Gender and Ideology in the Spread of Anti-Abortion Policy

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ABSTRACT
In the past few years an unprecedented wave of anti-abortion policies were introduced and enacted in state governments in the U.S., affecting millions of constituents. We study this rapid spread of policy change as a function of the underlying ideology of constituents. We examine over 200,000 public messages posted on Twitter surrounding abortion in the year 2013, a year that saw 82 new anti-abortion policies enacted. From these posts, we characterize people's expressions of opinion on abortion and show how these expressions align with policy change on these issues. We detail a number of ideological differences between constituents in states enacting anti versus pro-abortion policies, such as a tension between the moral values of purity versus fairness, and a differing emphasis on the fetus versus the pregnant woman. We also find significant differences in how males versus females discuss the issue of abortion, including greater emphasis on health and religion by males. Using these measures to characterize states, we can construct models to explain the spread of abortion policy from state to state and project which types of abortion policies a state will introduce. Models defining state similarity using our Twitter-based measures improved policy projection accuracy by 7.32% and 12.02% on average over geographic and poll-based ideological similarity, respectively. Additionally, models constructed from the expressions of male-only constituents perform better than models from the expressions of female-only constituents, suggesting that the ideology of men is more aligned with the recent spread of anti-abortion legislation than that of women.

Author Keywords
public policy; social media; political science; abortion; text analysis; policy diffusion

ACM Classification Keywords
H.5.3. Group and Organization Interfaces: Asynchronous interaction; Web-based interaction

INTRODUCTION
The landscape of abortion access in the U.S. has changed dramatically in only the last several years. Over 250 new state abortion restrictions were enacted from 2011 to 2013, which is more state abortion restrictions enacted than the entire decade prior [4]. Not only has there been a surge in policies introduced, but there is great variation and novelty in how the policies seek to restrict abortion, ranging from banning abortion at different gestational periods, to harsher regulations for abortion providers and clinics, to limitations on insurance coverage of abortion. All of these policies have chipped away at abortion coverage in the U.S. so that for many women, a legal operation has become one that is increasingly difficult to obtain, due to distance, money, time, and other barriers.

Given this significant amount of policy change on such an important issue, it is important to ask whether and how these changes reflect the will of the people. In this paper, we study how the spread of policy change is reflected in the public discourse on abortion. Given that abortion is a highly gendered issue, we also distinguish male from female ideology in order to compare the influence of each on the rapid evolution of abortion policy change.

To address these questions, we focus on the *language usage* of constituents in order to understand which policies align with their interests. Language, a reflection of common understanding within a social context, plays an important role in social and political movements. The terminology of different camps are constantly in competition to become part of mainstream public discourse, as one can see with the branding of "pro-life" and "pro-choice" for the opposing sides of the abortion debate [6]. By studying language use rather than using poll data, we also have much greater flexibility in choosing what to analyze as well as the ability to understand more nuanced measures, such as ideology and emotion.

But how can we observe the language usage of constituents engaging in public discourse? Today, social media sites such as Twitter offer a platform for users to express their thoughts and feelings on a wide range of topics, including their stance on major social and political issues. Recent research has used public expressions on social media as a way to obtain insights at the population level in a number of fields, including public health [31], financial markets [35], and politics [8]. By analyzing this data, we can also collect or infer metadata such as time, location, and gender of the speaker to better understand the context of the discussion and how these characteristics interact with public policy.

In characterizing the ideology expressed by constituents, we find many differences between anti-abortion versus pro-abortion states, such as an emphasis on the fetus, including

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references to it as a baby and concern towards its "death", versus an emphasis on the pregnant woman and her autonomy and freedom, respectively. We also find that the anti-abortion side exhibits greater unity and greater intensity of emotions expressed, and that male constituents overall express moral values and personal concerns that are more in line with anti-abortion than females.

Turning towards understanding the spread of anti-abortion policies across the U.S. states, we use our measures to build models for projecting how policies spread from state to state. We use a collaborative filtering approach in order to retroactively recommend policies to states based on the prior actions of similar states. We try several different ways of modeling similarity between states and find that using our Twitter measures outperforms other measures of similarity, such as geographic distance or poll-based ideology measures. We also find that using only male Twitter messages lead to a better fit for policy diffusion than using female Twitter users. This shows a dominant role for male ideology in the diffusion of recent anti-abortion policy. We conclude with a discussion of implications, including the unique insights and practical value derived from analyzing public policy through studying the expressions of constituents on social media.

BACKGROUND AND RELATED WORK

Much research has demonstrated the influence that constituents have over public policy in the U.S. [17, 30] and how policy diffusion from state to state occurs [3, 21, 22]. There has also been a great deal of research related specifically to abortion policy change, including how it is enacted in different countries and cultures [18], whether the makeup of legislatures have any effect on state abortion policy [2], and how Americans feel about abortion and the values they use to form those opinions [9]. While research has examined how public opinion affects policymaking in the specific case of abortion policy [29], most studies rely on outdated public opinion polling, analyzing data taken from before the recent swell of anti-abortion legislation.

While a great deal of public policy research makes use of polling data to understand public discourse, many researchers also analyze language usage in textual data. Prior research analyzing public discourse specifically around the issue of abortion have mainly focused on the language used by people in positions of authority, such as Supreme Court justices and politicians, or large organizations, such as public interest groups or mainstream media outlets. Study of the language used by Supreme Court justices in their decisions show a politicization of language that reflects terms such as "unborn child" and "baby" on decisions written against abortion and terms such as "fetus" in decisions for abortion [1, 18]. Rhetoric from law briefs from different political organizations have also been analyzed for the bias in their word choices. For instance, briefs from anti-abortion activists would frequently describe abortion clinics as abortion "industries", lending an ideological slant [18]. Study of language used by news organizations credit news outlets for bringing politicized phrases such as "partial birth abortion" into the mainstream, terms first coined by anti-abortion activists [25].

In our work, we focus on the public discourse available on public social media posts about abortion. This discourse is comprised mostly of the expressions of ordinary constituents in addition to politicians and organizations. While ordinary constituents may not individually have as much influence as a politician or an organization, their collective choice of language can signal prevailing opinions and their ideological values and reasoning behind them.

The conflict surrounding abortion is also a gendered conflict, since abortion affects females and males differently. In many cases, policymakers and organizations have chosen to frame abortion not in terms of women's rights but in terms of other issues, such as fetal rights or religion [37]. In the last few decades, women's movements have aimed to reframe the discussion to emphasize the pregnant woman and her autonomy, health, and privacy. Some research has looked into the use of gendered language and the emphasis on women by people on opposite sides of the gender debate. A study of Supreme Court decisions found that numerous anti-abortion opinions minimized the presence of the pregnant woman, speaking only of "wombs" [1]. There was also a striking difference in the reference of the pregnant woman as a "mother" as opposed to a "woman". There are other works that also look at the broader differences between language usage and values for men versus women [20, 28]. This prior work informed the collection of some of our Twitter measures and also assisted in our validation and analysis of our findings.

While most of the above studies use manual expert analysis and focus on specific terms or phrases, there are also methods to analyze public discourse language at a greater scale. Researchers have developed lexicons, including the Linguistic Inquiry and Word Count (LIWC) software [32] in order to capture the prevalence of certain concepts in text automatically. Many of these concept categories have been scientifically validated as performing well on short text and discussions on the Internet [10] for the purpose of understanding large populations. Other researchers have added supplemental categories to LIWC to capture aspects of political ideology, such as moral values [19]. We used these techniques and categories to develop many of our measures.

As can be seen, most prior work focuses on conducting opinion polling or analysis of texts written by politicians, organizations, journalists, and judges. In recent years, there has been more research on using social media to gain insights into politics, social movements, and public policy. In politics for example, some research has studied the network structures of opposing political sides [8], while others seek to predict elections using social media [16], or predict the political alignment of Twitter users [5], with different levels of success. Work on social movements has looked at how how social media itself is a platform for social movements to take off [36] and has examined the network structure of activists [7]. There have been fewer works that cover the interplay of social media and public policy however. One recent work analyzed social media for discussions on same-sex marriage in order to predict whether same-sex marriage legislation would pass [38].

Search Term	Number of Tweets	Search Term	Number of Tweets
abortion	577564	abort + baby	8101
prolife	61221	abort + birth	1466
prochoice	13682	antichoice	1094

Table 1. Top terms that were used to find tweets related to abortion on Twitter.

Gender	Min	State	Med	State	Max	State
All	258	WY	3011	SC	35682	TX
F	45	WY	850	AL	10789	TX
M	83	WY	1092	KY	12073	TX

Table 2. The states with the minimum, median, and maximum number of users in our Twitter abortion dataset broken down by gender.

DATA

First, we explain how we collected discussions on Twitter related to abortion and classified them to particular states as well as genders. Following that, we discuss our method of gathering both introduced and enacted policies related to abortion at the U.S. state level and how we coded them into specific categories.

Twitter Data

From a qualitative examination of current-day Twitter posts, organization and community wikis, and information pages, we manually constructed a set of key terms, phrases, and hashtags related to abortion. The most popular terms in our dataset are shown in Table 1. As can be seen, the vast majority of tweets came from the basic search term "abortion", though we also included specific terms from both the pro-abortion and anti-abortion side to capture more tweets. We searched for these terms from the Twitter Firehose, a dataset provided by Twitter containing all public tweets and made available to us through an agreement with Twitter. We limited our search to the year 2013, a year which saw many abortion-related bills introduced and enacted at the state level.

Tagging Twitter users to U.S. states

Because we wanted to compare the expressions of constituents of a certain state to the policies enacted in that state, we needed to geographically tag posts to a particular U.S. state. As shown in prior work, this is not always an easy task and may introduce biases, such as an overrepresentation of urban demographics when using geographically-tagged posts [23]. For this reason, we chose to not limit ourselves to only the posts that have an associated latitude and longitude, of which there are few. Instead we used manually-constructed dictionaries for each state to match to Twitter users' free-text profile location field. Prior research has demonstrated that it is possible to use this method for analysis at the level of granularity of a city or state [27]. Dictionaries were constructed for each state using terms such as the state name, the state abbreviation preceded by a comma, major cities within the state, as well as well-known nicknames for the state and the cities in the state. We constructed dictionaries much in the same way as prior work [38], which describes the creation of state dictionaries in more detail. Like that work, we found a strong correlation between our post volume tagged to each state and the population counts from each state from the 2013 U.S. Census ($\rho = 0.915$, $p = 6.5 \times 10^{-21}$). Having categorized each user to a state based on their profile location field, we then count each of their tweets as coming from that state. In total, from an original dataset of over 300,000 users and over 600,000 tweets, we were able to tag 102,888 users to a particular state, leaving 248,829 state-tagged tweets. In comparison, only 5,097 tweets in our original dataset have associated geographic coordinates.

Categorizing Twitter users to genders

We wished to understand how male Twitter users were discussing abortion differently from female users. To do so, we needed to infer the gender of the Twitter users as there is not a place in the profile to enter a gender. We thus leveraged users' self-declared first name, using dictionaries of male and female names taken from De Choudhury et al. [10]. That work collected names from the U.S. Census data as well as a public corpus of Facebook users' names and self-reported gender. They also validated their approach against manual labeling and obtained an accuracy of 83%. Given the approach we used, we were only able to use a binary classification of male and female.

In the end, out of 248,829 state-tagged tweets, 154,429 tweets were also gender-tagged. Of these, 67,988 were female and 86,441 are male. When we break down the dataset by state and gender, we find that the state with the least amount of data is Wyoming while the state with the most data is Texas, as seen in Table 2. While the state populations and tweet counts were highly correlated, this does mean that some states had very little data, which we discuss further in Limitations and examine more closely in our policy projection model.

Policy Data

We collected data on abortion-related policy events at the U.S. state level from the year 2011 to 2013. While we focused on projecting policy events happening in 2013, we collected policy information from 2011 onwards in order to have a picture of the policies introduced within a state leading up to 2013. We focused on the time period of 2011 to 2013 because this was a period that saw an unprecedented wave of over 400 new policies introduced regarding abortion.

We primarily used information provided by the Guttmacher Institute, a non-profit organization dedicated to reproductive health, including issues such as birth control and abortion. The Guttmacher Institute provides a centralized place that reports all abortion-related bills that have been introduced in a state senate or house as well as how that bill moves through the chambers, including if or when it gets enacted by the governor [24]. From the Guttmacher Institute, we collected all abortion-related policy events. We defined a policy event as anytime a bill is voted on by the state house, senate, governor, or by popular vote. We recorded the month the event took place, whether the bill was pro-abortion or anti-abortion, the outcome of the event, the state, and the group that voted on the event. We also collected other kinds of policy data, such as for each state, the week in the gestational period for which abortion is banned, as one measure for how harsh abortion restrictions are within that state.

We also categorized the policies into different groups. As stated earlier, there has been not only an explosion of

Abortion Policy Category	Event Count	States Passed
Abortion Coverage Limited in Health Plans Offered in the Health Exchange	39	18
Prohibits the Use of Telemedicine	30	19
Ban Abortion After Specific Gestational Age	28	16
Limits Medicaid Abortion Coverage	27	12
Amends Abortion Reporting Requirements	23	14
Funding for Alternatives to Abortion Services	19	17
Requires Abortion Providers to Have Hospital Admitting Privileges	19	12
Parental Consent Requirements	20	9
Amends or Establishes Clinic Regulations	19	9
Adds Counseling Requirements	16	8
Ban Abortion	15	2
Requires an Ultrasound Before an Abortion	15	10
Private Insurance Coverage of Abortion	14	8
Limits Medication Abortion to Physicians	15	9
Establishes "Choose Life" License Plates	13	7
Requires Abortion Counseling and a 24 Hour Waiting Period	11	1
Physician Liability	10	4
Amends Judicial Bypass Process for Minors	9	9
Abortion Coverage Limited in State Employee Health Plan	9	3
Ban Abortion for Race or Sex Selection	9	6

Table 3. Top 20 most active categories of abortion policies and their event occurrence from 2011 to 2013. Events include a bill passing or failing a particular branch of state government. We also show the number of states that passed one or more bills from each category.

abortion-related policies introduced in the last four years, but also a great deal of variety in the bills that have been introduced. For instance, some policies limit abortions by placing harsher restrictions on abortion clinics and requirements for abortion providers, while others ban abortion at specific stages or for specific reasons. The vast number of policies seek to limit abortion in a post-Roe vs. Wade era. Indeed in 2013, out of 82 policies that were enacted into law, only two were pro-abortion. In order to make sense of the many different kinds of bills introduced during this period, we grouped the policies into 45 major categories, primarily guided by the categories provided by the Guttmacher Institute. While other research has also categorized abortion policies into major groups, the results are often outdated, as many innovations in abortion restriction policy arrived in the last several years. For instance, work on abortion policies in the 1990s separated policies into only 7 categories [29], highlighting just how much more diverse the abortion policies are today.

In Table 3, we show the 20 categories that had the most policy events, the total number of policy events for that category from 2011 to 2013, and the number of states that passed into law a bill coming from that category in those years. In total there were 470 events from 2011 to 2013 and 108 events in 2013. A full 258 policies were signed into law in those years including 82 in 2013.

MEASUREMENTS

Our choices for measurements calculated from our Twitter dataset stem from prior research demonstrating the importance of certain concepts to social and political movements or to the specific case of abortion. The measurements are obtained from LIWC dictionaries [32], which are lists of words and word stems manually selected by linguists. Each dictionary specifies a specific language dimension, and using these dictionaries, we can find the proportion of terms using that dimension from Twitter posts tagged to each U.S. state. In Table 4, we show some example tweets that contain terms from a few of the measures that we collect.

We are interested in measuring aspects of the *ideological* makeup of a population. Thus we chose the following characteristics known to underlie reasoning and values people use to choose sides on abortion or have been emphasized by organizations, politicians, or media related to abortion:

Moral Values: Prior research has shown that people of different ideologies have different moral values and judgements. Researchers have distilled these moral values into five major categories of *purity*, *harm*, *fairness*, *ingroup*, and *authority*. We measure these moral values using a set of supplemental LIWC dictionaries developed by Graham et al. [19]. Of the categories, in particular the *purity* value has been shown to be an even better predictor of opposition to abortion than political orientation [26], suggesting an opposition mainly grounded in moral intuitions around sanctity and sexual purity. On the other side, the moral framing of *fairness* has been shown to be used by abortion proponents arguing for the individual rights of the pregnant woman [11].

Personal Concerns: Given that decisions and feelings about abortions are often of a very personal nature, many of the LIWC measures related to personal concerns are of relevance to this issue. We collected the measures of *home*, *money*, *religion*, and *death*. Particularly, *death* and *religion* are of great concern to opponents of abortion, as many believe that an abortion causes the death of a baby and that certain religions forbid abortion. In addition, money is one of the primary reasons women cite for why they obtain abortions [12], and many bills introduced involve the public funding or insurance coverage of abortion-related services.

Gender: Though abortions are only performed on women, policymakers have often framed the issue in terms of morality, religion, and other ideological values mentioned instead of as a woman's issue [37]. Thus we collected instances of gendered language, such as synonym terms for *woman*, *man*, *mother*, and *father*. These terms are taken from the LIWC dictionaries of *humans* and *family*, respectively, two measures that we additionally collect.

Biological Processes: We collected measures related to biological processes, including *body*, *health*, and *sex*, also taken from LIWC. These measures are all intimately related to the issue of abortion, as abortion can often be a medical issue that concerns a woman's body and her health, as well as the health of the fetus. In addition to these terms, we selected terms for two more measures more specifically related to abortion - synonym terms for *baby* and for *fetus*. This is due to research that has pointed out how the occurrence of "baby" synonyms was higher in anti-abortion texts while the occurrence of "fetus" synonyms was higher in pro-abortion texts in Supreme Court decisions [1].

Measures	Example Twitter Post
Purity	*Sorry but abortionists are very **sick**, creepy, **disgusting** people.*
Harm	*#Gosnell accused of **murdering** a woman & 7 newborn infants. Yet abortion always **violently** ends a human life. #prolife*
Fairness	*My body, my choice. Abortion **rights** are not going anywhere.*
Anxiety	*I would feel so **uncomfortable** if I had to tell the doctor that I had an abortion*
Anger	*Happy Mother's Day to all those **bitches** that had abortions.*
Sadness	*Abortion is the leading cause of death, not guns! Liberals make me sick! Like the most **helpless** do not matter*
Body	*Don't let your legislature ban #abortions as early as six weeks. Not your **body**, not your choice! #reprorights #northdakota*
Health	*Abortion is not a woman's right. **Life** is a child's right.*
Sex	*Less than 1% of abortions are due to **rape** or **incest**.*
Money	*Nowhere in the Constitution does it say anything about your right to a **taxpayer funded** abortion.*
Religion	*Want to talk about equal rights? What about all the precious **souls** whose rights were fully denied? #stopabortion*
Death	*Abortion is the leading cause of **death** in the U.S.A. NOT GUNS. 1,211,500 **deaths**!*
Tentative	*There's a **lot** to abortion. Y'all act like its so easy.*
Certainty	*If men could get pregnant, nobody would **ever** have THOUGHT of abortion.*
Baby	*I can't abort no **baby**. ...I would regret that for the rest of my life!*
Fetus	*Christians fight against abortion. But if that **fetus** you saved were gay, would you still fight for its rights?*
Woman	*This whole abortion thing is stupid. Let a **woman** do what she wants*
Man	*Some **guy** who my mom knows was on the news for forcing a 14-year-old girl to abort her baby.*

Table 4. Examples of tweets from several of the categories of measures that were collected, with the terms relating to that category in bold. Some words are altered to protect identities of the tweet authors.

We also collected the following measures to help contextualize the discussions surrounding abortion on Twitter.

Affective Processes: We collected several measures of affective processes in order to learn about the emotions and sentiment people use to discuss abortion. We collected the basic sentiment measures of *positive* and *negative* as well as the emotions *anxiety*, *anger*, *sadness*, *achievement*, and the prevalence of *swear words*.

Certainty: In addition to getting a sense of people's opinions towards an issue, we were also interested in understanding the degree to which their opinions hold. For this reason, we also collected the measures of *certainty* and *tentative* language use.

From our state-tagged and gender-tagged dataset, when we count the number of tweets that had a positive indication for each of the measures, the measure with the least tweets was *fear*, with 340 tweets. The measure with the median number of tweets was *family*, with 13,156 tweets. Finally, the measure with the most tweets was *negative*, with 53,747 tweets.

CHARACTERIZING LANGUAGE ON ABORTION

We begin by correlating our datasets against ideology scores taken from Gallup's State of the States poll from 2013 [14], which determines the percentage of liberals and conservatives in each state, starting with our abortion policy event dataset. We would expect that states with more pro-abortion policies would align more with liberal states and vice versa. For each state, we count the number of pro-abortion policy events minus the number of anti-abortion policy events from 2011 to 2013. The correlation with the Gallup ideology score was strong (ρ=0.606, p<0.0001). As mentioned we had also collected for each state the week in a woman's gestational period for which abortion is banned. This correlated weakly to moderately with the Gallup ideology score, at 0.286 (p<0.05). This may be because some states choose to seek other means of limiting abortions rather than outright banning it at certain stages, such as enacting more clinic regulations or restricting insurance.

Measure	ρ	p	Measure	ρ	p
death	0.605	p<.0001	money	-0.421	p<.005
baby	0.488	p<.0001	sex	-0.357	p<.05
purity	0.451	p<.005	woman	-0.339	p<.05
authority	0.362	p<.01	fairness	-0.249	p<.1
harm	0.305	p<.05			

Table 5. The Twitter measures related to ideology that had the highest correlation with Gallup's ideology score of percentage of conservatives minus liberals in a state. A positive correlation means the Twitter measure correlates with conservatism.

Turning to correlations between the Gallup ideology poll and our Twitter-based measures, in Table 5 we show the moral, personal, gender, and biologically-related measures that correlated with the Gallup score. Some measures correlate with ideology the way we would expect given prior research while others do not. For instance, prior research shows that *purity*, *authority*, and *ingroup* are more associated with conservatives, while *fairness* and *harm* are more important moral values to liberals [19]. We can see that *fairness*, *purity*, and *authority* correlate how we would expect, with *purity* exhibiting the strongest correlation. In contrast, *harm* is actually negatively correlated with liberalism and *ingroup* was weakly correlated with liberalism (ρ=0.230, p=0.108). In the case of *harm*, a qualitative analysis of the tweets showed that many of them described concern about harming the fetus as opposed to harming pregnant woman. For example, out of 31,839 harm-related tweets from our dataset, 24% mention the phrase "kill" and 16% mention "baby" or "babies".

Given the many tweets concerned about the "killing" of a fetus, it is unsurprising then that *death* is also correlated with conservatism, as many people on the anti-abortion side believe that having an abortion is tantamount to murder. And in agreement with prior work on the terminology used by pro-abortion and anti-abortion camps, *baby* is more correlated with conservatism while *woman* is more correlated with liberalism. The measure of *money* is moderately correlated with liberalism, which is in alignment with research showing that it is one of the primary reasons why women obtain abortions [12]. Finally, in analyzing why the measure *sex* is positively correlated with liberalism, we saw that 12.6% of the tweets mentioned "rape", which is often used as a reason on the left for why abortion should be legal.

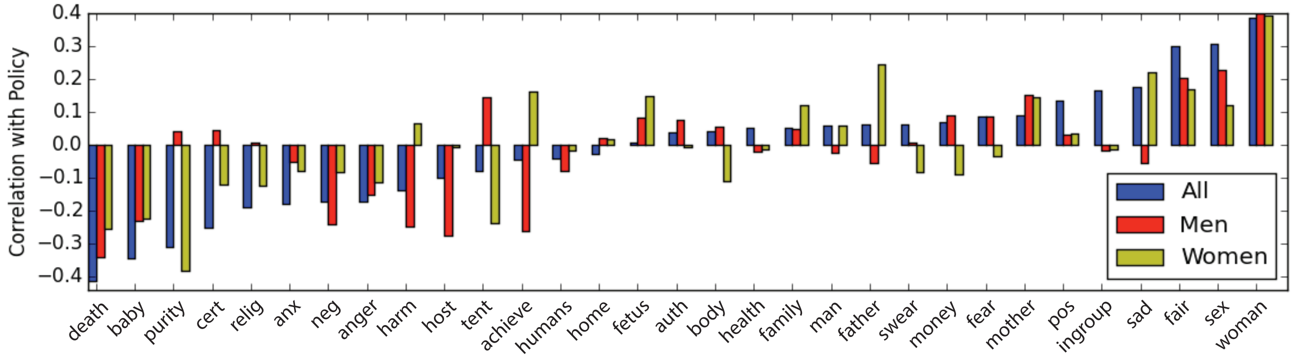

Figure 1. Correlation of Twitter measures in each state with abortion policy count of pro-abortion policy events minus anti-abortion policy events. Correlation is conducted for all Twitter users in a state, only the male ones, and only the female ones.

Measure	Male	Female	t	p	ES	ES-rand
woman	0.0097	**0.0138**	-8.097	p<.0001	-1.619	-0.214
humans	0.0306	**0.0344**	-5.300	p<.0001	-1.060	-0.043
harm	0.0122	**0.0137**	-2.948	p<.005	-0.590	0.122
death	**0.0148**	0.0129	2.942	p<.005	0.588	0.045
health	**0.1197**	0.1153	2.591	p<.05	0.518	-0.423
achieve	**0.0255**	0.0240	2.484	p<.05	0.497	0.173
religion	**0.0226**	0.0197	2.308	p<.05	0.462	0.243
fetus	0.0015	**0.0019**	-2.171	p<.05	-0.434	0.0
ingroup	0.0039	**0.0046**	-2.058	p<.05	-0.412	-0.068
purity	**0.0033**	0.0028	1.864	p<.1	-0.373	0.084
man	**0.0029**	0.0025	1.794	p<.1	-0.359	0.041

Table 6. Twitter measures and their average proportional occurrence in tweets by men and tweets by women across the 50 states, followed by the results of a t-test for difference between the two groups. Effect size (ES) is calculated using Cohen's d. ES-rand is the effect size from a random sample of all Twitter messages from the Streaming API.

Differences in Gender

Using the abortion policy count described earlier, we then calculate the Twitter measures for all Twitter users within a state, as well as for just the male users and the female users, and correlate each measure against the abortion policy count for each state. Figure 1 shows the correlation against the abortion policy count for the three populations and orders the measures in terms of increasing correlation with pro-abortion policy for the population of all users. Additionally, in Table 6, we show the measures that had the most significant difference between males and females. For each measure, we report the average occurrence of that measure for male Twitter users versus female Twitter users across the 50 states, followed by a t-test of difference in means, and Cohen's d measure of effect size.

When it comes to overall differences in moral values between genders, researchers have found that women are more concerned than men about *harm*, *fairness*, and *purity* [20]. We can see that overall, women are indeed higher than men on *harm* in Table 6, but in correlating with abortion events across the states in Figure 1, *harm* is correlated with anti-abortion policy for men, but has a weak correlation with pro-abortion policy for women. We can also see from Figure 1 that *purity* and *religion* are moderately correlated with anti-abortion for females while there is a weak opposite correlation to no correlation for males. Thus, even when men and women are expressing the same moral concepts, they are sometimes towards opposite ends. Some of these findings may be because when it comes to overall views on abortion, in the past several years men have identified more as pro-life over pro-choice, while women have been even to slightly more pro-choice [15]. Indeed, looking at the measures of *purity* and *religion* in Table 6, we see that they both are overall higher for males. Several other significant differences between men and women align with this, including the differences for the measures *death* and *fetus*. We can also see from Figure 1 that males in anti-abortion states express more negative emotions, as can be seen with the measures of *negative*, *hostility*, and *anger*, than males in pro-abortion states. Finally, the measure of *achievement* is correlated with anti-abortion for males and correlated with pro-abortion for females.

To compare the differences we found in abortion-related discussion to overall gender differences in discussion on Twitter, we collected 55,756 tweets from the Twitter Streaming API, which provides a random sample of real-time tweets from around the world. We sampled the data at two separate time periods in November of 2015, yielding 2,665 tweets that were tagged by state and gender. While this data does not come from the same time as our abortion dataset, they should still give some indication of overall gender differences in language on Twitter. As seen in the final column of Table 6, several measures, such as *woman* and *religion* showed gender differences in the same direction as the abortion dataset, but the effect sizes were small in comparison. Other measures such as *health* showed significant opposite differences between genders compared to the abortion dataset.

To see how far away the genders are from each other within different states, we collected the 20 most anti-abortion states according to their policies, with each having 12 or more anti-abortion policy events from 2011 to 2013. We also collected the 19 most pro-abortion states; given that there were so few pro-abortion policies introduced during this time period, we include any state with any pro-abortion policy events or a total of under four anti-abortion policy events. We then calculated our measures for both males and females in the anti-abortion and pro-abortion states, averaging them together, and then calculated their overall cosine distance. As seen in Figure 2, there is overall a greater distance between men

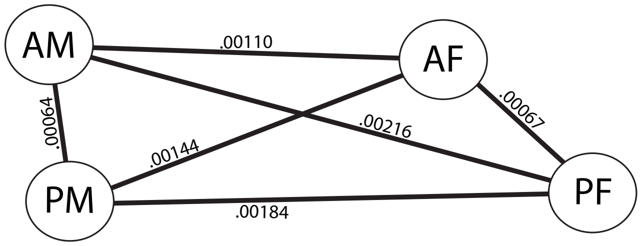

Figure 2. The cosine distance between what women versus men say in pro-abortion versus anti-abortion states. Distances are not exactly proportional, but are approximate. A=Anti-abortion state, P=Pro-Abortion state, F=Female, M=Male.

and women than there is between people in pro-abortion and anti-abortion states, with men in anti-abortion and pro-abortion states slightly closer to each other than women in anti-abortion and pro-abortion states. The two groups that are the farthest apart are anti-abortion state males and pro-abortion state females.

Comparing anti-abortion versus pro-abortion states, the males and females in states with anti-abortion policies are closer together than males and females in states with pro-abortion policies. Overall the average cosine distance within the 20 anti-abortion states was 0.0397, and within the 19 pro-abortion states, it was 0.0508, with a significant difference between the two groups ($t=2.348$, $p<0.05$). According to polling data, anti-abortion supporters have been found to generally exhibit a higher degree of intensity, refusal to compromise, and are ideologically opposed to abortion on moral and often religious grounds, while pro-abortion supporters are less united in their views and reasonings [33]. Indeed many of the measures signifying intensity are overall slightly correlated with anti-abortion states, such as *certainty*, *anxiety*, *anger*, and *hostility*.

POLICY PROJECTION BY STATE

Given the measures we have examined, we now consider how we might use them to model the spread of different anti-abortion policies from state to state. We know from prior literature that states tend to learn from and emulate the activities of other states [21, 22]. Thus we formulate our task as projecting what types of policies a state will enact given similar states and the policies that they have enacted in the past. For instance, if a state's geographically neighboring states or its ideologically similar states have enacted harsh clinic regulations in the last two years, is it likely that the state will also enact it? To model policy change over our dataset, we utilize a collaborative filtering approach, generally used in recommendation systems, which is constructed around the assumption that similar users are a good source for new recommendations [34]. In this case, we assume that states that are similar will enact similar abortion policies, and we compare different similarity metrics based on our different data sources.

Performing Policy Projection

We use a nearest neighbor approach to perform policy projection. This can be visualized as a graph with nodes for both states and policies, where our task is to fill in missing edges between states and policies. It can alternatively be seen as a matrix of states and policies with missing cells. There are 95 nodes (50 states and 45 policy types) in total. Edges go from a state to a policy if there has been a policy event related to that policy category in that state. The weight of the edge is equal to the number of policy events from that state in our dataset from 2011 to 2013. However, if a particular policy event resulted in a failure, such as a vote that did not pass or a veto, then that policy event subtracts one from the weight of the edge. Thus some edges may actually have negative weights. There are also edges between states, with the weight equal to some measure of similarity between the two states, which we will describe further. Figure 3 shows a small portion of that graph with three pro-abortion states and three anti-abortion states. We also show all the policy categories that have been introduced or enacted in those three states. We do not show the edge weights between states and policies for space reasons. As can be seen, some states have many edges while others have very few. In this figure, the weights between states are their Twitter measures' cosine distance. The graph is not static but updates with time. Given a particular month, the similarity function between states could be recomputed. Also the edges from states to policy categories update depending on when policy events happen.

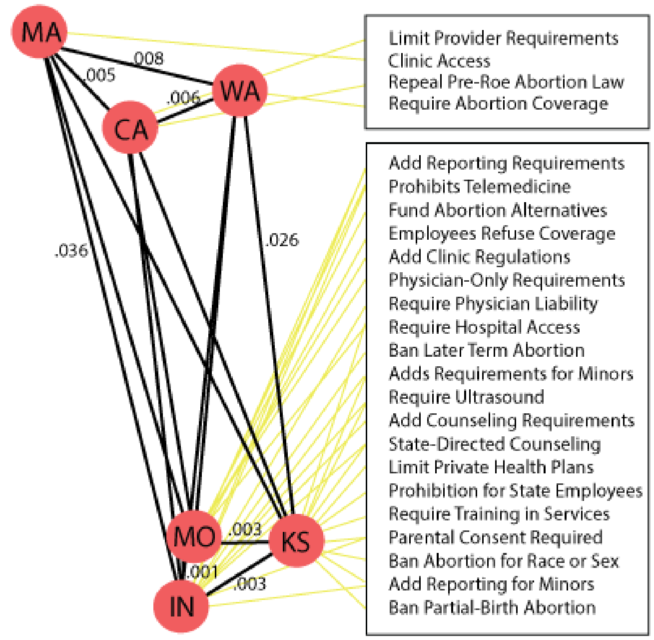

Figure 3. A small portion of the graph connecting states and policy categories, with the three most pro-abortion states and the three most anti-abortion states shown. Weights on many edges are left out for space reasons. We separate pro-abortion policies from anti-abortion policies to show the differences in policy adoption. Distances between states are not exactly proportional, but are approximate.

Projection Algorithm

In order to perform the projection task, our system builds off the aforementioned nearest neighbor approach that assumes that similar states will enact similar policies. For each of the

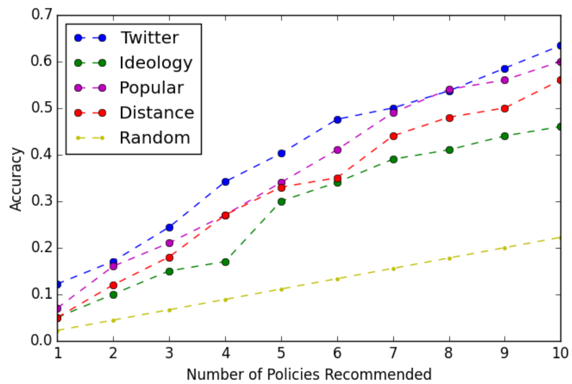

Figure 4. The accuracy of several of the recommendation models we built as we increase the number of policy categories recommended for each policy event. The model using Twitter measures for similarity between states performs the best overall.

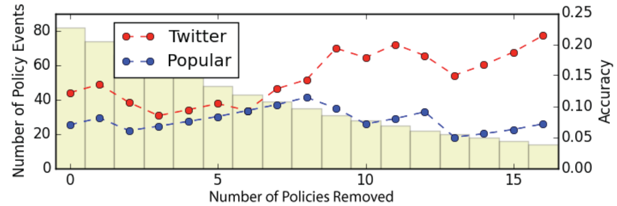

Figure 5. We compute the accuracy of the Twitter model and the Popular model when recommending one policy for each event in 2013. To see how the two models compare with less skewed data, we remove one policy category from the dataset at a time in descending policy category popularity. The yellow bars show how many events remain after removal of the most popular policies.

82 policies that were enacted in 2013 within a state, we attempt to project its policy category using the prior enacted policies of similar states, where similarity is defined in a number of different ways, which we detail below. Using a given similarity function, we order the other 49 states by decreasing similarity, so that each state has a rank K which is its position on the list. Then we go through each state in order of decreasing similarity and collect the policies that have already passed in that state and record the policy category. We continue going through successively less similar states in this way. The overall score assigned to each policy category is equal to $\sum W * (1.0/K)$, where W is the weight of the edge from each of the similar states to the policy category. Thus instead of specifying a cut-off after a certain K, we go through the entire list of states but only lightly weigh the contributions of states that are more dissimilar. Finally, after reverse ordering by score, we collect the N policies with the highest score. Like a typical collaborative filtering recommender system, these are the items that we "recommend" to the state to see if the correct policy is within that list. In Figure 4, we can see the accuracy of our model as we increase the number of policy categories to recommend out of the 45. In total there were 82 policies enacted throughout 2013 that we project.

Different Similarity Metrics Between States

We now turn to explaining the different similarity metrics we experimented with to determine similarity between the states. As mentioned earlier, one metric called TWITTER takes the cosine similarity of the Twitter measures we described earlier. We calculate all of our aforementioned Twitter measures for the one month prior to the projection event for all 50 states. We perform feature selection by correlating each measure with prior policy events in our policy dataset and choosing only the features with correlation coefficient greater than ± 0.2. Thus, the calculation of this similarity metric has no lookahead bias in feature selection or state modeling. Then the cosine distance was calculated between each pair of states.

A second metric called IDEOLOGY is the Gallup ideology score that we used earlier that took the percentage of conservatives minus the percentage of liberals from each state in 2013. Some research has shown that states will adopt new policies by copying other states that are ideologically similar [21]. We also tried a metric called DISTANCE that uses the geographic distance between states, where we took the average longitude and latitude of each state and calculated the distance between the two points. There has been other research that shows that policy adoption across states may be more of a regional matter, where states will adopt the policies of nearby states over farther ones [3]. Similarly to findings from previous work analyzing Twitter data [38], we find that geographic distance overall performs better for projecting policy adoption than ideology.

A final metric we developed called POPULAR disregards the most similar states and simply orders each policy category in reverse order of how many of them have already passed in other states and uses that to recommend policies. This turned out to perform rather well, due the imbalance of enactment of policy categories across the states, as evidenced by Table 3. Finally, as a baseline, we calculated the chance of randomly picking the correct policy category out of 45 categories using RANDOM.

Results

We can see from Figure 4 that the similarity metric taken from Twitter improved policy projection over the similarity taken from the Gallup ideology metric and geographic distance by on average 12.02% and 7.32%, respectively, for recommendations from 1 to 10 policies. It also had an absolutely improvement over the popular baseline by 3.62% on average.

While the popular baseline performs relatively well compared to the Twitter model, it benefits from projections of the top couple of policies. In Figure 5, we recommend a single policy category for each event, after removing a certain number of the most popular categories. As we remove the most common policies from the set of possible policies, the Twitter model greatly improves on the Popular model. For instance, when we remove the top 10 most popular policies out of 45, we are left with 28 events to project, at which point the Twitter model accuracy is 10.7% better at projecting them than the Popular model. In other words, beyond the more mainstream policy enactments, the Twitter measure-based model performs better than the Popular model at projection.

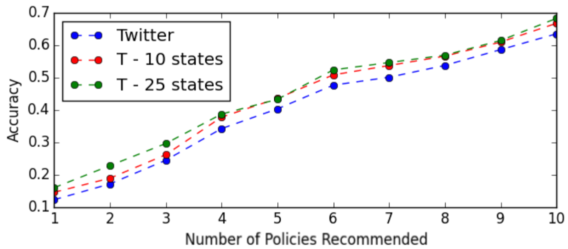

Figure 6. The accuracy of the Twitter model as we recommend 1 to 10 policy categories for each event, when removing the 10 states and the 25 states with the least number of Twitter messages across our dataset.

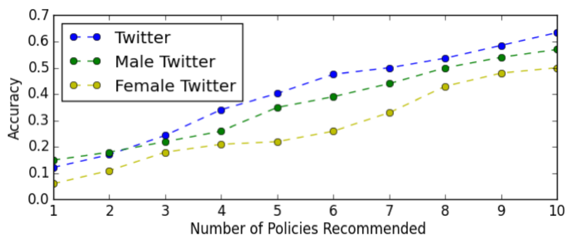

Figure 7. The accuracy of using only male Twitter discussions versus only female Twitter discussions, along with all Twitter discussions for comparison. We show accuracy as we increase the number of policy categories recommended for each policy event.

Projection with States with More Data

Earlier, we mentioned that some states do not have as much data from Twitter due to different factors. We considered whether our Twitter model improves when focusing on projecting policies for the states with more data. Specifically, we tried running our policy projection using the Twitter model but ignoring policy events from the 10 states with the least data and the 25 states with the least data. This left us with 69 and 44 policy events out of 82 to project, respectively. As seen in Figure 6, when we ran the Twitter model on the policy events not occurring in the 10 states with the least Twitter data, the projections are 2.78% more accurate absolutely compared to before. When we project policy events from only the 25 states with the most Twitter data, we are 4.20% more accurate compared to projecting policies from our entire dataset. Thus the Twitter model does better when applied to the states with the most data.

Projection using Male and Female Discussions

We also ran the projection task using a similarity metric calculated using only male Twitter discussions from the prior month in each state as well as only female Twitter discussions, as can be seen in Figure 7. The male Twitter similarity metric performed 4.12% worse than the similarity metric using all abortion discussions on average. However, we saw that a similarity measure using only male Twitter users performed better than only using female Twitter users by 8.20%.

DISCUSSION

We found that using states with similar Twitter measures performed better as a projector of what policies would get enacted then a traditional poll-based measure of ideology collected from Gallup, and better than state similarity based on geographic distance. One explanation for the improvement in the Twitter-based model is that it may contain latent characteristics beyond what we immediately measured. For instance, since language use and the importance of events varies by region, it might be taking regional differences into account. We also saw that similarity between states as defined by male Twitter users was more predictive of policy than using female Twitter users. This signifies that male Twitter users are perhaps a better reflection of the state of abortion policy than females. We studied the difference in language between males and females, finding that males and females are further apart than the most pro-abortion versus anti-abortion states, with the furthest pair of groups being males in anti-abortion states and females in pro-abortion states. Our measures also demonstrated that male Twitter users express values more aligned with anti-abortion than female Twitter users. While these findings make sense given the wave of abortion legislation in the anti-abortion direction, they are also disconcerting because of the outsize impact of abortion policies on the lives and bodies of women.

From our analysis of language usage in states passing pro versus anti-abortion policies, we found that pro-abortion states have a greater prevalence of terms related to *woman*, while anti-abortion states have a greater prevalence of terms related to *baby*. This demonstrates how the two sides choose to emphasize the pregnant woman versus the fetus, respectively. When it comes to differences in moral values, we saw that anti-abortion states were more likely to invoke *purity* and *religion* language, while pro-abortion states mentioned *fairness* more. As in many contentious social and political issues, the underlying struggle can often be attributed to differing ideological outlooks and moral judgements. We also saw greater similarity as well as intensity in the language from anti-abortion states as opposed to pro-abortion states, which suggests that anti-abortion states are more unified and passionate about the issue. This is in accordance with the intense upswing in anti-abortion policy that has occured in the last several years.

Methodologically, we demonstrate how studying the language use of constituents on Twitter can help us understand at a population level their feelings and associations with the issue of abortion. This has implications for the study of public policy and of social and political movements. We study the language usage of everyday people instead of focusing on public statements by political figures, news outlets, judges, and organizations. While everyday people are not as influential as large organizations or politicians, their language in aggregate serve as an important source of information about public discourse and one that may provide a different signal than the language of political elites. In the past, studying the discussions by constituents on important issues was much more difficult. By leveraging social media, we can analyze the language use of everyday constituents like these at scale.

In terms of practical implications, we believe that the reporting of aggregate statistics on the language usage on Twitter much as we have done in this paper could be an impactful way to convey people's opinions and ideologies. Today much reporting on social and political issues involves some form of polling data as well as interview quotes. Many outlets are more recently providing social media posts for contextualization, as these are simple to search for and quote on the web. Measures and techniques such as the ones we demonstrated can be useful also as reporting mechanisms to provide aggregate opinions while also adding greater context and underlying ideological reasonings.

These social media-based policy analyses may also lead to better tools for policymaking. In the last several years, anti-abortion legislators have introduced an alarming number of bills to state governments. For instance, in just the first month of 2015, legislators introduced over 100 new bills restricting abortion, and according to the Sunlight Foundation, multiple new restrictions are still being introduced every day [13]. Many point to organizations such as Americans United for Life that provide pre-written legislation and pioneer new bills as the catalyst for increased legislative activity. This strategy wastes taxpayer money and slows down the legislative process as legislators must deliberate over each new bill, slowing chipping away at abortion access from every angle. Tools that provide better projection of what policies will get enacted and better understanding of what people within a state feel about abortion will better allow policymakers to draft and introduce legislation that reflects the will of the people.

Finally, tools that present real-time aggregate analyses, projections, and visualizations of the graph we developed could be useful for activists, political organizations, media outlets, and the public to monitor public discourse and policy change on important issues over time. The analysis of people's language usage on social media can provide a great deal more understanding and nuance than the insights that can be gathered via traditional means. Using this information, organizations can better tailor their messages and direct their resources, news organizations can better contextualize their stories, and the public can better understand how their fellow constituents feel towards an issue.

LIMITATIONS

Some limitations arise because we are using data from Twitter. The population of Twitter users, while large, is not necessarily representative of constituents nor is it unbiased. Some prior work has shown that it is biased towards urban areas [23] and generally is used by more technically literate people, which may interact with our results. The use of Twitter may also exacerbate issues with data scarcity in some states. We noted earlier that there were some states, notably Wyoming, that had very few tweets to analyze. We also demonstrated that when focusing only on states with more data, our projection models improved in accuracy. This may mean that alternative methods aimed specifically at states with fewer data traces on social media might produce better results. In addition to location-based biases, there also may be biases in the way in which we tagged users to specific states or to specific genders. However, we made efforts to use approaches that have been validated, such as by showing strong correlations between the amount of per-state data and state populations. Other limitations arise because of our use of linguistic terms as measures. Our method of using a lexicon-driven approach with LIWC dictionaries cannot take into account concepts such as irony, sarcasm, or other contextual information. Thus we cannot say that a particular user feels a certain way based on these measures. At a population level, such variances due to individual differences in language use are more likely to be averaged over, reflecting how a population generally feels about a topic. This has some benefits and drawbacks compared to opinion polling. Opinion polling offers a more direct method of inquiry, though is also subject to various response biases.

FUTURE WORK

Though the best policy projection model performed much better than chance, there is still room for improvement. Given that we used a user-based collaborative filtering approach, the next step would involve incorporating content-based aspects. A content-based approach assumes that if a state has enacted a policy, then they will more likely enact similar policies. While there is prior work examining topics like the diffusion of language from bill to bill, now one could potentially look at similarity of policies based on the text of the bills and incorporate that into policy recommendation models. Tools such as the Sunlight Foundation's Scout program [13] which tracks bills as they get introduced and collects the text of the policy documents may be useful in this regard.

CONCLUSION

In this work, we conducted a quantitative analysis of the language use of constituents in the U.S. around the issue of abortion on social media and how that aligns with public policy activity on abortion. We analyzed different aspects of ideology that help to contextualize the underlying moral values and personal reasons people draw upon to decide if they are for or against abortion. We documented a number of differences between states enacting anti versus pro-abortion policies. We also distinguished male from female ideology and found a greater emphasis for males on values aligned with anti-abortion. From these features, we construct collaborative filtering models to project policies that a state will introduce based on similar states, with the best model defining similarity using our Twitter measures, and in particular measures from male-only Twitter users. Overall this work serves to show how the analysis of language usage of constituents on social media can help with understanding questions in public policy and illuminating the interplay between constituents and the policies that govern them.

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