Moral Foundations of U.S. Political News Organizations

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Abstract

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Something clever to start

##Moral Foundations Theory

Jonathan Haidt and Jesse Graham formulated Moral Foundations Theory as a method by which to capture the entirety of humans' moral domain. The researchers argued older theories of moral psychology were focused primarily on issues of justice, fairness, and caring - indvidually focused foundations of morality that align with the beliefs of political liberals (**???**). In other words, moral psychology ignored the valid moral foundations of conservatives. Moral Foundations Theory (MFT) holds that people's moral domain can be mapped by quantifying their endorsement of five moral foundations: *harm/care*, *fairness/reciprocity*, *ingroup/loyalty*, *authority/respect*, and *purity/sanctity* (**???**).

The researchers settled on these specific foundations after the completion of a literature survey of research in anthropology and evolutionary psychology (**???**). *LET'S CHECK THIS CITATION IN MENDELEY*!.The first two foundations (*harm/care* and *fairness/reciprocity*) are termed the "individualizing foundations," as they are centered on the concerns of individuals rather than groups. *Harm/care* represents an endorsement of compassion and kindness, while opposing cruelty and harm. *Fairness/reciprocity* represents concerns centered on guaranteeing individual rights as well as justice and equality among all people. The other three foundations (*ingroup/loyalty*, *authority/respct*, and *purity/sanctity*) are the "binding" foundations, owing to their focus on group-related concerns, rather than those of individuals. *Ingroup/loyalty* represents endorsements of patriotism and heroism and discourages nonconformity and dissent. *Authority/respect* represents an endorsement of social hierarchies and traditions while denigrating disobedience. Finally, *purity/sanctity* represents concerns regarding chastity and piety, while discouraging vices and indulgences, including lust, avarice, and gluttony (**???**). Liberals tend to endorse the individualizing foundations more than conservatives. Endorsements for the three binding foundations, however, are lower than conservatives. Conservatives, on the other hand, tend to endorse all five foundations equally, implying they base judments (at least partially) on each foundation (**???**).

##Moral Foundations Dictionary

In order to capture language's role in moral and political reasoning, (**???**) formulated the Moral Foundations Dictionary (MFD) in order to capture moral reasoning and justification as used in speech and text. The MFD is composed of 259 words, with around 50 words assigned to each of the five foundations. The researchers created a preliminary list of words that they believed would be associated with the five foundations. Then, using the Linguistic Inquiry and Word Count (LIWC; **???**) computer program, they analyzed transcripts of liberal and conservative Christian sermons in order to obtain frequencies of the occurrence of words from the researchers' initial list. The researchers manually checked the results from LIWC in order to make sure the results make sense given the contexts and rhetorical devices used in the sermons. Similar to previous research on Moral Foundations Theory, liberal ministers used *harm*, *fairness*, and *ingroup* words more often than conservative ministers. Conversely, conservative ministers used *authority* and *purity* words more often than liberal ministers. However, conservative ministers did not use *ingroup/loyalty* words more than liberals. Rather, liberal ministers used words pertaining to *ingroup/loyalty*, but in contexts that promote rebellion and independence - causes *opposite* to positive endorsements of that foundation (**???**).

To this point, most text analysis utilizing the Moral Foundations Dictionary operationalizes endorsement of any one of the foundations as percent occurence of words from the foundation's respective word list. As such, most analyses assume that zero percent occurence is indicative of no endorsement, while any non-zero percent occurence indicates endorsement of the foundation. This may not be sufficient in describing the true nature of the writer or speaker's endorsement of one of the sets of moral intuitions. A quick glance at the MFD words for *harm/care* reveals the presence of words that are more closely associated with universally accepted conceptions of *harm* over *care* and vice-versa (**???**). For example, the word “cruel” has relatively negative connotations compared to “benefit.” For the *harm/care* foundation, it is conceivable that use of the word “cruel” might indicate a greater attentional focus of the idea of *harm* rather than *care*.

For *harm/care*, the definition of the foundation well as its name clearly distinguishes between two somewhat opposite sides of an attentional continuum, with *harm* on the negative end and *care* on the positive side. In other words, the entries in the MFD for *harm/care* have somewhat clear positive and negative valences. The same pattern can be seen in the MFD entries for the other four foundations. *Purity/sanctity* features words that likely have a negative valence to most observers, including “disease”" and “trash,” along with more positive words, including “right” and “sacred” (**???**). T however, brings up other questions regarding the definition and names of the other four foundations apart from *harm/care*: *fairness/reciprocity*, *ingroup/loyalty*, *authority/respect*, and *purity/sanctity*. The latter four foudnations have names that are harder to understand as a valence continuum, as the concepts in the names are more similar, even to the point of being virtually synonymous in the case of *fairness/reciprocity*.

When considering the issue of positive versus negative valence in MFD words, the question of how texts are analyzed vis-a-vis the MFD remains. How can raw percentage of MFD word occurence capture the valence and focus of the writer or speaker? If 2% of a politician’s speech features positive words (i.e. “benefit” and “defend”) from the MFD *harm/care* list, how can researchers be sure the level and nature of the speaker’s “endorsement” of the foundation equals that of another politician whose speech contained negatively connoted MFD words from the *harm/care* list? They would have equal endorsements as far as the numbers are concerned, but the words used and focus given are on opposite sides of the *harm/care* spectrum.

This issue is compounded by the fact the Moral Foundations Questionnaire (MFQ) and its subscales assume endorsement lies on a continuum. One item under the *fairness/reciprocity* judgment subscale reads, “Justice is the most important requirement for a society” (**???**). The survey respondent must select a number on a scale from 1 to 6 indicating responses spanning “strongly disagree” at 1 to “strongly agree” at 6. While the scales in the MFQ do not represent true valence as it pertains to individual words, it does allow for a greater degree of specificity in terms of an individual’s endorsement of a particular moral foundation. When a respondent selects a 4 for the aforementioned MFQ statement, they clearly are indicating they “slightly agree” with the statement (**???**). This specificity is not present in most analyses involving the MFD and percent occurence, unless they also take into account the valence of the words used in the text or speech of interest.

##Valence

Borrowing from Osgood’s work in the 1950s, (**???**) recognized valence as one of three related dimensions comprising emotion when developing their Affective Norms for English Words (ANEW). As mentioned before, “valence,” the first dimension, denotes the pleasantness of a given word. “Arousal,” the second dimension, describes the stimulating nature of a word. Lastly, “dominance” or “control” describes the extent to which a word makes one feel in or out of control (**???**). The researchers developed ANEW by presenting participants with a list of 100-150 words and asking for them to rate the word on all three dimensions using the Self-Assessment Mannikin (SAM), which allows ratings along either a nine-point scale when using traditional paper instruments or a twenty-point scale when using a computerized version.

Participants saw the stimulus word and responded on each scale. The valence scale featured a smiling figure at one end (representing pleasantness) and a frowning figure at the other end (for unpleasantness). The arousal scale had a “wide-eyed” figure at one end with a sleepy figure at the other, representing stimulating and unstimulating respectively. Finally, the control scale featured a large figure, indicating the highest degree of control, at one end and a small figure, indicating a lack of control, at the other end (**???**). The end result of this procedure yielded affective norms along the three dimensions for 1,040 English words (**???**). ANEW represented an important first step in establishing affective norms for large numbers of English words. However, later researchers found the 1,040-word list to be limiting for a language consisting of thousands of words.

(**???**) exponentially lengthened the list of words with affective norms to 13,915 English lemmas, the base forms of words without inflection (i.e. "watch" rather than "watched" and "watching"). The researchers recognized the importance of affective norms in several areas of study, including emotion, language processing, and memory (**???**). They argue the list of words included in ANEW is sufficient for small-scale factorial research designs, but the list is "prohibitively small" for larger-scale "megastudies" that are common in psycholinguistic research today (**???**).

In order to source a large number of lemmas for affective ratings, the researchers drew from several validated sources. These include the 30,000 lemmas with age-of-acquisition (average age at which a particular word is learned) ratings gathered by Kuperman, Stadthagen-Gonzalez, and Brysbaert as well as the content lemmas from the SUBTLEX-US corpus consisiting of subtitles from various forms of visual media (**???**). This resulted in the final list of 13,915 lemmas. Lists of 346-350 words were presented to participants recruited through the Amazon Mechanical Turk subject pool. Particpants rated the words along one of the three dimensions, unlike the ANEW project in which participants rated each word along all three dimensions at once. The researchers used a nine-point scale similar to the one used by (**???**) when collecting ratings for ANEW (**???**).

The researchers noted several points of interest upon observing ratings. First, they found that valence and dominance ratings had a negative skew, indicating more words elicited feelings of happiness and control than their respective opposites. Also, when examining the relationship between valence and arousal ratings, the researchers found a U-shaped relationship. This indicates words with high degrees of positivity and negativity elicited higher arousal (**???**). These observations along with the now-greatly expanded list of affective norms has been applied to several lines of inquiry in psycholinguistics.

(**???**) utilized the new affective norms list in order to investigate the validity of the Pollyanna hypothesis, or the prevalence of a generally optimistic outlook in humans as reflected in langauge. The researchers were able to conclude the existence of a greater number of positive-valence English words in the list of 13,915 lemmas. Additionally, after observing token frequency in a number of text corpora, including SUBTLEX-US, COCA, BNC, TASA, and HAL, the researchers found that words with postive valence were also used more frequently (**???**). While the researchers concede the possiblility of an acquiensence bias in ratings as a possible explanation for the observed positivity bias, this investigation represents one application of the (**???**) list in emotional studies.

One cognition-based study investigates the relationship between emotion and response latencies in word recognition. (**???**) sought to use the (**???**) norms to fill in the knowledge gaps regarding variance in word recognition. The researchers drew several conclusions regarding emotion and word recognition (specifically in naming and lexical decision tasks). First, (**???**) found higher response latencies in negative-valence words, lower response latencies in neutral words, and even lower response latencies in words with positive valence. The researchers also concluded that words causing higher arousal tend to have higher response latencies than less-arousing words. They found valence had a stronger effect on recognition than arousal (both effects were independent, not interactive). They found an interaction between emotion and word frequency such that valence and arousal are more effective on lower frequency words than high frequency words. Finally, (**???**) found a greater effect for lexical decision tasks than for naming tasks. This research serves as further evidence that the (**???**) list can be used for research inquiries both within and without the field of psycholinguistics.

In the present studies, the researchers used the 2013 Warriner list in order to denote the valence of the words appearing in the news articles scraped from the internet. Valence was considered as another independent variable and its relationship with the words comprising the Moral Foundations Dictionary were of chief interest to the researchers. The valence was used as a means to determine whether individiual words in the MFD represented more positive aspects of their respective foundation or if they denoted a more negative aspect of the foundation. Incorporating word valence into a study involving the MFD is meant to alleviate some of the issues regarding the aforementioned ambiguity regarding the words in the Moral Foundations Dictionary.

News Media and Politics

Research into politics, language, and media has illuminated the complex relationships between all three. Any politically-oriented discussion of word occurence as an implication of moral or poltical position assumes that langauge and ideology are intrisincally linked. Deborah Cameron (**???**) points out the expressive nature of ideological beliefs and how that expression is conveyed through langauge, thus implying a connection between ideology and language. She goes on to criticize the notion that language is either the "pre-existing raw material" used to shape ideologies or the "post-hoc vehicle" for their propogation. Rather, the structure of language itself is shaped by ideology and social processes even when it is used to explain or express ideologies (**???**).

The use of language both to express and further an ideological goal has been documented in the techniques employed by candidates for political office in the U.S. For example, Druckman, Jacobs, and Ostermeier ((**???**)) investigated issue and image priming on the part of candidates as implied by the disproportionate attention candidates paid to particular issues over others. In their research, the authors consider "issues" as communication that attmepts to persuade constituents to vote for the candidates based on their strengths in matters of public policy. "Image" priming, on the other hand, describes techniques deployed in order to sway votes based on favorable aspects of the candidate's behavior and personality (**???**). The researchers found numerous examples of issue and image priming during the 1972 re-election campaign of Richard Nixon. They linked the Nixon adminstration's awareness of the issues for which the president had public support to the issues he should emphasize (and prime) during the campaign. Likewise the researchers found evidence that Nixon's team was aware of negative evaluations of his warmth and trustworthiness, and thus took steps to prime his purportedly positive qualities, including strength and competence (**???**).

(**???**) also cited research from Iyengar and Kinder (1987) suggesting the news media affected perceptions of President Jimmy Carter's competence by emphasizing (re[illegible] priming) issues related to energy, defense, and the economy. This implies news media may affect perception of politicians based on where the media places emphasis. Other research into news media suggests certain media outlets, at least indirectly, may have an effect on the voting records of representatives in Congress (**???**). Specifically, the researchers identified a pattern of declining support for President Bill Clinton's policies chiefly among Republicans in the House of Representatives after the Fox News Channel began broadcasting on cable and satellite systems in their respective districts. As Fox News was, at the time of its launch in 1996, the only outwardly ideological national news network, the reserachers were able to track its spread across the country and observe voting records of members of Congress both before and after Fox News' arrival (**???**). The researchers concluded that members of Congress, excluding those newly elected at the time of Fox News Channel's emergence, attempted to anticipate resultant conservative-leaning shifts among their constituents by bolstering their conservative voting record before the next election (**???**).

Talk about political discourse, nature of news media in 2018/Trump era/Kavanaugh

This project brings the two together in holy matrimony.

Experiment 1

Method

Sources

Political articles were scraped from the websites of four notable U.S. news sources. The sources were *The New York Times*, *National Public Radio (NPR)*, *Fox News*, and *Breitbart*. They were selected for their widespread recognition and the fact they are easily categorized (by the general public) according to perceived political lean. In general, *The New York Times* and *NPR* are perceived by many to have a liberal bias or lean. In contrast, Fox News and Breitbart are believed to have a conservative bias or lean. Political articles in particular were identified and subsequently scraped by including the specific URL directing to each source's political content in the *R* script. For example, rather than scrape from nytimes.com, which would return undesired results (non-political features, reviews, etc.), we instead included nytimes.com/section/politics so that more or less exclusively political content was obtained. All code for this manuscript can be found at OSF LINK, and the scripts are provided inline with this manuscript written with the *papaja* library (**???**).

Identification of the sources' political URLs presented a problem for two of the sources owing to complications with how their particular sites were structured. While in the multi-week process of scraping articles, we noticed word counts for *NPR* and *Fox News* were not growing at a similar pace as those from *The New York Times* and *Breitbart*. Upon investigation, we found another, more robust URL for political content from NPR: their politics content "archive." The page structure on NPR's website was such that only a limited selection of articles is displayed to the user at a given time. Scraping both the archive and the normal politics page ensured we were obtaining most (if not all) new articles as they were published. We later ran a process in order to exclude any duplicate articles. *Fox News* presented a similar issue. We discovered *Fox News* utilized six URLs in addition to the regular politics page. These URLs led to pages containing content pertaining the U.S. Executive Branch, Senate, House of Representatives, Judicial Branch, foreign policy, and elections. Once again, duplicates were subsequently eliminated from any analyses.

Materials

Using the *rvest* library in the statistical package *R*, we pulled body text for individual articles from each of the aforementioned sources (identified using CSS language) and compiled them into a dataset (**???**). Using this dataset, we identified word count and average word count per source. This process was run once daily starting on *DATE* until *DATE.* Starting on *DATE,* the process was run twice daily - once in the morning and again in the evening. Data collection was terminated once 250,000 words per source was collected on *DATE.*

Data analysis

Once data collection ended, the text was scanned using the *ngram* package in *R* (**???**). This package includes a word count function, which was used to remove articles that came through as blank text, as well as to eliminate text picked up from the Disqus commenting system used by certain websites. At this point, duplicate articles were discarded.

Using the (**???**) dictionary, the words making up each of the five foundations in the MFD were assigned their respective valence value. Once the MFD words' valences were added to the dataset, the article text was processed using the *tm* and *ngram* packages in *R* in order to render the text in lowercase, remove punctuation, and fix spacing issues (**???**). The individual words were then reduced to their stems (i.e., *abused* was stemmed to *abus*). The same procedure was applied to the MFD words and the words in the (**???**) dataset.

DESCRIBE MTMM NEW STUFF HERE? Basically, words found through that project were imported and added to each foundation, with reduncies removed at the end.

The source article words were compiled into a dataset where they were matched up with their counterparts in the MFD along with their valence and a percentage of their occurrence. Therefore, for each article, the percentage of the number of *harm/care* words occurring in the articles were calculated, and this process was repeated for each of the foundations. This procedure created five percentages that were included as the dependent variable for the following analyses.

Results

To analyze if news sources adhered to differences in word use based on their target audience, we utilized a multilevel model (MLM) to analyze the data. MLM is a regression technique that allows one to control for the repeated measurement and nested structured of the data, which creates correlated error (**???**). Using the *nlme* library in *R* (**???**), each foundation's weighted percentage was predicated by the political lean of the news soource, using the individual news sources as a random intercept to control for the structure of the data.

Discussion

Experiment 2

##Kavanaugh Supreme Court Hearing

In the wake of Justice Anthony Kennedy's retirement from the Supreme Court of the United States, President Donald Trump nominated Brett Kavanaugh as the new Associate Justice. Kavanaugh was previously on the U.S. Court of Appeals for the District of Columbia. The Senate Judiciary Committee began his confirmation hearing on September 4, 2018 (**???**). Following allegations of sexual assault by high school classmate Dr. Christine Blasey Ford, the committee postponed its vote on whether or not to open the confirmation to the entire Senate.

On September 27, the committee questioned Dr. Ford before commencing a second round of questioning for Judge Kavanaugh (**???**). During the intervening weeks between hearings, two more women came forward with two separate allegations of sexual assault on the part of Kavanaugh. According to Nielsen reports, more than 20 million people watched the September 27 proceedings on television (**???**). This figure does not take into account viewers who watched online, nor does it account for viewers outside the United States. On September 28, the Senate Judiciary Committee voted to send the nomination to the Senate floor. Senator Jeff Flake of Arizona, however, lobbied for a week-long FBI investigation on Kavanaugh and the allegations facing him, which the committee, and later the President, approved. The investigation concluded with no significant findings. The Senate voted 50-48 to approve Kavanaugh's appointment on October 6, 2018 (**???**).

The Kavanaugh nomination, confirmation hearing, and eventual swearing-in, as well as the news media's coverage of all three events, feature many moral dimensions that likely differ depending on one's morals. On one side of the debate, Kavanaugh's Supreme Court tenure presents a prime oppurtunity to bring morality back into interpretation of the Constitution. Kavanaugh's confirmation creates a conservative stronghold among the justices on the court. Commentators have noted this might help advance a judicial agenda that backpedals certain rights previously upheld by the Supreme Court, including abortion and gay marriage - social issues challenged by their opponents at least partially on moral grounds. On the other side of the debate, the assault allegations have energized Kavanaugh's opponents to advocate for his rejection from the court owing to misdeeds resulting from Kavanaugh's own alleged lack of morals. Additionally, the moral duty of the Senate as the upper chamber in the U.S. legislature has been scrutinized in public discourse with respect to its handling of the assualt allegations vis-a-vis Kavanaugh's confirmation.

Method

Sources

Experiment 2 largely followed the same method as Experiment 1. Political articles specifically referring to Brett Kavanaugh and his Supreme Court confirmation hearing were scraped

Materials

Expected material stuff - we are going to pick liberal and conservative sources from that thing document linked stuff - list those here: Sources used by LIBERALS (according to the document thing): The New Yorker Slate The Daily Show (is it wise to use satirical news for this??) The Guardian Al Jazeera America NPR New York Times Buzzfeed PBS BBC Huffington Post Washington Post The Economist Politico MSNBC CNN NBC News CBS News Google News Bloomberg ABC News USA TODAY

Sources used by CONSERVATIVES: Fox News Drudge Report Breitbart Rush Limbaugh Show The Blaze Sean Hannity Glenn Beck (does he still report "news"??)

- pick a specific date range we want to pull articles from
- list that here:

START DATE: September 13, 2018

(September 27, 2018: Ford and Kavanaugh testimony before Senate Judiciary Committee)

END DATE: October 11, 2018

here's when the stuff was happening and so picked two weeks before and after

Data analysis

How you would run the data analysis

Experiment 2 results

Discussion

Conclusions

How it turned out

Limitations of this one (no rationale behind choosing sources except "people say NPR's liberal??")

What to do for future project (focus on one MF? Different sources? More sources?)

Argue: why is still a good thing to study?? (probably something about current state of discourse, information, truth, "alternative facts," subjective reality - philosophical stuff)

References