each point, which is a set of words, we define it as such:

$$\mathcal{AR}(p) = \frac{|p \cap LWIC_{high\_arousal}| - |p \cap LWIC_{low\_arousal}|}{|p|}$$

$$\mathcal{EMO}(p) = \frac{|p \cap LWIC_{pos\_emotion}| - |p \cap LWIC_{neg\_emotion}|}{|p|}$$

**Relevance, Novelty** ($\mathcal{R}$, $\mathcal{N}$): Diakopoulos measured relevance by taking the tf-idf vectors of New York Times comments and computing the cosine similarity of this to both previous posts as well as from the original article [6]. For this analysis, the data is too sparse for tf-idf to be meaningful so I will instead use the vector of semantic categories as used in LWIC[16]. Each point will have 2 relevance scores, the similarity of a point to the original ballot measure (R, Relevance), and one minus the similarity of a point to the other points made (N, Novelty). We will denote by $\mathcal{L}(p)$ the vector whose $i$th component is the frequency of words in the $i$th LWIC category for the set $p$. Then the relevance and novelty are defined as:

$$\mathcal{R}(p) = \frac{\mathcal{L}(p) \cdot \mathcal{L}(ballotmeasure)}{||\mathcal{L}(p)|| \cdot ||\mathcal{L}(ballotmeasure)||}$$

$$\mathcal{N}(p) = 1 - \frac{\mathcal{L}(p) \cdot \mathcal{L}(\bigcup_{p' \in \mathbb{P}} p')}{||\mathcal{L}(p)|| \cdot ||\mathcal{L}(\bigcup_{p' \in \mathbb{P}} p')||}$$

**Certainty** ($\mathcal{CE}$): This model, brought up in [10], can be derived using the same LWIC counts, as demonstrated in the feature set for [22].

$$\mathcal{CE}(p) = \frac{|p \cap LWIC_{certain}| - |p \cap LWIC_{tentative}|}{|p|}$$

**Comments** ($\mathcal{CO}$): Our last measure of discourse quality is the count of comments based off a point over the maximum number of comments for a point in the debate.

## METHODS & RESULTS

### Predicting Values

I will use Support Vector Machines to predict the values present in the text of points that the users have written. I tried out will 4 types of input matrices, 3 types of output matrices and 2 SVM kernels.

**Input Matrices:** Posts are represented as vectors of Unigram Counts and LWIC Counts. The LWIC count vectors have some features not in the standard LWIC dictionary that have been adopted by my research in email-sentiment analysis: arousal, emotion x arousal and emoticon counts.

The text vectors are sparse and there may be topical relations between the text so they are also grouped using cooccurrence using used Singular Value Decomposition as used in Latent Semantic Analysis. The amount of singular values (the rank) is included in table for the best models using the reduced input matrices.

**Output Matrices:** There are three desired output labelling schemes: The 9 value types, the 5 moral foundations (both manually annotated) and the 5 moral foundations determined using word count dictionaries. The word count based moral foundations were as reliably predicted as the 5 moral frames or worse so they are not reported.

**Support Vector Machines:** Each SVM is a binary classifier to determine if a value/moral is present in an argument or not. For the complete input vectors I used a linear kernel, but the linear kernel did not return reasonable results for the reduced input vectors. Instead, for them, I used a radial basis kernel function.

| Input Features | Output | Precision | Recall | F1 |
|---|---|---|---|---|
| **Using full input vectors** | | | | |
| Unigram Counts | Values(9) | 0.50 | 0.01 | 0.02 |
| LWIC Counts | Values(9) | 0.40 | 0.43 | 0.41 |
| Unigram Counts | Morals(5) | 0.00 | 0.00 | - |
| LWIC Counts | Morals(5) | 0.39 | 0.44 | 0.42 |
| **Using SVD to reduce input dimensionality** | | | | |
| Unigram, rank = 5 | Values(9) | 0.56 | 0.02 | 0.03 |
| LWIC, rank = 6 | Values(9) | 0.41 | 0.08 | 0.13 |
| Unigram, rank = 5 | Morals(5) | 0.67 | 0.04 | 0.08 |
| LWIC, rank = 7 | Morals(5) | 0.65 | 0.07 | 0.13 |

**Table 2. Value Prediction Models**

The precision, recall, and F1 scores are all determined using 10-fold cross validation. The results of the support vector machines in labeling values are very underwhelming. Unigram counts had very F1 scores.

Unigram count inputs performed quite poorly, no F1 score greater than 0.10. Generally, recall was an issue with these models. The best precision and recall were in the models that used the complete LWIC counts, regardless of whether they were predicting values or morals. However, none of these models performed remarkably well and better semantic analysis techniques (and more data) are necessary.

### Correlation between Discourse Quality Metrics, Values, and Morals

I'll investigate the relationship of these metrics by computing the correlation coefficients between each pair. This was done using the Matlab function `corrcoef()`.

After running the correlation test, there are some interesting and some underwhelming connections between different variables. Arousal, Valence, Relevance, Novelty and Certainty did not strongly correlate to other factors in the analysis. Nor did the values of Benevolence, Self-Direction, Stimulation, Hedonism, Power, and Conformity, and the morals of In-Group/Loyalty and Authority/Respect. Table 3 highlights the factors with notable correlations and indicates the p values of positive and negative correlations.

| | | IN | S | DA | CO | UNI | ACH | SEC | TRA | HAR | FAI | PUR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Inclusions | IN | | 0.21 | 0.87 | 0.42 | 0.38 | 0.34 | 0 | -0.1 | -0.22 | 0.38 | -0.18 |
| Average User Stance | S | 0.21 | | 0.39 | -0.32 | 0.34 | 0.05 | -0.27 | -0.45 | -0.09 | 0.37 | -0.48 |
| Diverse Appeal | DA | 0.87 | 0.39 | | 0.17 | 0.45 | 0.27 | -0.02 | -0.08 | -0.3 | 0.47 | -0.22 |
| Comments | CO | 0.42 | -0.32 | 0.17 | | 0.04 | 0.32 | 0.09 | 0.24 | -0.07 | 0 | 0.22 |
| Universalism | UNI | 0.38 | 0.34 | 0.45 | 0.04 | | -0.01 | -0.33 | -0.25 | -0.42 | 0.84 | -0.37 |
| Achievement | ACH | 0.34 | 0.05 | 0.27 | 0.32 | -0.01 | | -0.09 | 0.08 | -0.06 | 0.07 | -0.03 |
| Security | SEC | 0 | -0.27 | -0.02 | 0.09 | -0.33 | -0.09 | | -0.04 | 0.41 | -0.38 | 0.1 |
| Tradition | TRA | -0.1 | -0.45 | -0.08 | 0.24 | -0.25 | 0.08 | -0.04 | | -0.32 | -0.22 | 0.73 |
| Harm/Care | HAR | -0.22 | -0.09 | -0.3 | -0.07 | -0.42 | -0.06 | 0.41 | -0.32 | | -0.46 | -0.29 |
| Fairness/Reciprocity | FAI | 0.38 | 0.37 | 0.47 | 0 | 0.84 | 0.07 | -0.38 | -0.22 | -0.46 | | -0.4 |
| Purity/Sanctity | PUR | -0.18 | -0.48 | -0.22 | 0.22 | -0.37 | -0.03 | 0.1 | 0.73 | -0.29 | -0.4 | |

p < 0.05
p < 0.01
p < 0.001

**Table 3. Correlation Coefficients for Selected Measures**

There are some interesting connections. Points with the most inclusions had greater Diverse Appeal and Comments ($p < 0.001$), while they used the frames Universalism, Achievement, and Fairness ($p < 0.01$). However, these correlations are also tied with the political skew of the participants. Exceptionally, the most commented points were included by people against the proposal and the value Achievement was not tied to people's stance, so there could be something to say about those effects on how many times people include points.

As expected, moral frames and values organized on political alignment, with affinity of Purity to Tradition and Fairness to Universalism (both $p < 0.001$). Harm/Care frames and Security values were correlated ($p < 0.001$), likely do to discussion of Family Security.

Based on the argumentation correlations, Achievement positive effectives agreement (inclusions), diverse appeals, and commenting while not being too partisan. Posts with Achievement values generally had frames talking about being Capable of doing something and taking action.

Harm/Care frames were also less partisan, but they were negative correlated with diverse appeal –the specifics of each Harm/Care frame may be more aligned towards a side of the debate even if both sides use them. Interestingly, Harm/Care frames were strongly negatively correlated with Universalism ($p < 0.001$), Fairness ($p < 0.001$) and Tradition ($p < 0.01$), the other most common argumentation frames. Potentially, arguments that appeal to Harm/Care are more tangible and are notably different than more abstract notions of equality and religious rights so they aren't often argued at the same time.

The full correlation table is listed in the appendix as Figure 9.

## FUTURE WORK

**Common Ground**: Pro arguments often used values often regarded as "conservative": Security and Power value types, as shown in Figure 4. The top constituent value for Security is Family Security and for Power is Social Recognition. This illustrates that supporters of same-sex marriage may have more in common with opponents than polarizing media may portray. Thereby, it may be easier to get both sides to recognize their mutual value of Power and Security rather than demonstrating the opposition of Tradition and Universalism. In terms of Moral frames, sides were polarized on whether using Fairness or Purity frames, but Harm/Care frames were more common between both sides. So getting two sides to talk about the impact of Same-Sex parenting on raising families may be more constructive. Furthermore, Achievement (values such as ability) as a frame was used rarely but correlated with favorable discourse. Self-Direction (values such as independence) had almost no correlations to discussion involvement or other value/moral frames (which is why it isn't included in the results, see it's entry in the appendix). Perhaps Self-Direction is a "boring" or "incontestable" frame, but it also may be one of the least partisan frames in the Same-Sex Marriage debate and may be good to use for that reason.

**Intelligently Parsing Values and Morals**: This work focused on primarily bag-of-words analysis of values. This is clearly insufficient and many modern NLP techniques may do much better at determining value frames and moral frames. One such idea is parsing sentences for dependencies and labeling the relationship between words. Take the example sentence "`For same`$^{1}$ `sex marriage in wa state`$^{2}$`, we need to treat gay and straight couples the same`$^{3}$". `same`$^{1}$ is topical but not the moral frame because it is part of the phrase "same sex marriage". `state`$^{2}$ is topical as well, not indicative of a moral frame since the state is an location, not an agent. `same`$^{3}$ qualifies the verb of the sentence (in particular a verb about action) so it does contribute to the moral frame of Fairness/Reciprocity or the value of Universalism.

**Value Tensions**: This work explored the relationship between values and measures of discourse but it did not sufficiently cover the territory it desired to of "Value Tensions". In a future study, it would be good to look at chains of arguments and measure the mismatch between values in those arguments, paired with similar discourse measures. Ideally this study would involve greater direct user feedback and not just computed metrics from content analysis.

**Intervention**: The HCI community is moving to mobilize users to be more open to new information and deliberation using new tools [17]. Individuals that participant in active forums or seek out new information do not represent the complete population of the Internet. While challenge-averse individuals consume news that primarily just reinforces their beliefs, subtle interface changes can change how receptive they are to new information [15]. Furthermore, to counteract further polarization when people terminate friendships during disagreements [12], we can inform their conversations about other factors, like the history of their friendship or make value tensions apparent.

## CONCLUSION

This class project offered a novel look into the role of values in an online debate. Their are many expected, and a handful of exciting correlations. I would like to continue this analysis and open it up to more domains, use more involved semantic techniques, and apply it directly to online conversations. This work suggests less polarized value frames for the issue of Same Sex Marriage and tradeoffs of particular frames in their effect on online discourse.

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| | | IN | S | DA | AR | EMO | R | N | CE | CO | BE | UNI | SD | STI | ACH | POW | SEC | CNF | TRA | HAR | ING | AUT | FAI | PUR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Inclusions | IN | 1 | 0.21 | 0.87 | -0.11 | -0.01 | 0.14 | -0.02 | -0.09 | 0.42 | -0.21 | 0.38 | 0.02 | -0.04 | 0.34 | -0.15 | 0 | -0.01 | -0.1 | -0.22 | -0.01 | -0.02 | 0.38 | -0.18 |
| Average User Stance | S | 0.21 | 1 | 0.39 | -0.22 | 0.01 | 0.13 | -0.07 | -0.19 | -0.32 | 0.08 | 0.34 | 0.04 | 0.08 | 0.05 | -0.05 | -0.27 | 0.08 | -0.45 | -0.09 | 0.12 | 0.15 | 0.37 | -0.48 |
| Diverse Appeal | DA | 0.87 | 0.39 | 1 | -0.18 | -0.19 | 0.29 | -0.05 | -0.06 | 0.17 | -0.27 | 0.45 | 0.12 | 0 | 0.27 | -0.09 | -0.02 | 0.04 | -0.08 | -0.3 | 0.03 | 0.06 | 0.47 | -0.22 |
| Arousal | AR | -0.11 | -0.22 | -0.18 | 1 | 0.38 | -0.14 | 0.1 | 0.08 | -0.1 | 0.21 | 0.02 | 0.23 | -0.03 | -0.15 | -0.03 | -0.25 | 0.01 | 0.06 | 0.08 | -0.1 | -0.14 | 0.06 | 0.04 |
| Valence | EMO | -0.01 | 0.01 | -0.19 | 0.38 | 1 | -0.53 | 0.12 | 0.14 | -0.03 | 0.29 | 0.06 | -0.11 | 0.06 | 0.04 | -0.09 | -0.02 | -0.05 | -0.28 | 0.2 | 0.02 | -0.04 | 0.02 | -0.26 |
| Relevance | R | 0.14 | 0.13 | 0.29 | -0.14 | -0.53 | 1 | -0.13 | -0.06 | -0.13 | 0.04 | 0.11 | -0.1 | 0.03 | -0.04 | 0.07 | 0.14 | 0.01 | -0.01 | -0.11 | -0.03 | -0.01 | 0.15 | 0.03 |
| Novelty | N | -0.02 | -0.07 | -0.05 | 0.1 | 0.12 | -0.13 | 1 | -0.01 | 0.08 | 0.15 | 0.07 | -0.28 | 0.04 | -0.19 | -0.13 | -0.09 | -0.01 | 0.2 | -0.18 | 0.12 | -0.02 | -0.03 | 0.14 |
| Certainty | CE | -0.09 | -0.19 | -0.06 | 0.08 | 0.14 | -0.06 | -0.01 | 1 | -0.05 | 0.02 | 0.01 | 0.03 | -0.13 | 0.11 | -0.01 | 0.05 | 0.04 | -0.01 | -0.05 | 0.12 | 0.13 | -0.11 | 0.01 |
| Comments | CO | 0.42 | -0.32 | 0.17 | -0.1 | -0.03 | -0.13 | 0.08 | -0.05 | 1 | -0.23 | 0.04 | -0.13 | -0.06 | 0.32 | 0.09 | 0.09 | -0.06 | 0.24 | -0.07 | -0.11 | -0.09 | 0 | 0.22 |
| Benevolence | BE | -0.21 | 0.08 | -0.27 | 0.21 | 0.29 | 0.04 | 0.15 | 0.02 | -0.23 | 1 | 0.09 | -0.17 | -0.07 | -0.17 | -0.01 | -0.18 | -0.07 | -0.2 | 0.04 | 0.02 | -0.15 | 0.12 | -0.08 |
| Universalism | UNI | 0.38 | 0.34 | 0.45 | 0.02 | 0.06 | 0.11 | 0.07 | 0.01 | 0.04 | 0.09 | 1 | -0.12 | -0.09 | -0.01 | -0.25 | -0.33 | 0.17 | -0.25 | -0.42 | -0.05 | -0.21 | 0.84 | -0.37 |
| Self-Direction | SD | 0.02 | 0.04 | 0.12 | 0.23 | -0.11 | -0.1 | -0.28 | 0.03 | -0.13 | -0.17 | -0.12 | 1 | -0.06 | -0.03 | 0.01 | -0.33 | -0.06 | 0.18 | -0.2 | -0.13 | 0.14 | 0.07 | 0.13 |
| Stimulation | STI | -0.04 | 0.08 | 0 | -0.03 | 0.06 | 0.03 | 0.04 | -0.13 | -0.06 | -0.07 | -0.09 | -0.06 | 1 | -0.04 | -0.08 | 0.19 | -0.02 | -0.07 | -0.07 | 0.49 | -0.04 | -0.1 | -0.06 |
| Achievement | ACH | 0.34 | 0.05 | 0.27 | -0.15 | 0.04 | -0.04 | -0.19 | 0.11 | 0.32 | -0.17 | -0.01 | -0.03 | -0.04 | 1 | 0.03 | -0.09 | -0.04 | 0.08 | -0.06 | -0.08 | 0.11 | 0.07 | -0.03 |
| Power | POW | -0.15 | -0.05 | -0.09 | -0.03 | -0.09 | 0.07 | -0.13 | -0.01 | 0.09 | -0.01 | -0.25 | 0.01 | -0.08 | 0.03 | 1 | -0.05 | -0.08 | -0.12 | 0.18 | -0.03 | 0.45 | -0.24 | -0.16 |
| Security | SEC | 0 | -0.27 | -0.02 | -0.25 | -0.02 | 0.14 | -0.09 | 0.05 | 0.09 | -0.18 | -0.33 | -0.33 | 0.19 | -0.09 | -0.05 | 1 | -0.08 | -0.04 | 0.41 | -0.03 | -0.06 | -0.38 | 0.1 |
| Conformity | CNF | -0.01 | 0.08 | 0.04 | 0.01 | -0.05 | 0.01 | -0.01 | 0.04 | -0.06 | -0.07 | 0.17 | -0.06 | -0.02 | -0.04 | -0.08 | -0.08 | 1 | -0.07 | -0.07 | -0.03 | -0.04 | 0.16 | -0.06 |
| Tradition | TRA | -0.1 | -0.45 | -0.08 | 0.06 | -0.28 | -0.01 | 0.2 | -0.01 | 0.24 | -0.2 | -0.25 | 0.18 | -0.07 | 0.08 | -0.12 | -0.04 | -0.07 | 1 | -0.32 | -0.14 | -0.02 | -0.22 | 0.73 |
| Harm/Care | HAR | -0.22 | -0.09 | -0.3 | 0.08 | 0.2 | -0.11 | -0.18 | -0.05 | -0.07 | 0.04 | -0.42 | -0.2 | -0.07 | -0.06 | 0.18 | 0.41 | -0.07 | -0.32 | 1 | -0.15 | -0.17 | -0.46 | -0.29 |
| In-Group/Loyalty | ING | -0.01 | 0.12 | 0.03 | -0.1 | 0.02 | -0.03 | 0.12 | 0.12 | -0.11 | 0.02 | -0.05 | -0.13 | 0.49 | -0.08 | -0.03 | -0.03 | -0.03 | -0.14 | -0.15 | 1 | -0.08 | -0.21 | -0.13 |
| Authority/Respect | AUT | -0.02 | 0.15 | 0.06 | -0.14 | -0.04 | -0.01 | -0.02 | 0.13 | -0.09 | -0.15 | -0.21 | 0.14 | -0.04 | 0.11 | 0.45 | -0.06 | -0.04 | -0.02 | -0.17 | -0.08 | 1 | -0.23 | -0.15 |
| Fairness/Reciprocity | FAI | 0.38 | 0.37 | 0.47 | 0.06 | 0.02 | 0.15 | -0.03 | -0.11 | 0 | 0.12 | 0.84 | 0.07 | -0.1 | 0.07 | -0.24 | -0.38 | 0.16 | -0.22 | -0.46 | -0.21 | -0.23 | 1 | -0.4 |
| Purity/Sanctity | PUR | -0.18 | -0.48 | -0.22 | 0.04 | -0.26 | 0.03 | 0.14 | 0.01 | 0.22 | -0.08 | -0.37 | 0.13 | -0.06 | -0.03 | -0.16 | 0.1 | -0.06 | 0.73 | -0.29 | -0.13 | -0.15 | -0.4 | 1 |

$p < 0.05$
$p < 0.01$
$p < 0.001$

**Figure 9. Correlation Coefficients for All Measures and Values**