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Hybrid Recommender for Online Petitions with Social Network and Psycholinguistic Features

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HYBRID RECOMMENDER FOR ONLINE PETITIONS WITH SOCIAL NETWORK AND PSYCHOLINGUISTIC FEATURES

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DISSERTATION APPROVAL FORM

This dissertation is approved as a credible and independent investigation by a candidate for the Doctor of Science in Information Systems degree and is acceptable for meeting the dissertation requirements for this degree. Acceptance of this dissertation does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department or university.

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https://github.com/aelnoshokaty/PETREC

https://github.com/aelnoshokaty/GroundTruth

ABSTRACT

The online petition has become one of the most important channels of civic participation. Most of the state-of-the-art online platforms, however, tend to use simple indicators (such as popularity) to rank petitions, hence creating a situation where the most popular petitions dominate the rank and attract most people's attention. For the petitions which focus on specific issues, they are often in a disadvantageous position on the list. For example, a petition for local environment problem may not be seen by many people who are really concerned with it, simply because it takes multiple pages to reach it. Therefore, the simple ranking mechanism adopted by most of the online petition platforms cannot effectively link most petitions with those who are really concerned with them. According to previous studies online, petitions seriousness has been questioned due to the rare chance of succeeding. At most, less than 10% of online petitions get the chance to fulfill their causes.

To solve this problem, we present a design of a novel recommender system (PETREC). It leverages social interaction features, psycholinguistic features, and latent topic features to provide a personalized ranking to different users. Hence, it can give users better petition recommendations fitting their unique concerns. We evaluate PETREC against matrix factorization collaborative filtering and content-based filtering with the bag of words (Bow) features as two baseline recommenders for benchmarking. PETREC prediction performance outperformed Matrix factorization collaborative filtering, Bow petition-based content filtering, and Bow user-based content filtering with 4.2%, 1.7%, and 2.8% respectively as improvements in Root Mean Square Error (RMSE).

The recommendation system described in this paper has potential to improve the user experience of online petition platforms. Thus, it is possible that it could encourage more public participation. Eventually, it will help the citizens to make a real difference through actively participating in online petitions that are matching their personalized concerns.

DECLARATION

I hereby certify that this dissertation constitutes my own product, that where the language of others is set forth, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions or writings of another.

I declare that the dissertation describes original work that has not previously been presented for the award of any other degree of any institution.

Signed,
Ahmed Elnoshokaty

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CHAPTER 1

INTRODUCTION

The right of the people to petition their government as guaranteed in the First Amendment to the Constitution of the United States (U.S.) is undergoing an Internet revolution powered by Internet-based information and communication technologies (ICTs). ICTs have changed, probably fundamentally, the way that people interact with their government and with society. They also have posed novel societal and political phenomena, opportunities, and challenges to societies and to researchers (Majchrzak, Lynne Markus, & Wareham, 2013). One noticeable political phenomenon is the migration of politics from the physical space to cyberspace, a transition that has been defined as e-politics (Wattal, Schuff, Mandviwalla, & Williams, 2010). Along with this migration, websites for online petitioning have emerged and became a powerful public tool to affect society. They serve as platforms from which millions of people can easily express their views and opinions on issues of their choosing, participate in democracy and political dialogue, and eventually create societal impacts and influence policy and/or decision making (Hagena et al., 2016; Huang, Suh, Hill, & Hsieh, 2015). In the United States, online petition websites, such as Change.org and We the People (WtP), have become the most popular means of empowering citizens to influence decision makers in both government and business. In countries such as Australia, Germany, and the United Kingdom, online petition systems have become a feature of e-government. In these countries, the right to petition the government, the parliament, or public authorities is also one of the fundamental rights codified in their laws or constitutions (e.g., the German Basic Law in Germany). Prior IS, research on ICT-based communication has drawn considerable attention to media, media use, and media theories (Carte, Price, & Chidambaram, 2004; Daft & Lengel, 1986; A. R. Dennis & Kinney, 1998; Alan R Dennis, Fuller, & Valacich, 2008; Te 'eni, 2001). IS researchers have also investigated the effect of message elaborations and message forms on conveying information in ICTs (Angst & Agarwal, 2009; Te 'eni, 2001). Recently, IS scholars have investigated the role of ICT enabled-media in social development, change, and movement (Gil de Zúñiga, Jung, & Valenzuela, 2012; Njihia & Merali, 2014; Oh, Agrawal, & Rao, 2013). Nevertheless, the content of messages in ICT-based communication is no less important than the media that transmits it (Orlikowski & Scott, 2008). Orlikowski and Scott (2008, p. 463) argued that "we lose the possibility of seeing the technical and social as inextricably fused. Part of the problem … is linguistic." They further emphasized the "inseparability between the technical and the social" (p. 434) and the importance of studying the huge amount of content created by social media to "generate deep insights into the contemporary world" and into ICTs' societal influences (p. 465). Additionally, Internet-based media carries rich content generated through millions of participants' actions (e.g., posting and reposting, and liking and disliking). This data-rich environment offers researchers an unprecedented opportunity to study various aspects of social and political phenomena along with their large societal impacts. Seizing this opportunity, IS researchers recently demonstrated a growing interest in the content of ICT-based communications by conducting micro-level analyses of content such as online reviews, blogs, and microblogs (Kuan, Hui, Prasarnphanich, & Lai, 2015; Singh, Aggarwal, Gopal, & Gupta, 2012; Stieglitz, 2013). Furthermore, user-generated political content, such as online petitions, disseminated via Internet media, shows an ever-increasing influence on political activism, social movements, and national and societal progress (Majchrzak et al., 2013). Consequently, IS researchers have also recently demonstrated a growing interest in ICTs' societal impacts and consequences that prior research has largely ignored (Majchrzak et al., 2013; Majchrzak, Markus, & Wareham, 2016; Wattal et al., 2010). This new interest also capitalizes on the availability of the large amount of real-world data (A. Abbasi, Sarker, & Chiang, 2016; Miranda, Young, & Yetgin, 2016; Stieglitz & Dang-Xuan, 2013).

Background of the Problem

A petition is a formal request to authorities, usually co-signed by a group of supporters (Ergazakis, Askounis, Kokkinakos, & Tsitsanis, 2012). Authorities may or may not take action as a response to the request. If it does, the petition turns to be successful "victory" (Lindner & Riehm, 2011). As Web 2.0 emerged, more and more petitions are initiated, signed, and submitted online. Online petitions have been an effective tool for governmental and societal changes, it empowers individuals to make an impact (Alathur, Ilavarasan, & Gupta, 2012). Online petitions can be created without much effort, their seriousness and the quality of content are being questioned (Earl & Schussman, 2008). Organizing petitions on the Internet reduces the cost of participation, dissemination, and organization (Briassoulis, 2010). Online petitions provide a cost-efficient means for even the most obscured individuals to initialize a cause and gain support from others. For instance, supporters could spend 5 minutes to register at an online petition website instead of physically participating in a protest rally or demonstration (Alathur et al., 2012). Moreover, online petitions are scalable, where there is no limit on how many people can sign a petition online. One of the most popular general-purpose online petition websites is Change.org. It has over 114 million users and hundreds of thousands of online petitions in different categories including Women's Rights, Economic Justice, Human Rights, Sustainable Food, Health, Animals, Environment, Criminal Justice and Education, etc. Users can initialize or sign a petition on the website. A petition's initiator can post updates of the petition in a chronological manner. The number of signatures is also displayed on the petition page. Each petition is accompanied by a letter addressed to the target of the petition. A petition is considered a victory if the target entity has made a response to the creator's satisfaction. Otherwise, the petition is closed.

For example, in Figure 1 as an effort to protect animals, a petition for banning the transportation of hunting trophies was addressed to Delta Airlines at Change.org. The petition accumulated 395,259 signatures within a few months and Delta Airlines announced that it would "officially ban shipment of all lion, leopard, elephant, rhinoceros, and buffalo trophies worldwide as freight." During the period of the petition, nine other airlines also have taken similar actions.

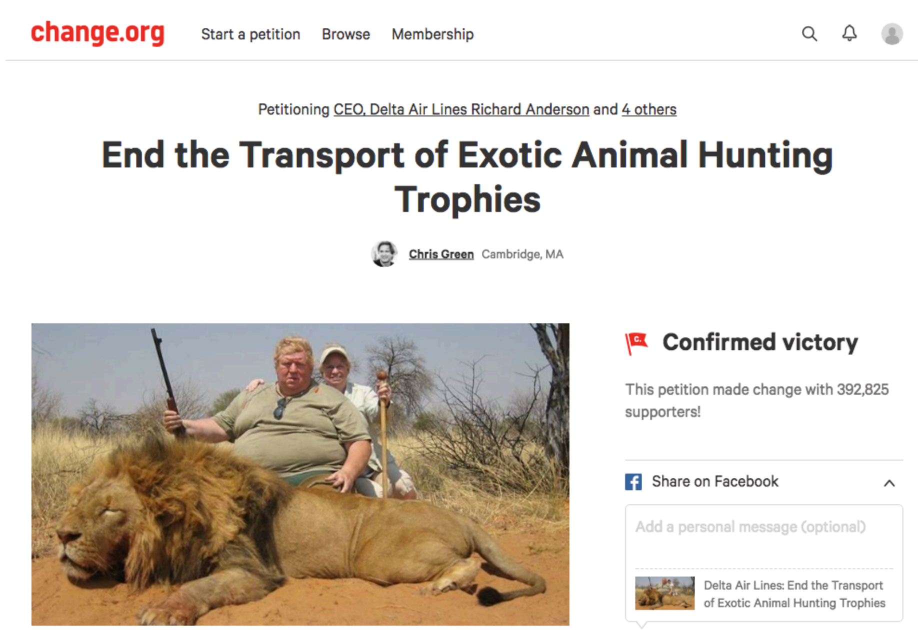


Figure 1. Petition to End the Transport of Hunting Trophies at Change.org

Firstly, given the importance of online petitions, governments and public online petition platforms have invested a significant amount of time and resources to build such systems. Despite the real change that some online petitions make, the success rate of online petitions is usually meager. (Dumas et al., 2015) studied 3,688 petitions from the online petition system of the White House, We the People (WTP), and found that only 252 (6.8%) of them were reviewed. Also, on Change.org, more than 99% of the petitions were never marked as "victory" (Huang et al., 2015). Despite all of the findings that support an enormous impact of online petitions and the low success rate of online petitions, little research has tried to examine the important features of online petitions that could persuade users to engage or to recommend online petitions to reach success. Thus, it is essential to identify important features influencing online petition success.

Secondly, the current search functions provided by major online petition platforms to a user are largely implemented through simple keyword matching and ranking results according to some popularity measurements and may suggest similar petitions to user's signatures history. Figure 2 shows the results from searching the keyword "climate change" by major online petition platform Change.org that ranks result according to some popularity measurements. Considering the scenario that an activist, who has climate change concerns resulting from unsustainable agriculture, may use the general search term "climate change'" and find general petitions to popular political leaders as the first set of results. One of the major challenges for the activists is that they often have to take extra efforts to find the petition of their concerns. One may need to go through maybe a few dozens of pages to reach the petition related to her special concerns, or becomes impatient after going through the first few pages. The state-of-art online petition platforms fail to effectively help activists to find the petitions related to their concerns. We sought to mitigate the above problem through designing a recommender system PETREC with informative features to connect activists with the petitions that are mostly related to their specific interests.

Objectives of the Research

To achieve this goal and develop PETREC to effectively help activists to find the petitions related to their concerns, assume climate change petitions are in set P $\{p_1,\ p_2, \dots, p_M\}$ and users are in set U $\{u_1,\ u_2, \dots, u_N\}$. Each user in U is interested differently in climate change subtopics numbered *1, 2…, K*. In this paper, we highlight the following essential features; psycholinguistic, social network, and latent topic modeling features for petitions. Also, for users concerned with climate change on social networks, the study spots social network features from users' profile and through latent topic modeling features extracted from their social network profiles. The main task is to identify the most relevant subset of P for every user u_i in U.

In this piece of work, we employed both social and psycholinguistic features extracted from activists' social media activities and petition narratives to construct a recommender system PETREC that could better connect users with their specific concerns. Emotions and other psycholinguistic features which are discussed in-depth in next sections are thought to be important in the particular context of online petitioning and social networks. Although our recommender system is general to petitions of any topic, in this piece of work we focus on climate change for data collection purposes. The study follows the standard guidelines to do a design science research (Hevner, March, Park, & Ram, 2004).

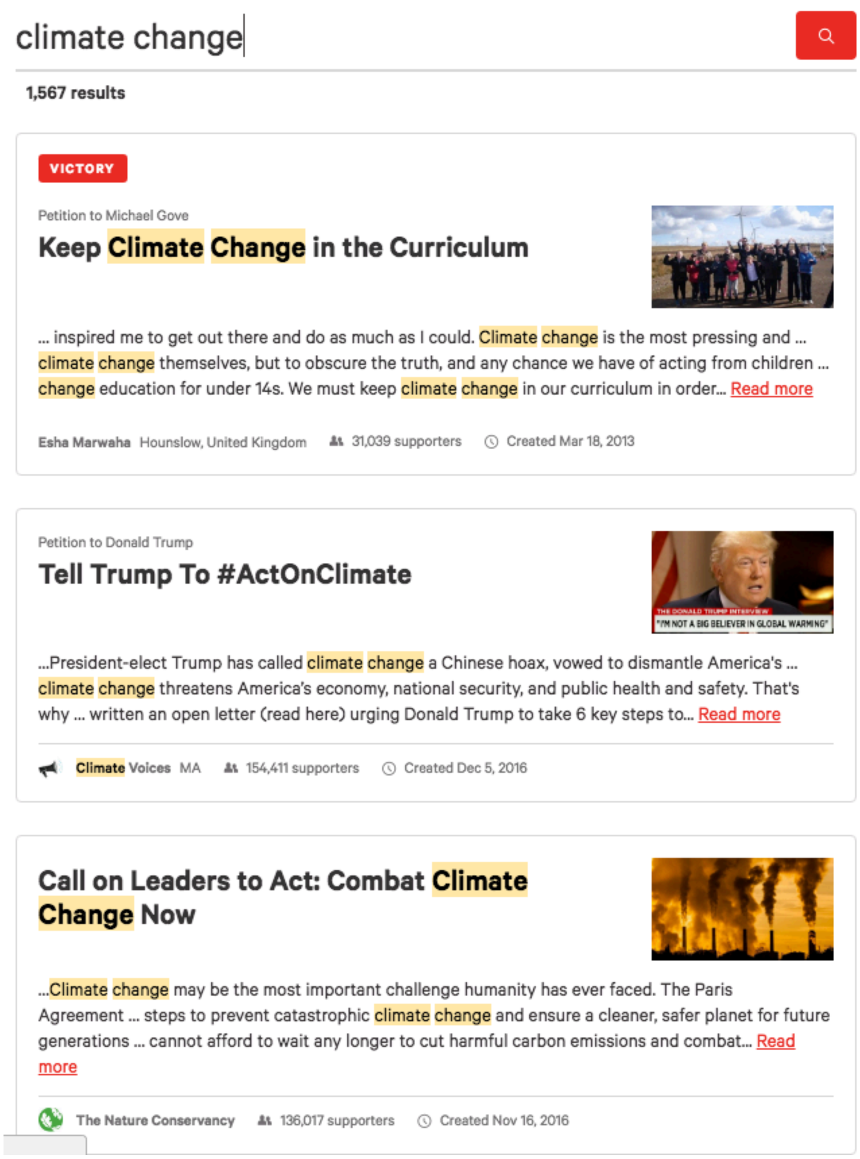


Figure 2. Top search results from change.org for the keyword “climate change.”

CHAPTER 2

LITERATURE REVIEW

Research on Online Petition

Early research on online petitions focused on user behaviors. For instance, a study aiming to classify and cluster online petitions from petitiononline.com (Earl & Schussman, 2008) found that non-political petitions represent a significant amount on non-government online petition websites. Some critical qualitative insights and research questions in studying online petitions were highlighted to question the subjectivity of signatories' comments through principal explanatory. Subjectivity included familiarity with the topic, locality and other factors influencing agreeing or opposing a particular petition. Most existing studies on online petitions are qualitative and descriptive. Many of them focused on the political functions of online petitions. Even some of the previous research have focused on the earlier forms of online petitions, which are email based before the emerging of web platforms (Lindner & Riehm, 2011).

Online petitions are playing an increasingly important role in political systems. A study on the online petitions in the German Parliament web portal found that online petitions to the government received unprecedented public attention (Lindner & Riehm, 2011). E-governments have been adopting web portals for online petitions to facilitate the interaction between governments and citizens (Tetlock, 2007). As a result, governments can increase trust and transparency (Alathur et al., 2012). Nowadays, online petitions are not limited to political purposes and have several other categories. In the US, the Whitehouse petition website, "We the People" (https://petitions.whitehouse.gov), was launched in September 2011, where petitions that receive at least 100,000 signatures within 30 days can receive a response from the US Administration (Jungherr & Jürgens, 2010). For instance, at "We the People" (Ravi, 2013), electronic petitioning had functioned as collective political action against gun control. Moreover, it was found that there were multiple petitions related to the same issue.

In sum, numerous researches have came to the conclusion that online petitions significantly impact political systems and societies. A variety of public campaigns have used social platforms to increase awareness or mobilize people (Huang et al., 2015). As a result of Activists and Non-governmental Organizations NGOs encouragements, more users began to petition online to decision-makers in different causes including climate change (Earl & Schussman, 2008). Social network sites are defined as web-based services that allow individuals to construct a public or semi-public profile within a bounded system, articulate a list of other users with whom they share a connection, and view and traverse their list of connections and those made by others within the system (Boyd, 2007).

Recommender Systems

Recommender systems narrow down the suggested items to a user using content filtering and/or collaborative filtering. Firstly, the content filtering approach creates a profile for each user or product to characterize its nature. For example, a movie profile could include features regarding its genre, the participating actors, its box office popularity, and so forth. User characteristics might include demographic information or answers provided on a suitable questionnaire. The profile characteristics allow programs to associate users with matching items. Of course, content-based strategies require gathering external information that might not be available or easy to collect (Koren, Bell, & Volinsky, 2009). Secondly, social collaborative filtering associates a recipient user with other users based on the degree of similarity of their item ratings profiles (Upendra, 1995). Also, collaborative filtering groups items together based on the degree of similarity of users' preferences (Linden, Smith, & York, 2003). Collaborative filtering through matrix factorization allows incorporating information about a user-item relationship and has a better performance over traditional classifiers of collaborative filtering (Koren et al., 2009). Hybrid models of content based and collaborative recommendation were used to better recommend web pages in search engines over content filtering or collaborative recommendation alone (Shoham, 1997).

There are two types of recommendation problems as shown in Figure 4. First, the traditional recommendation (AKA sparsity problem) which is the problem of making a prediction based on rating history where ratings are scarce but the recommendation is made for a petition that has been rated at least once or to a user who rated at minimum one petition. Second, the cold start, as depicted in Figure 4 for the table on the right for p_3, p_4, and u_5 are problems of predicting a recommendation for a petition or a user with no rating history. In this context, traditional collaborative filtering algorithms like matrix factorization cannot make predictions because predictions are computed based on ratings which are missing. Previous research indicated that content features could improve recommendation systems over traditional collaborative filtering that cannot suggest items before anyone has rated them "cold start problem" (Li, Lu, & Xuefeng, 2005; C. Wang & Blei, 2011). Accordingly our proposed recommender, PETREC, uses a hybrid model of content filtering and collaborative filtering together.

a) Traditional Recommendation Problem

U\P	p1	p2	p3	p4
u1	√	X	√	?
u2	√	√	?	?
u3	X	?	√	X
u4	?	√	?	X
u5	X	?	√	√

b) Cold Start Recommendation

U\P	p1	p2	p3	p4
u1	√	X	?	?
u2	√	X	?	?
u3	√	√	?	?
u4	X	√	?	?
u5	?	?	?	?

Figure 4. Illustration of the traditional recommendation and cold start problems.

The importance of psycholinguistic features in the recommendation systems context was highlighted, especially the cognitive appeal (W. Wang, Qiu, Kim, & Benbasat, 2016). As the use of social media evolved, recommender systems included additional indicators of social relationships to associate a user with other users in their social network such as friendship ties (Shani & Gunawardana, 2010; Victor, Cock, & Cornelis, 2011). Also, status count and social network size were sought as significant features (K. Chen et al., 2012). It is encouraged to collect social data by linking to existing online applications that capture these relations. Usually, both profile similarity and social relationship are used together to rank users' similarity.

Psycholinguistic Theoretical Research

This study takes into consideration both theory and data to select important features of the online petitions narrative (Y. Chen, Deng, Kwak, Elnoshokaty, & Wu, 2018). Indeed, IS researchers using content analysis have increasingly adopted this approach in other research contexts (Kuan et al., 2015; Miranda et al., 2016; Stieglitz & Dang-Xuan, 2013). The theory-guided approach provides a theoretical angle with which we identify essential factors in the form of linguistic cues associated with political persuasion in online petitioning. Identifying these factors is important because online petitioners are unable to use a range of persuasion strategies similar to face-to-face communication, especially those involving nonverbal cues (Wilson, 2003).

Cognitive appeal depends on thoughts and elaboration. It works on a process built on a person's cognitive, reflective, rational, explicit, or fast thinking. Specifically, by providing factual information and arguments, cognitive appeal tries to motivate an elaborative process through which a person carefully inspects and scrutinizes all the relevant information (e.g., message and content) to accurately judge the issue of interest. Such judgment ultimately leads to a change in a person's attitude or behavior. Because of their needs for cognition, people naturally seek, acquire, think about, and reflect on information in their environment (Cacioppo & Petty, 1982). They often have positive attitudes toward tasks and stimuli that require cognitive skills such as reasoning and problem solving (Cacioppo, Petty, & Morris, 1983). In general, individuals with higher needs for cognition tend to enjoy cognitive activities and think more (Petty, Brinol, Loersch, & McCaslin, 2009). IS literature also has shown the persuasive effect of cognitive appeal on attitude and behavioral change. Grounded in the Elaboration Likelihood Model ELM, prior IS research has found that an argument relying on the cognitive process (e.g., fact-based arguments on system functionality and performance) is persuasive in changing attitudes and behaviors (Angst & Agarwal, 2009). In persuasive system design, design principles and models (Fogg, 2009; Oinas-Kukkonen & Harjumaa, 2009) suggest the essential role of cognitive design elements in determining the persuasive power of the system. In summarizing the above discussion, we derived content features of online petitions from a multi-appeal model of persuasion and identified linguistic cues in each appeal. Specifically, we identify four factors in cognitive appeal in the form of linguistic cues; cognitive orientation, enlightenment, overstatement, and understatement. The selection is based on the literature of the framing theory in communication (Borah, 2011). The literature shows that in addition to cognitive reasoning and causal interpretation, political campaigning often uses cognitive framing such as (de)emphasis framing and uniqueness framing. Cognitive orientation is a category of linguistic cues that reflect a persuader's general cognitive commitment to cognitive reasoning and causal interpretation about the issue of interest. Cognitive enlightenment is a set of linguistic cues that a persuader uses in uniqueness framing to reveal insight and truth or to disclose misunderstood and misguided information. Cognitive overstatement refers to a set of linguistic cues overly emphasizing validity, exceptionality, intensity, certainty, and extremity of information and reasoning; cognitive understatement refers to linguistic cues that use uncertainty and ambiguity to overly deemphasize information and reasoning.

Emotional appeal, the second appeal in our research model, is also anchored in the dual-process theory of persuasion (Petty & Briñol, 2014). As the theory posits, emotions work on both affect and thinking to influence persuasion. When appealing to affect, emotional appeal is based on feeling, mood, impulsion, and intuition, reflecting the amount of affection expressed in content through positive or negative valences. Prior studies have found that a person's emotions can be induced by a persuasive message or content, attitude figures, or other mechanisms of emotional manipulation. Such emotions can affect a person's evaluations and judgments (Cacioppo & Petty, 1982). Thus, emotional appeal tries to induce emotions by injecting feelings and moods into persuasive material in an attempt to influence the recipients' feelings and moods and ultimately their attitudes and behaviors. On the other hand, when appealing to thinking, emotions can interfere to some extent with cognition and thus influence attitudes and behaviors (Schwarz & Bless, H., & Bohner, 1991). Prior IS research has investigated users' emotions and their effect on human computer interaction, IS artifact design, and digital and social media communication (Deng & Poole, 2010; W. Wang et al., 2016; Zhang, 2013). For example, IS research on ICTs in conjunction with the psychological literature on affections and emotions has led to the development of information infusion theories in which emotion is a salient factor in attitude change. Those studies show that effective cues and characteristics are focal factors that address the effects of emotion in ICTs (Zhang, 2013). As in the literature (Kuan et al., 2015; Petty & Briñol, 2014; Stieglitz & Dang-Xuan, 2013), this study examines both positive and negative emotional appeals in online petitioning. Our choice is based on prior research in various fields that have shown the relevance of positive and negative emotions in ICT communication (e.g., (Stieglitz & Dang-Xuan, 2013)). Moreover, positive and negative emotions have been shown to exert different influences, depending on the research context (Kuan, Hui, Prasarnphanich, & Lai, 2015; Lau, Sigelman, & Rovner, 2007). Thus, how linguistic cues of positive and negative emotions merits special attention.

The effects of cognition and emotion on persuasion are often discussed in parallel in the literature because they fall along a bipolar continuum from irrational to rational (Petty & Briñol, 2014). However, moral appeal appears to be missing from the discussion of persuasion appeals, although prior research has investigated the effect of morality on persuasion (Bartels, 2008; Ben-Nun Bloom & Clark Levitan, 2011). The inclusion of the moral appeal is salient and well-suited to the current research context because political issues often involve moral debates and judgments. The literature conveys two views of moral appeal, one rational and the other intuitive (Haidt, 2001). In the rational view, moral appeal and judgment rely mainly on a process of reasoning and reflection and function under the umbrella of cognition appeal. In contrast, the intuitive view argues that moral judgment is based on perceptions and intuitions and driven by unconscious motives and feelings (Haidt, 2001). Nevertheless, empirical research has found that although moral judgment has both emotional and cognitive components, the moral appeal is an independent dimension of persuasion appeal and derived from both thinking and feeling. In addition, past research shows inconsistency in the persuasive effect of moral appeal (Ben-Nun Bloom & Clark Levitan, 2011; Kaplow & Shavell, 2007). When appealing to reasoning and thinking, persuasion messages inculcating moral senses limit individuals' cognitive capacity because their morality restricts how they think and act. In other words, the instilled guilt or virtue from individuals' moral senses become the power of persuasion (Kaplow & Shavell, 2007). In contrast, when moral appeal is directed at feelings, moral elements in persuasive messages tend to trigger moral emotions such as anger and disgust that undermine the persuasive power of such messages (Ben-Nun Bloom & Clark Levitan, 2011). Therefore, persuasive efforts via moral appeal sometimes seem to have the opposite effect. On the other hand, many studies (e.g., (Clifford & Jerit, 2013)) found that morality-related factors are influential in debates and persuasion. Findings in IS research also show that factors related to morality (e.g., subject norm) are influential in users' behaviors and intentions (Sutirtha Chatterjee et al., 2015; Venkatesh, Morris, Davis, & Davis, 2003). For example, moral beliefs and moral intensity can increase security policy compliance and deter deviant behaviors such as unethical IT use (Sutirtha Chatterjee et al., 2015). Morality and ethics as well as moral appeal have been influential factors in information use (Kent & Walsham, 2010). This study also identifies two moral factors in moral appeal based on the moral psychology literature (Clifford & Jerit, 2013; Shtulman & Tong, 2013). The two factors are rectitude and linguistic modality. According to the literature, moral cognition involves cognitive parallels of moral judgment built upon moral foundations such as purity and fairness, and modal judgment referring to moral permissibility. Rectitude links to moral judgment and refers to linguistic cues related to morality in the text. Rectitude cues convey the persuader's moral foundations on virtue, righteousness, goodness, and ethics. Modality based on modal judgment shows how strongly a persuader stands by her moral values by using words such as should, ought, must, etc. (Clifford & Jerit, 2013; Siering, Koch, & Deokar, 2016). This study focuses on strong modal cues representing a persuader's strong propositions on desirability, permission, and obligation concerning moral judgment and conduct (Lillian, 2008).

Psycholinguistic features have been proved crucial for online petitions, and we expected them to provide informative features for the recommender model as shown in Figure 3. Research showed that extreme language, such as arrogant and aggressive words, negatively impacted online petitions popularity (Panagiotopoulos, 2011). Another investigation showed that an online petition with word count less than a hundred words shows poor quality (Cruickshank & Smith, 2009). Also, the average number of words per sentence was perceived in literature as a measure of expressiveness (Crawford, Edelson, Skwerer, & Tager-Flusberg, 2008). In addition, a previous study highlighted the importance of psycholinguistic pronouns and social elements in attracting reader's attention (Whorf, Lee, Levinson, & Carroll, 2012).

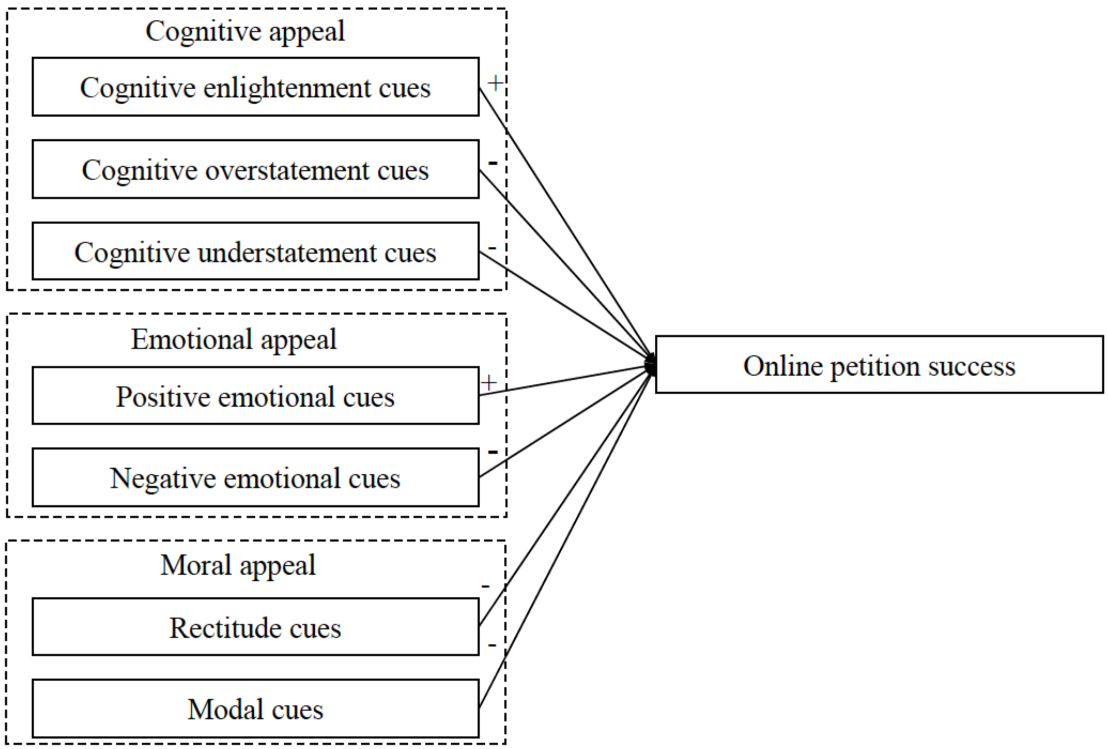


Figure 3. Multi-Appeal Model of Persuasion for Online Petition Success (Y. Chen et al., 2018).

Social Network Features

In Twitter context, literature highlighted relevant features, particularly for the instant blogging Twitter platform. Among these features are length of a tweet (usual tweets from ordinary users are shorter than official accounts), the influence of tweets (Favorite Count, Retweeted Count), and the number of hashtags (tweets with more hashtags are found irrelevant) (Daniulaityte et al., 2015; Ghiassi, Zimbra, & Lee, 2016; Tian, Lagisetty, & Li, 2016).
Also, user's total number of tweets, and term frequency-inverse document frequency TF-IDF for the bag of words were highlighted as important (K. Chen et al., 2012; Cortés, Velásquez, &

Ibáñez, 2017). On the other hand, stylistic attributes were perceived informative as well in web blogging, such as the number of unique words, number of pronouns…etc. (Ahmed Abbasi, Chen, & Salem, 2008; Elgersma & Rijke, 2008; Jiang & Zheng, 2013)

Lexicon Analyzers

Researchers used lexicons to extract linguistic features in the text. Lexicon Inquiry and Word Count LIWC was developed through a comprehensive study that extracted the psychological meaning of words and identified 80 language categories for the English language such as attentional focus, dominance, emotionality, honesty, deception...etc. (Tausczik & Pennebaker, 2010). LIWC was used to extract psycholinguistic features for online content. Also, Harvard General Inquirer GI (Stone, C., Dunphy, Smith, & Olgilvie, 1968) provides in-depth psycholinguistic categories. It has around 182 categories such as morals, cognitive, emotional and others. GI has been widely used by business researchers for content analysis and emotion detection, including extracting sentiment from forum discussions and financial statements (Das & Chen, 2007; Tetlock, 2007). Furthermore, NRC Word-Emotion Association Lexicon EmoLex is available for over twenty languages including English, French, Spanish, German, Chinese, and Arabic (Mohammad & Turney, 2013). EmoLex assesses categories such as anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. A previous study showed that LIWC and Harvard General Inquirer GI are among the most accurate lexicons for the English Language (Nadeau, Sabourin, De Koninck, Matwin, & Turney, 2006).

Topic Modeling

Topic models are statistical-based algorithms for discovering the main themes (i.e., set of topics) that describe a large and unstructured collection of documents. Topic models provide summarization to textual data at a scale that is impossible to be tackled by human annotation. Earlier scholars used Latent Semantic Analysis LSA model to extract latent topics from corpora (Dumais, Furnas, & Landauer, 1990). An extension to LSA by (Hofmann, 1999) introduced heuristics to the model and suggested a modified Probabilistic Latent Semantic Analysis PLSA. Although PLSA had improvements in performance over LSA, however, researchers widely used Latent Dirichlet Allocation LDA (Blei, Ng, & Jordan, 2003) to extract hidden subtopics in corpora on social networks.

Research on Climate Change

There were several observed impacts of climate change on physical and ecological systems over the past century (Parmesan & Yohe, 2003). Climate change threatens wildlife, animals such as polar bears that are facing extinction (Solomon, Plattnerb, Knuttic, & Friedlingsteind, 2009). Although some people try to deny the existence of climate change, scientists and researchers argue the opposite. Previous studies classified climate change as one of the top critical vulnerabilities that the environment is facing (Patwardhan, Semenov, Schnieder, & Burton, 2007). As awareness about climate change increased, people took action for their climate change concerns through signing and endorsing related online petitions. Climate Change is becoming a serious issue, and a behavioral model proposed that the importance of judgments about global warming is a function of beliefs about the existence of the phenomenon, attitudes toward it, and beliefs about human responsibility for causing global warming (Krosnick, Holbrook, Lowe, & Visser, 2006). Also, a survey study showed that there is an overall tendency for respondents to endorse a pro-ecological belief (Dunlap, Liere, Mertig, & Jones, 2000).

Information systems research can make a significant contribution to knowledge at the nexus of information about the natural environment and innovative environmental strategies (Melville, 2010). Previous literature highlighted the ontology of keywords in climate change including “climate change”, “methane emissions”, “global cooling”, “nuclear winter”, “carbon dioxide”, “pollution”, “arctic”, “forest degradation”, “environmental vulnerability”, and “deforestation” (Esbjörn-Hargens, 2010; Liu, Weichselbraun, Scharl, & Chang, 2005; Sasaki & Putz, 2009). Derived from the motivation that information systems could play an essential role in encouraging people to endorse a pro-ecological behavior, this dissertation aims to better link social media users with climate change petitions through designing a recommender model.

CHAPTER 3

SYSTEM DESIGN (RESEARCH METHODOLOGY)

Content-Based Filtering Recommender

First, we utilize the content-based recommender, and compute predictions through weighted average of ratings based on content similarities.

$$CB\widehat{R_{ui}} = \frac{\sum_{j=1}^{n}(s_{ij}\ R_{uj}\ )}{\sum_{d=1}^{n} s_{ij}} \qquad \{1\}$$

In equation {1} above, $CB\widehat{R_{ui}}$ is the predicted ratings for user u ∈U and petition i ∈ P that is computed through a similarity weighted average of R_{uj} which is the actual rating of user u and petition j ∈ P. Also, content similarities s_{ij} is the similarity between i and j. s_{ij} is the similarity of $x^{(i)}$ and $x^{(j)}$, where x is either petition feature vector (item-based content filtering) or user feature vector (user-based content filtering), and n is the number of similar petitions or users. s_{ij} is derived through cosine similarity as shown in equation {2}:

$$s_{ij} = \frac{x^{(i)}.\, x^{(j)}}{\|x^{(i)}\|\ \|x^{(j)}\|} \qquad \{2\}$$

Matrix Factorization Collaborative Filtering Recommender

Second, we utilize collaborative filtering and derive predictions based on rating similarities. In equation {3}, vector q_i represents the latent features for petition i ∈ P, and vector v_u represents the latent features for user u ∈ U, where q_i and v_u ∈R (real numbers between 0 and 1). The result of dot product $q_i^T v_u$, captures the interaction between user u and petition i and the overall interest of user u in petition i, leading to the estimate $MF\widehat{R_{ui}}$.

$$MF\widehat{R_{ui}} = q_i^T v_u \qquad \{3\}$$

Initially, collaborative filtering is directly derived from observed ratings only, while avoiding overfitting through a regularized model in equation {4} to minimizes the objective squared error through gradient descent (Fletcher & Powell, 1963) and to learn the factor vectors (v_u and q_i).

$$min_{q^*,v^*} \sum_{(u,i)\in k} (r_{ui} - q_i^T v_u)^2 + \lambda(\|q_i\|^2 + \|v_u\|^2) \qquad \{4\}$$

The notation κ is the set of the *(u,i)* pairs for which r_{ui} exists i.e. known. The model learns by fitting the known ratings. However, the goal is to generalize those known ratings in a way that predicts future, unknown ratings. Thus, to avoid overfitting the known data by regularizing the learned parameter λ in equations {4,6, and 7} (Koren et al., 2009). For each given training case, the system predicts r_{ui} and computes the associated prediction error e_{ui} as in equation {5}:

$$e_{ui} = r_{ui} - q_i^T v_u \qquad \{5\}$$

In gradient descent minimization takes place through iterations that are repeated number of times (epoch), wherein each iteration the parameters are modified by a magnitude proportional to γ in the opposite direction of the gradient, yielding equations {6, 7}:

$$q_i := q_i + \gamma(e_{ui} v_u - \lambda q_i) \qquad \{6\}$$

$$v_u := v_u + \gamma(e_{ui} q_i - \lambda v_u) \qquad \{7\}$$

PETREC Hybrid Model Recommender

In this study we design a hybrid recommender model approach and name it "PETREC", we compute the rating $HB\widehat{R_{ui}}$ through a weighted average between matrix factorization collaborative filtering $MF\widehat{R_{ui}}$ and content-based filtering $CB_1\widehat{R_{ui}}$ and $CB_2\widehat{R_{ui}}$ as shown in equation {8}. $CB_1\widehat{R_{ui}}$ and $CB_2\widehat{R_{ui}}$ are predictions of ratings through petition-based content and user-based content filtering that are derived from the petitions and users feature vectors respectively. Firstly, to address the traditional recommender problem we put more weight on predicting ratings through matrix factorization collaborative filtering over content-based filtering by putting more weight on ω over parameters η_1 and η_2.

Secondly, to address the cold start problem, we put more weight on the content-based filtering parameters η_1 *and* η_2 over ω. Content-based feature vectors are derived through extracting psycholinguistic features, topic modeling latent features, as well as social network features as illustrated in Table 1, Table 2, and Table 3 in subsequent sections.

$$HB\widehat{R_{ui}} = \omega\, MF\widehat{R_{ui}} + \eta_1\, CB_1\widehat{R_{ui}} + \eta_2\, CB_2\widehat{R_{ui}} \quad \{8\}$$

PETREC Topic Modeling Features

In our study, we applied topic modeling on two different. First, we applied unsupervised text modeling process by using LDA (Latent Dirichlet Allocation) to extract subtopics for climate change for each petition document. Second, we calculated topic modeling to extract the latent topics for social media posts, where user's posts are aggregated in one document as shown in Table 1.

Table 1. LDA topic modeling features

Feature	**Description**
Online petition's LDA latent topics	LDA latent topics extracted from all petitions' narratives through computing TF-IDF after removing stop words, punctuation, URLs, converting words to lowercase, parts of speech, and lemmatizing. Latent topics are derived for all petitions and then the probability that every petition (document) belongs to each of the extracted latent subtopics is computed.
User's LDA latent interests	LDA latent topics extracted from all users' posts through computing TF-IDF after ignoring retweets and posts containing URLs, then removing stop words, punctuation, and converting the remaining tweets to lowercase, computing parts of speech, and lemmatizing. Latent topics are derived for all users' posts and then the probability that every user (document) belongs to each of the extracted latent interests is computed.

We selected the LDA model, since it is the most common topic model that is currently being used due to its conceptual advantage over other topic modeling techniques (Blei et al., 2003). The model generates automatic summaries of topics regarding a discrete probability distribution over words for each topic, and it also infers per-document discrete distributions over topics which makes it a method of dimensional reduction. The interaction between the observed documents and hidden topic structure is manifested in a probabilistic generative process associated with LDA. This generative process can be thought of as a random process that is assumed to have produced the observed document (Bao & Datta, 2014). To illustrate the results of LDA, Let *M, K,* and *N* be the number of documents in a collection, the number of topics, and the number of words in a document respectively. The first result is an $M \times K$ matrix, where the weight $w_{m,k}$ is the association between a document d_m and a topic t_k. The second result is an $N \times K$ matrix, where the weight $w_{n,k}$ is the association between a word w_n and a topic t_k. The notations Dirichlet(·) and Multinomial(·) represent Dirichlet and multinomial distributions with parameter (·) respectively as shown below:

1) For each topic $t \in \{1, 2, \ldots, K\}$
   a. Draw a distribution over vocabulary words
      $\beta_t \sim Dirichlet(\eta)$
2) For each document $d \in \{1, 2, \ldots, M\}$
   a. Draw a vector of topic proportions
      $\theta_d \sim Dirichlet(\alpha)$
   b. For each word w_n in document d, where $n \in \{1, 2, \ldots, N\}$
      i. Draw a topic assignment
         $Z_n \sim Multinomial(\theta_d)$
      ii. Draw a probability that word belongs to topic z
         $w_n \sim Multinomial(\beta_{zn})$

The graphical representation of LDA is shown in Figure 5, and the corresponding generative process is shown in figure. The notation β_t is the V-dimensional word distribution for topic *t*, and θ_d is the K-dimensional topic proportion for document *d*. The notations η and α represent the hyper-parameters of the corresponding Dirichlet distributions. The probabilities that word W belongs to topic Z, and topic Z belongs to document θ is captured in equation {9}

$$P(W, Z, \theta, \eta, \alpha, \beta) = \prod_{i=1}^{K} P(\eta_i; \beta) \prod_{j=1}^{M} P(\theta_j; \alpha) \prod_{t=1}^{N} P(Z_{j,t}|\theta_j) P(W_{j,t}|\eta Z_{j,t}) \quad \{9\}$$

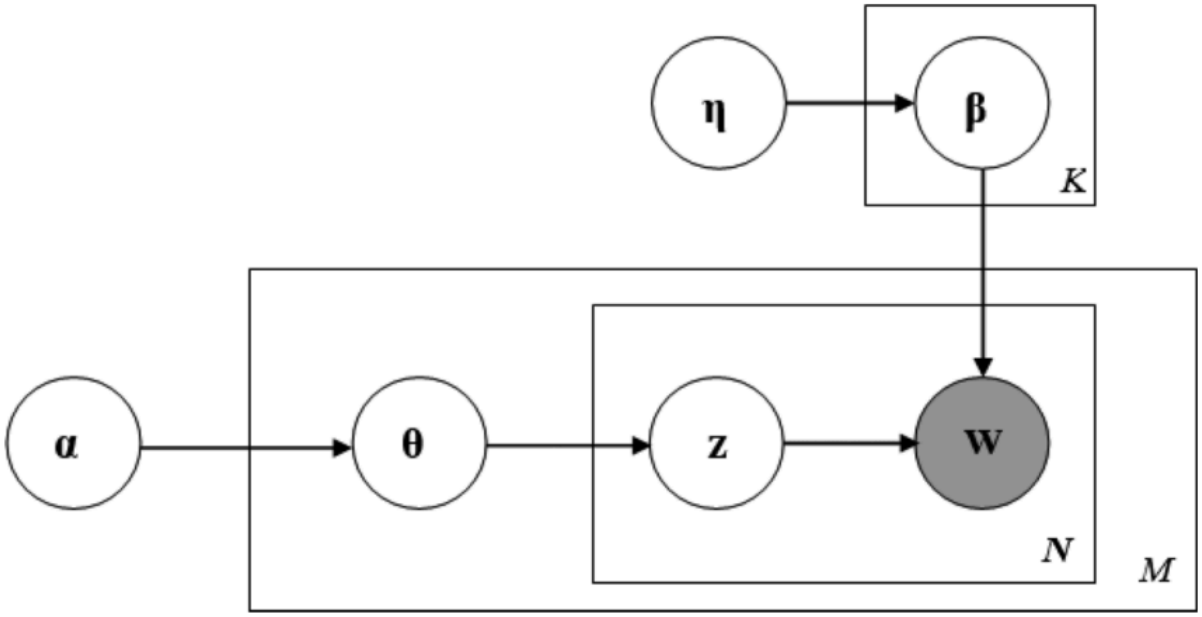


Figure 5. The Graphical model of LDA (Blei et al., 2003)

The Term Frequency Inverse Document Frequency TF-IDF measure is computed instead of the number of words in a document to highlight the distinctive words

$$TF - IDF(w_d, d, D) = tf(t, d).idf(t, D) \qquad \{10\}$$

$$idf(t, D) = log\left(\frac{N}{1 + |\{d \in D : t \in d\}|}\right) \qquad \{11\}$$

In equation {10, 11}, the Notation N is the total number of documents in the corpus N =|D|, and $d\,|\{d \in D : t \in d\}|$ denotes a document where the term *t* occurs at least once (i.e. $tf(t, d)$ >0) (Blei et al., 2003).

The most typical evaluation of topic models includes measuring how well a model performs when predicting unobserved documents. Specifically, when estimating the probability of unseen held-out documents given a set of training documents, a "good" model should give rise to a higher probability of the held-out documents. Therefore, to measure the predictive power of LDA models with different numbers of topics, we use a metric called perplexity that is conventional in language modeling (Azzopardi, Girolami, & Rijsbergen, 2003). Perplexity is the predicted number of equally likely words for a word position on average and is a monotonically decreasing function of the log-likelihood. Thus, a lower perplexity over a held-out document is equivalent to a higher log-likelihood, which indicates better predictive performance (i.e., lower perplexity indicates better generalization performance) (Blei et al., 2003). Formally, for a test set D_{test} of M documents, the per-word perplexity

$$Perplexity(D_{test}) = exp\left(-\frac{\sum_{d=1}^{M} log\, p(w_d)}{\sum_{d=1}^{M} N_d}\right) \qquad \{12\}$$

The notation $p(w_d)$ is the predictive probabilities of these held-out words and N_d is the number of words in document d. In our recommender, we extract topic modeling for online petition's narrative and user's posts on social network as illustrated in Table 1. We trained a number of LDA models with a different number of topics (k) and evaluated them against a held-out test set as shown in Figure 6 and 7 in Chapter 4.

PETREC Psycholinguistic and Social Network Features of Online Petitions

GI and LIWC are recommended lexicons for extracting linguistic features (Nadeau et al., 2006). In our recommender we derive the psycholinguistic features on the petition level as an average score of both GI and LIWC categories. Past literature, strengthened the expectations to include the following psycholinguistic features: emotion, extreme, moral, cognitive, social, expressiveness (ratio of adjectives and adverbs to nouns and verbs), and pronouns (Y. Chen et al., 2018; Hagena et al., 2016; Whorf et al., 2012) from the petition's narrative. A study highlighted the importance of word count and showed that an online petition with word count less than a hundred words indicates poor quality (Cruickshank & Smith, 2009). Table A1 in the appendix shows examples of sample words of psycholinguistic categories and usages in petitions on Change.org. Also, we perceive the number of times a petition was updated, the number of associated supporting comments, and the number of times the petition was retweeted as important social network features to describe the petition. Also, since visual complexity strongly influence online behavior (Deng & Poole, 2010), we take into consideration the existence of pictures among the petition's features. All features shown in Table 2 are further normalized and scaled over all petitions.

Table 2. Psycholinguistic and Social Network Features of online petitions

Feature	Description
Word count	The total number of words in petition's narrative (petitions with word count < 100 are assigned value 0 and petitions with word count > 100 are assigned value 1 to detect petition's quality as advised in literature).
Average number of words per sentence.	Average number of words per sentence in a petition's narrative.
Visuals	Boolean value to denote the existence of an image describing the petition.
Positive emotions	Score for words with positive sentiment. "Achieve, harmony, improve, and great" are examples of words that score high in the positive emotions category.
Negative emotions	Score for words with negative sentiment. "Hassle, embarrassment, and alienation" are examples of words that score high in the negative emotions category.
Cognitive enlightenment	Score for words that are stating facts. "Clue, deliberation, and evidence" are examples of words that score high in the cognitive enlightenment category.
Cognitive overstatement	Score for words that tend to include exaggeration. "Absolute, always, enormous, and extraordinary" are examples of words that score high in the cognitive overstatement category.
Cognitive understatement	Score for words that tends to deemphasize. "Appear, anyway, and insignificant" are examples of words that score high in the cognitive understatement category.
Moral	Rectitude and modal factors form the moral score for words in a petition's narrative. "God, right, heaven, and must" are examples of words that score high in the moral category.
Expressiveness	The ratio of the number of adjectives and adverbs to the number of nouns and verbs in petition's narrative
Pronouns count	The total number of pronouns including first, second, and third person pronouns in petition's narrative.
Supporters to goal ratio	The current number of supporters of a petition to the goal set (goal is AKA requested number of supporters for the petition to win) by petition owner (Intuitively users are persuaded to engage more with petitions that are about to reach victory, i.e. with supporters to goal ratio closed to 1).
Social network mentions	The number of times users mentioned a petition on social networks.

Social network comments	The number of supporting comments to a petition.
Social network updates	The number of times a petition owner updated her petition.

PETREC Social Network Features of Users

Secondly, we derive user's features from user's profile and aggregating social media posts per user and retrieve the total number of posts, number of retweeted posts, number of hashtags in posts, number of friends, number of followers, number of favorites tweets as labeled by followers, and the number of lists either subscribed by the user or tagged by followers as shown in Table 3. Since social networks Application Programming Interfaces APIs are having limitations and retrieves only a sample of user's posts, accordingly we normalized user related features over the number of posts retrieved for each user. Also, all features are further normalized over all users.

Table 3. User's Social Network Features

Feature	Description
Posts count	The total number of social network posts of a user.
Friends count	The total number of friends in the social network of a user.
Followers count	The total number of followers in the social network of a user.
Lists count	The number of lists to which a user is subscribed to or tagged by followers.
Favorites count	The number of times user's posts were labeled as favorite.
Retweets count	The retweets count of user's posts.
Hashtags count	The number of hashtags in all user's posts.
Average length of posts	The average length of a post by a user.

In this piece of work, we employed both social and psycholinguistic features extracted from petitions' narratives and activists' activities on social media to construct the recommender's model PETREC to better connect users with their climate change concerns. Following the design science guidelines by (Hevner et al., 2004), next section is the instantiation of the model through developing a recommender to link activists on Twitter to climate change petitions on Change.org.

CHAPTER 4

RECOMMENDER INSTANTIATION (RESULTS AND DISCUSSION)

Data Collection and preprocessing

Firstly, we collected online petitions from Change.org; we chose Change.org as it is a popular online petitioning platform. We have included petitions with open status labeled English and have climate change related keywords mentioned in their narratives (as described previously in Chapter 2). On the other hand, petitions marked as a victory or closed were excluded as there is no sense in recommending ended petitions. The total petitions used are 2,929 petitions. We have mined petitions' narratives to extract psycholinguistic petition-based features discussed in Table 2 in Chapter 3 using GI and LIWC. Also, we filtered out stop words, and miss spelled words using enchant spell check library. Also, using Natural Language Toolkit (NLTK) library we identified parts of speech tags to label terms and perform lemmatization as a preprocessing for topic modeling LDA and expressiveness. For topic modeling, we followed best practices suggested by (Arun, Suresh, Veni Madhavan, & Narasimha Murthy, 2010), we computed TF-IDF and perplexity of a held-out test set to evaluate LDA models using different number of topics. Accordingly, we held out 20% of the data for test purposes and trained the models on the remaining 80%. Figure 6 and Figure 8 shows the predictive power of the LDA models for each of the petitions' narratives and users' posts respectively in terms of the held-out per-word perplexity by varying the number of topics. The perplexity decreases with the increase of the number of topics, but somehow tends to converge at certain threshold (as it occurs at around 50 topics in Figure 6 and Figure 8). We were able to manually label and group 19 topics from among the 50 topics of petitions. For each of the 19 topics we visualized the top 6 words with the highest unigram TF-IDF score as shown in word clouds in Table 4. Also, for each petition we computed the probability that it belongs to each of the 50 topics; the bubble chart in Figure 7 visualizes the distribution of petitions' LDA latent subtopics. Also, Table A1 and Table B1 in the appendix psycholinguistic and topic modeling features respectively for online petitions.

Secondly, we study activists who are following Change.org twitter account and further mine their profile and tweets to extract user-based features discussed earlier in Table 3. Also, we collected activists' retweets and looked up Change.org climate change petition's URL pattern in retweets to extract ratings to petitions. Since retweeting online content is a significant interest of a user in the content (K. Chen et al., 2012). Accordingly, we consider retweeting a petition as a strong implicit rating of a user to the retweeted petition. Next, we were faced by the traditional recommender's which is sparsity as discussed earlier in literature in Chapter 2. After analyzing 19,158,793 tweets for activists who are following Change.org Twitter account, we were able to only collect 939 retweets of petitions. As a result, we designed a questionnaire that randomly selects 12 petitions for activists to explicitly rate petitions and provide ground truth for the recommender model. The questionnaire is available at https://goo.gl/KqTJE5 (Appendix D contains more details about the questionnaire) to login into the questionnaire participants would need to login through OAuth login Twitter gateway and should have an active Twitter account with at least 100 tweets to be eligible for participation. The 100 tweets history criterion protects the study from the participation of fake accounts who are aiming to increase their chance of winning our monetary gift cards. In addition, we consider tweets history as rich raw data to help derive the user-based interests features through topic modeling. Furthermore, to guarantee the validity of the questionnaire submissions, we have two attention questions, which, when answered incorrectly, the whole submission was ignored. We collected 121 valid submissions out of 376 in total (32% valid submissions). The 121 valid submissions added another 1,458 explicit ratings over the implicit 939 retweets which helped to train the recommender model. Figure 10 visualizes our data collection, preprocessing module. It was more challenging to mine tweets history as we were faced with lots of noise where users tweet with non-English words and slang in English labeled tweets. Also, we ignored all retweets to focus only the user's personal interests and experiences as suggested in the literature (Ghiassi et al., 2016; Jiang & Zheng, 2013). For each of the 9 topics, we visualized the top 6 words with the highest unigram TF-IDF score as shown in word clouds in Table 5. Also, for each user, we computed the probability that she belongs to each of the 50 topics of interest. The bubble chart Figure 9 visualizes the distribution of the users' LDA latent interests.

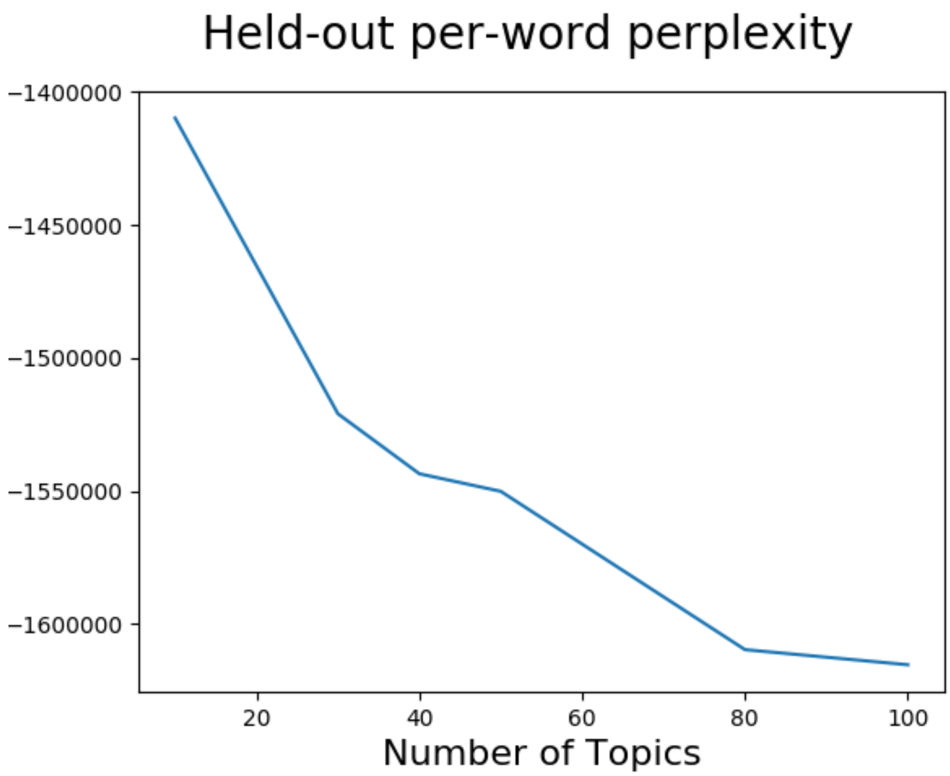
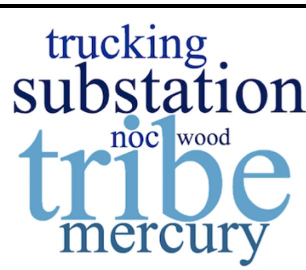
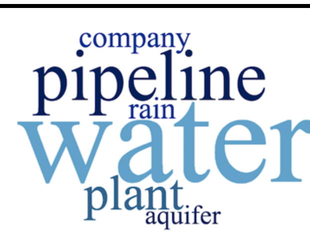
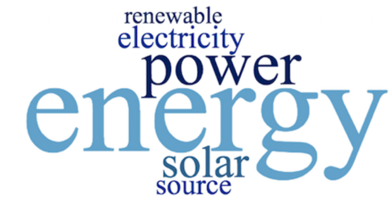


Figure 6. Held-out per-word Perplexity for Change.org Online Petitions Corpus

Table 4. Change.org CC Online Petitions' LDA Latent Topics (PT) Word Cloud

Topic	**Top words**	**Topic**	**Top words**
PT1: Animal & Plant Health		PT2: Religious Practices	
PT3: High Voltages		PT4: Water Pollution	

PT5: Renewable Energy		PT6: Authority	
PT7: Taxes & Environment		PT8: Indigenous Rights	
PT9: Wastes & Recycling		PT10: Caribbean Heritage	
PT11: Air Pollution		PT12: Pollution	
PT13: Green Politics		PT14: Politics	
PT14: Deforestation		PT15: Traffic Pollution	

PT16: Africa & Asia		PT17: North & South America	
PT18: Arctic		PT19: Others	

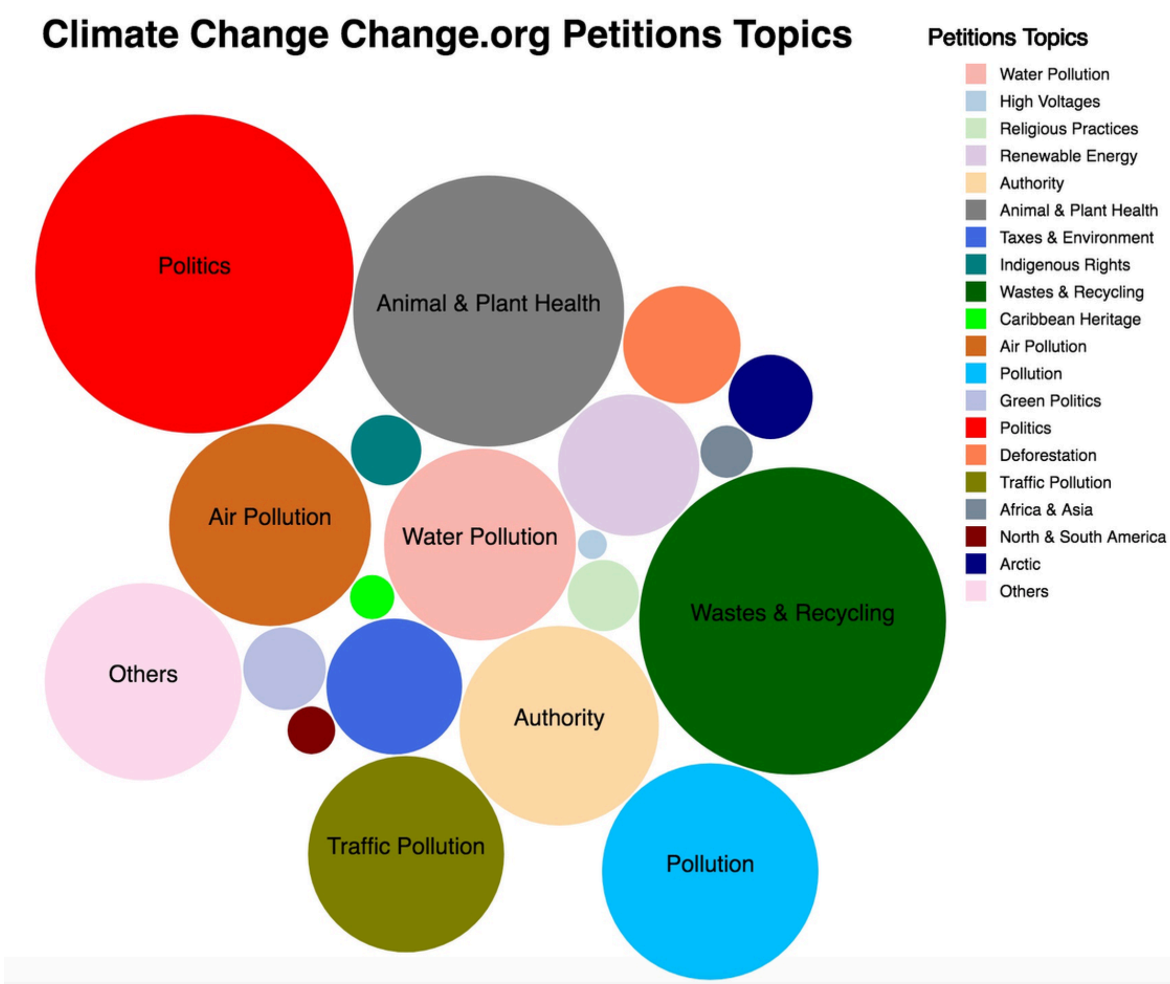


Figure 7. Climate Change Online Petitions LDA Latent Topics Weights on Change.org

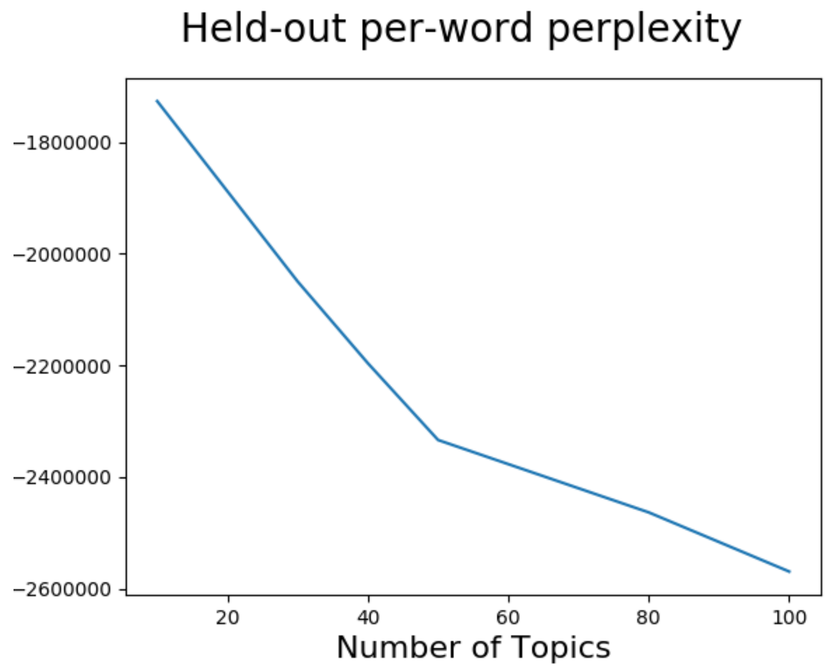


Figure 8. Held-out per-word Perplexity for Tweets of Users Corpus from Twitter

Table 5. Twitter Users' LDA latent Interest Topics (UT) Word Cloud

Topic	**Top words**	**Topic**	**Top words**
UT1: American Politics		UT2: Syrian Crisis	
UT3: Animal Rights		UT4: Soccer	
UT5: UK Conservative Party		UT6: Food & Business	
UT7: Positive Vibes		UT8: Music	

UT9: Pollution		

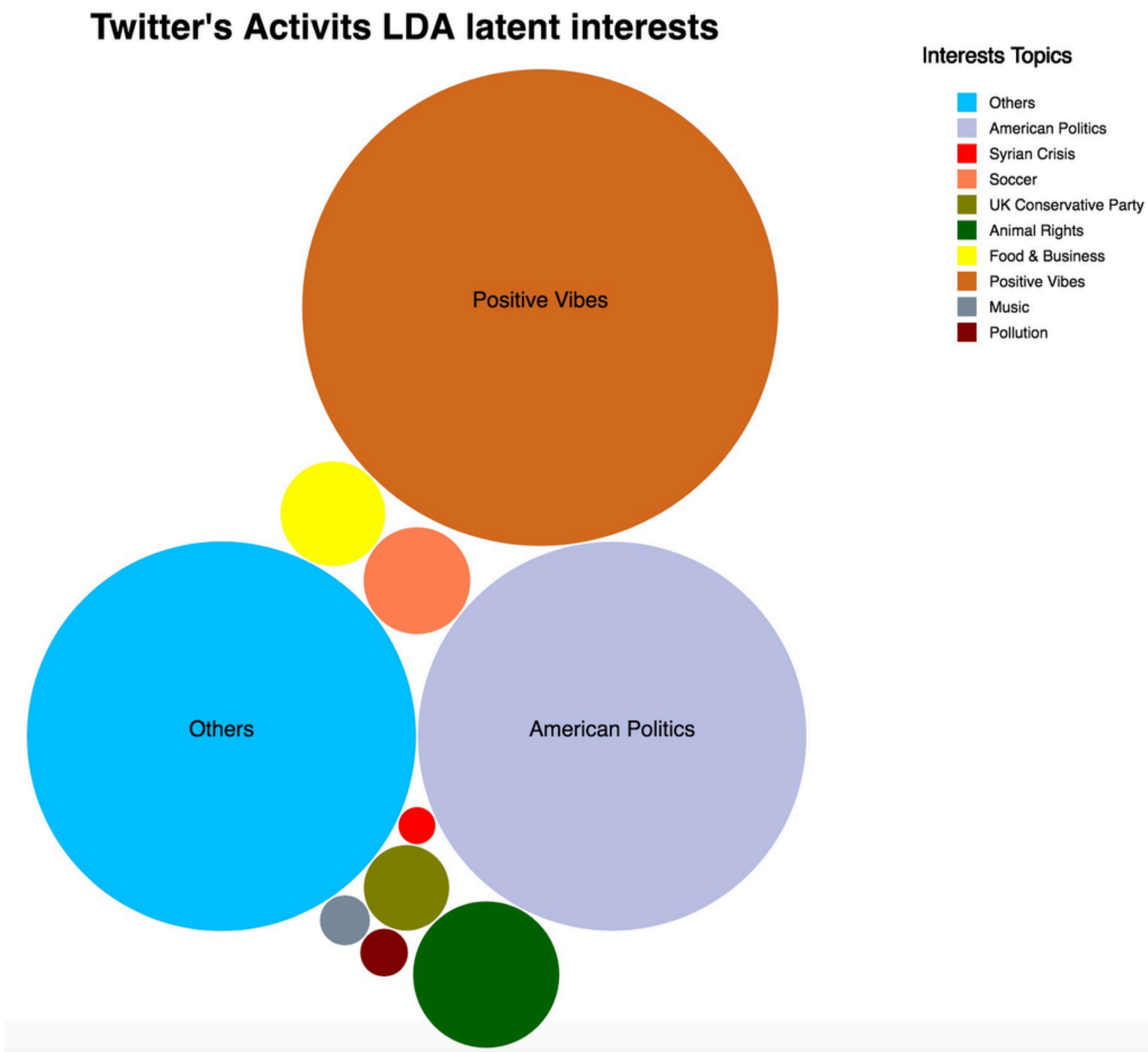


Figure 9. Activists LDA Latent Topics Weights on Twitter

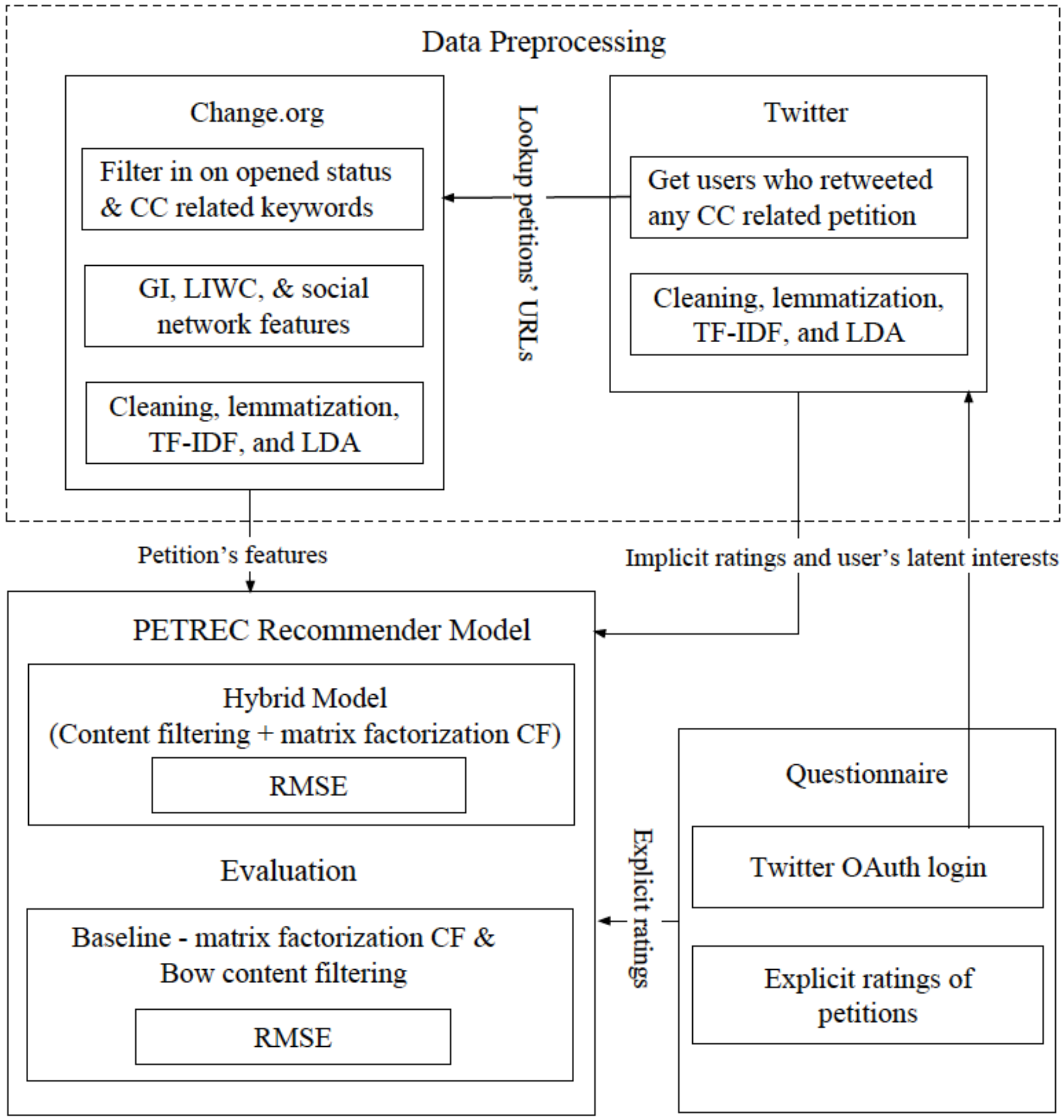


Figure 10. PETREC Hybrid Recommender Model for Online Petitions: Evidence from Change.org and Twitter

At preprocessing stage, the petition and users features vectors are normalized. Table 6 and Table 7 provide insights on petitions and users datasets. Also, the user's ratings are collected from the explicit ratings through the questionnaire and implicitly from retweets as shown in Table 8.

Table 6. Data Collection Summary of Online Petitions

Item	Description	Count
Total number of climate change petitions	The total number of climate change open status online petitions on Change.org.	2,929

Table 7. Data Collection for Activists' (Users) Information

Item	Description	Count
Activists with valid questionnaire submissions	Valid participants who have successful submissions in the ground truth questionnaire.	121
Tweets count of activists with valid questionnaire submissions	The total number of tweets collected from participants with valid submission in the ground truth rating questionnaire.	218,043
Activists with no ratings history	Randomly selected sample of activists who follows Change.org Twitter's account and did not rate any climate change petition.	500
Tweets count of activists with no ratings history	The total number of tweets collected from activists who follows Change.org Twitter account and did not retweet any climate change petition (users that did not implicitly or explicitly rate a petition).	2,426,512
Twitter activists with implicit ratings	Activists on Twitter who implicitly rated at least one climate change petition through retweeting.	884
Tweets count of Activists with implicit ratings	The total number of tweets collected from activists who implicitly rated at least one climate change petition through retweeting.	2,589,971
Total number of users	The total number of activists who submitted valid questionnaires + number of activists who implicitly rated climate change petition(s) + activists who follows Change.org Twitter account and did not rate any climate change petition.	1,505

Table 8. Data Collection Summary of Ratings

Item	Description	Count
Explicit ratings	Valid submissions ground truth ratings from questionnaires.	1,458
Implicit ratings	The total number of retweets Twitter's activists of climate change online petitions.	938
Total number of ratings	The total number of implicit ratings from retweets + the total number of explicit ratings from questionnaires.	2,397
Users with ratings	The total number of activists who participated in the questionnaires + the total number of twitter activists with implicit retweets.	1,005
Petitions with ratings	A total of 1247 petitions (43%) were rated either explicitly through questionnaires or implicitly through retweeting.	1,247

PETREC Performance in the Traditional Problem

After deriving petitions and users feature vectors, we ran petition-based content filtering alone and got a Root Mean Square Error RMSE ≈ 3.915. We also ran the user-based content filtering alone and got a very high RMSE and poor prediction performance. Unsurprisingly as stated in literature (Koren et al., 2009), we found that collaborative filtering matrix factorization performed much better than content filtering techniques, and after running the algorithm for 100 epochs, after dividing the dataset into 75% training and 25% testing, we got a much lower RMSE ≈ 1.17 (223% better score) as shown in Figure 11. Therefore, for the traditional recommender's problem discussed earlier in Chapter 2, the benchmark for PETREC is collaborative filtering matrix factorization. For the traditional recommender problem, we compute a weighted average of the predictions from matrix factorization collaborative filtering, petition-based content filtering, and user-based content filtering. In PETREC, we put more weight on matrix factorization collaborative filtering section (substitute ω=0.95, $\eta_1 = 0.02$, and $\eta_2 = 0.03$ in equation {8}). As shown in Figure 12 PETREC has an RMSE ≈ 1.12 which is a 4.2% improvement in RMSE over the benchmark of matrix factorization collaborative filtering as shown in Figure 12.

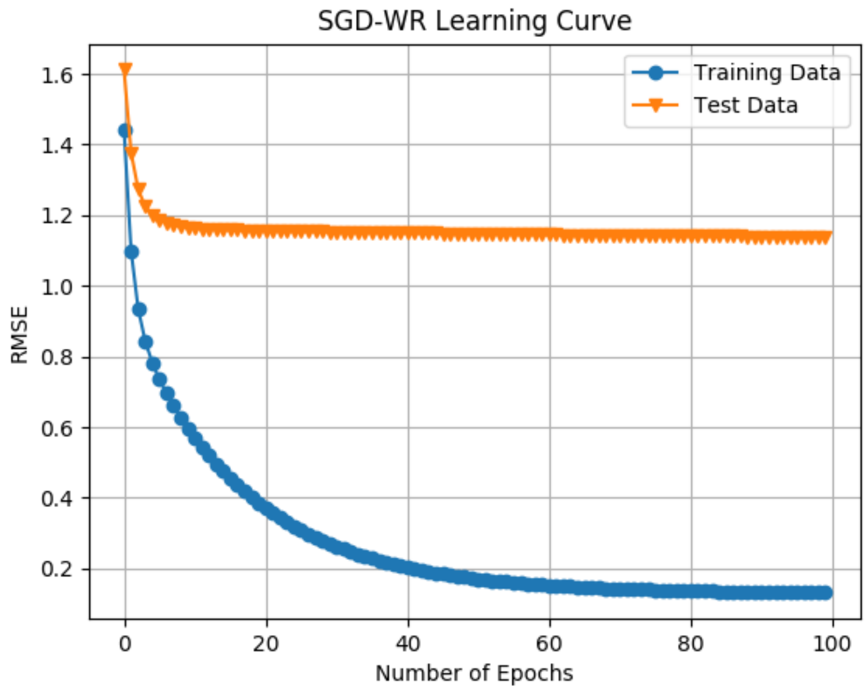


Figure 11. RMSE of Matrix Factorization Collaborative Filtering Recommender

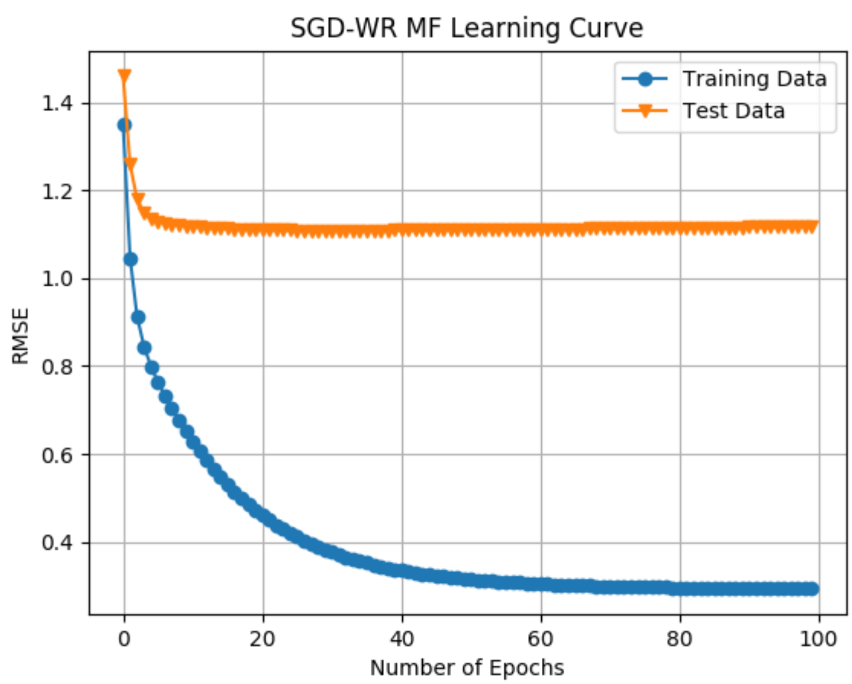


Figure 12. RMSE of PETREC Hybrid Recommender Model

PETREC Performance in the Petition Cold Start Problem

Although collaborative filtering matrix factorization performs better than content filtering techniques in the traditional problem, but for the cold start problem introduced earlier in Chapter 2 this is not the case. Content filtering outperforms matrix factorization collaborative filtering in the cold start problem since that later poorly performs due to the predictions being derived only from rating history which does not exist in a cold start situation (as shown in equation {4} no ratings exist to minimize the squared error function and predict feature vectors) (Li et al., 2005; C. Wang & Blei, 2011).

If a petition did not receive any ratings, in this particular situation PETREC relies solely on petition-based content filtering (substitute ω=0, $\eta_1 = 1$, and $\eta_2 = 0$ in equation {8}). As shown in Table 9 that lists the performance of different petition-based content filtering models. The psycholinguistic features, social network features, and topic modeling features in PETREC had an RMSE ≈ 3.915 (1.7% better score) versus an RMSE ≈ 3.981 for the traditional bag of words (Bow) content filtering technique. We also reduced the feature vector space from 1,667 predictors of the Bow approach to only 65 content-based features for online petitions.

Table 9. Petition-based Content Filtering Recommendation RMSE

Features set	**Description**	**RMSE**
PETREC features	Psycholinguistic, social network, and latent subtopics features	3.915
Latent Topic modeling	50 latent subtopics features	3.956
Social network features	Social network mentions, comments, updates, and supporters to goal ratio.	3.98
Psycholinguistic features	Word count, average number of words per sentence, positive emotions, negative emotions, cognitive score (enlightenment, overstatement, and understatement), moral, expressiveness, and pronouns count	3.975
Benchmark bag of words features	Unigram bag of 1,667 words	3.981

PETREC Performance in the User Cold Start Problem

If a user did not have any ratings, in this particular situation PETREC relies solely on user-based content filtering (substitute ω=0, $\eta_1 = 0$, and $\eta_2 = 1$ in equation {8}). As shown in Table 10 that lists the performance of different user-based content filtering models. The social network features and topic modeling features in PETREC had an RMSE ≈ 3.77 (2.8% better score) versus an RMSE ≈ 3.88 for the traditional bag of words (Bow) content filtering technique. We also reduced the feature vector space from 1,642 predictors of the Bow approach to only 59 content-based features for users.

Table 10. User-based Content Filtering Recommendation RMSE

Features set	Description	RMSE
PETREC features	The social network, and latent subtopics features	3.77
Latent Topic modeling	50 latent subtopics features	3.78
Social network features	Number of tweets, number of followers, number of friends, lists count, number of favorites by followers, number of retweets by followers, number of hashtags, expressiveness, and the average length of a tweet.	3.981
Benchmark bag of words features	Unigram bag of 1,642 words	3.88

Discussion

Our hybrid recommender model PETREC performs better than the benchmark matrix factorization with an improved prediction performance of 4.2% (better RMSE score) for the traditional recommender's sparsity problem. We also argue that the PETREC-suggested petition-based and user-based content features becomes of more importance particularly when solving the cold start problem. In the online petitioning context, it is essential that the cold start problem to be taken into consideration, since many online petitions were never rated (in our random data collection 57% of petitions were never rated, not even once). Furthermore, in practice, many users did not rate (in our random data collection 34% of users have no rating history and did not even rate one petition).

PETREC outperformed the baseline recommenders in RMSE, which happens to measures the error in predictions from the actual ratings. Better RMSE results of PETREC would lead to better user experience regarding the satisfaction and perceived system effectiveness. However, several researchers have argued that for evaluating recommenders, other factors influence the user experience (users' subjective evaluation of their interaction with the system) (Knijnenburg et al., 2012; Pu & Chen, 2010). Accordingly, for future extension, we plan to perform an online field experiment for activists to evaluate PETREC's recommendation quality against the baseline recommenders from the user's point of view (user-centric evaluation).

CHAPTER 5

CONCLUSIONS

The study responds to a call to IS scholars to investigate ICTs' societal impacts, digital activism and e-politics in the form of petitioning (Miranda et al., 2016; Newton, 2002; Wattal et al., 2010). The hybrid recommender system PETREC described in this work incorporates collaborative filtering and content filtering with informative psycholinguistic and social network features. In several contexts, emotional features like positive and negative sentiments were highlighted as essential in content filtering for recommender systems (Alam & Riccardi, 2014; Moshfeghi, Piwowarski, & Jose, 2011; Stammatatos et al., 2015). In addition to emotional appeals, this research sheds light on cognitive and moral appeals as informative psycholinguistic features. IS researcher would need to consider the influence of more psycholinguistic features over the emotional sentiments in future recommender system studies. Practically, PETREC improves the recommendation performance and hence the user experience of activists on online petition platforms. Eventually, it will help the citizens to make a real difference through actively participating in online petitions that closely matches their actual direct concerns. Moreover, it could be able to encourage more public participation and increase the chances of success for petitions (most recent studies show that petitions are having 1% chance of success (Huang et al., 2015)).

Previous research highlighted the importance of user's demographics, network structural equivalence and trust as important social network features for recommenders (Fang, Hu, Li, & Tsai, 2013; Jamali & Ester, 2010). Arguably, user-based content filtering portion of PETREC might even improve performance, however, the lack of informative user's demographic information in this research is attributed to Twitter's data collection limitation. Since we have depended on Twitter API to collect user's profile, we were not able to acquire important user demographics (gender, age, location…etc.) and complete social network structure for each user. Another limitation is that user's perception about a petition might change over time (Koren et al., 2009), we did not take into consideration the temporal dynamics of change in user's inclination and redefinition of their interests over time. Although the proposed model PETREC focuses on climate change petitions, its implication may not necessarily be restricted to climate change petitions. Since online petitions share common characteristics in their content and process, it is expected that the proposed model will be easily adapted to support online petitions related to other critical issues such as healthcare and democratic reforms. As a future extension of the research, we aim to collect and reference census data to predict user's demographic information through machine learning techniques to provide more informative user-based content features to our recommender model. Also in the future, we plan to evaluate PETREC in an online field experiment, where activists will evaluate PETREC's recommendation quality from the user's point of view.

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APPENDICES

APPENDIX A: SAMPLE LIWC AND GI WORD USAGE IN PETITIONS AT CHANGE.ORG

Table A1. Sample of Online Petitions with Psycholinguistic Features

Linguistic Cue Category	**Sample words from GI & LIWC**	**Usage in Online Petitions (with Petition ID)**
Enlightenment	Clue	To answer this question, the Iowa State University website's page for diversity and inclusion was visited. Although no definition of the word was given, there were a few ***clues*** that might lead a reasonable person to conclude that Iowa State University - quite frankly - doesn't give a damn about any form of meaningful diversity. (10581785)
	Deliberation	Food Animal Well Being 1993 Conference Proceedings and ***Deliberations***, USDA and Perdue University Office of Agricultural Research Papers, West Lafayette, IN, p. 41 (259440)
	Evidence	***Evidence*** shows and it is well documented that these programmes, activities and operations induce droughts, cause floods and other man-made weather anomalies and extreme weather events. (12828411)
Overstatement	Absolute	***Absolutely*** love the idea of rail service, would be just great. Such a shame we don't have it now. (6850178)
	Always	Nevertheless, entire packs could ***always*** be removed as part of wolf management control actions. (1067131)

	Enormous	The obvious cause of all life and environmental destructive outcoming effects, namely the ***enormous*** overpopulation of the earth by the human beings, wasalso in the past climate conferences not openly addressed, which is why also no comprehensive measures in the form of birth-controls were adopted, that still could mitigate the effects of climatic change. (1271940)
	Extraordinary	However, the Obama Administration defends the illegal wiretapping program, leaves the door open to outsourcing torture through "***extraordinary*** rendition", and argues that prisoners can be denied habeas corpus if they are shipped to the Bagram prison in Afghanistan instead of Guantanamo! (21449)
Understatement	Appear	There appears to be some misalignment in the walking and talking of right action. (11665720)
	Anyway	Bearing in mind that we the undersigned do not accept these prognostications as having any basis in fact ***anyway***, what possible justification can then be offered for the expenditure? (12834033)
	insignificant	Human trafficking is Crap, selling humans is crap, the worth of a human no matter how great or insignificant it maybe to you is priceless. (12808830)
Positive	Great	By supporting global efforts to limit climate change we can protect our ***great*** lifestyle and make sure our kids can have the clean energy jobs of the future. (5100770)
	Achieve	Parliament is expected to make proper amendment of the PCA Act to provide a effective deterrent to ***achieve*** the object of and purpose of the Act and for violation of section 11, adequate penalties and punishments should be imposed. (8120123)
	Harmony	This is nothing new for us. For centuries, Indigenous Peoples have struggled to keep safe the affirmations of life that matter most to us:

		harmony, respect, relationships, hope, and dignity. (70361)
	Improve	Over the last 30 years, we have seen first-hand how the EPA and its partner organizations can improve public health for Angelenos through environmental policies and regulations. (10188941)
Negative	Alienation	Rohith managed to get into a friend's room in the hostel and hanged himself, leaving a suicide note expressing his ambition to be a writer and his profound ***alienation*** in a society that had lost all authenticity. (10715231)
	Hassle	We do not kill unwanted children when the orphanages are full so why are these poor animals having to lose their lives simply because someone doesn't want the ***hassle*** of it anymore. (11681149)
	Embarrassment	For these reasons, I think it is highly suitable that Donald Trump, the 45th President of the United States, be officially declared a global ***embarrassment***! (12387268)
Rectitude	Justification	In general, SF Rec and Park staff continues to claim that "80% of the trees in the Natural Areas are in poor to fair condition and need to be removed" as ***justification*** for deforestation and conversion to scrub and grassland. (9054401)
	Right	There are also environmentally issues existing in their own ***right***, when extracting petroleum from the Earth. (12806576)
	God	In a country where we think kids are equal to ***god*** where the better future of tommorow lies with them, are having the faded faces with empty stomaches. (12834511)
	Heaven	you wake up to the ***heavenly*** scent of coffee brewing in the kitchen, a freshly tossed fruit salad awaits you at the table. (9973787)

Should	So owners of older cars are also subsidising the Water Services of those who can afford new cars. Water Services ***should*** be funded by general taxation or metered usage, "with exemptions for inability to pay", BUT NOT by penal tax loaded on pre-2008 car owners! (118624)
Must	To mitigate our Climate Change Disaster, action ***must*** be immediate, must be massive and requires a level of mobilization of all our resources similar to what this country experienced during the New Deal and World War II. (7951289)
Ought	Politicians and corporations ***ought*** to admit what they already know, instead of treading water while the clock winds down for us all – for us, for them, for all of us, our children, our friends, our human family, and life as it exists on Earth. The greatest gift of all, and it doesn't cost or owe a penny. (11076653)

APPENDIX B: SAMPLE OF LDA LATENT SUBTOPICS FROM PETITIONS AT CHANGE.ORG

Table B1. Latent Subtopics of Climate Change petitions on Change.org

Latent subtopic	Petition ID	Online Petitions
Water Pollution	10878377	Coca-Cola’s second largest bottling plant in India – located in Hapur in Uttar Pradesh – remains shut down due to court orders because the company has been found to be discharging untreated wastewater from the plant.
High Voltages	11310131	Mallory contamination: 30 Andrews Lane was remediated for lead and mercury contamination, along with all our properties, but does that make it safe enough for the construction of an apartment complex? Will there be a study? Will there be oversight during construction, with proper equipment, like air contaminant sensors?
Religious Practices	12466291	It is therefore absolutely necessary that the use of cow’s milk, ghee and any other form of dairy for personal, religious & spiritual practices within the Hindu temple (and home) should be fully abolished.
Renewable Energy	11138492	By turning this iconic wilderness over to oil and gas companies, while simultaneously changing tax codes to impose more obstacles on the solar, wind and energy efficiency companies, Congress is picking winners and losers and gambling with the public lands that we all own. Ultimately, we’ll all end up losing.
Authority	5125442	In order to reduce the amount of garbage going into the gyre, the government should require stores to charge a price for plastic bags.

Animal & Plant Health	11242364	Instead of putting up housing we should be thinking about green initiatives; using it for community gardening projects, putting in a park with a soccer field for children, making it the first fenced dog park in West St. Paul or even using the space for all of the above would be more suitable options for our community rather than filling land with housing that would overcrowd our street and destroying a healthy forest.
Taxes & Environment	12837040	In a gallop poll, the Washington Examiner found that 29 percent of Americans favor the tax cut while 56 percent disapprove. What happened to the voice of the people?
Indigenous Rights	12747499	If the debate in the name is about reconciliation with our indigenous peoples and imperialism, aboriginals need to know that reconciliation is two fold, we recognize our errors and history of genocide in Canada's past but also that the aboriginals recognize that non-aboriginals don't all spout hate/ discrimination/ slander!
Wastes & Recycling	7949588	According to Ocean Conservancy "San Francisco County Board of Supervisors unanimously passed a ban on the sale of polystyrene foam. Foam packing, cups and mooring buoys will be prohibited starting January 1, 2017." On August 9, 2016 The Folly Beach Newsletter reported "The Folly Beach City Council unanimously voted to ban polystyrene coolers (best known by the brand name Styrofoam) or single use plastic bags, typically associated with bags handed out to customers after a purchase", countries in Europe encouraged a large decrease in single use plastic bags by charging for them, and France just banned single use/disposable plastic-ware all together. It's time to join other coastal areas around the Nation and the globe in taking the necessary steps to ensure that our coastal ecosystems remain intact, and pristine for future generations.

Caribbean Heritage	9005573	Community members cite a municipal ordinance which prohibits use of coal ash in the town of Peñuelas as the basis for their opposition to the coal ash. Approximately 43 other municipalities in Puerto Rico have prohibited the use of coal ash as fill material at construction sites and in their landfills.
Air Pollution	12601186	Bursting Firecrackers causes harmful and poisonous air pollution which causes breathing problems, diseases, illness and death. Environmental Pollution causes Global Warming due to Greenhouse effect and also depletion of Ozone layer.
Pollution	12770180	The school has already suffered from noise and air pollution caused by the current work being carried out on the old Gala Bingo Hall site. Kingston borough does not have the benefit of many sites that are appropriate for schools and school places remains a key issue for both the council and its residents.
Green Politics	12465832	The Taj, the country's biggest tourism draw, was not allotted any cultural heritage funds in the state budget for the coming year. And the monument was omitted from the state's official tourism brochure last week, prompting yelps of protest from the main national opposition party.
Politics	12911117	Last but not least Global Warming stays a risk factor for our planet. I believe the trump administration is not doing enough, in fact, recnt decisions by the administration is making the problem worse.
Deforestation	8953019	If today, We boycott the palm oil, we can succeed to change the increasing tendency of the request of palm oil and thus to reduce considerably the destructive production of this oil. Let's use our consumer's power by stopping multinationals to sell us products that are responsable of the destruction of the planet.

Traffic Pollution	10909772	This includes building a flyover at Barasat Dakbanglo crossing, an underpass at Madhyamgram Chowmatha and widening of a 7km stretch between the airport and Dakbanglo More to ease traffic flow, say offici.
Africa & Asia	12553303	The historical city and most important city of the state chhattisgarh bilaspur is now has turned into junk of bad roads (khodapur) , pollution , climate changed , over heating , no development , trees are cutting quickly , river arpan has almost lost , peoples are suffering , no managment of waste , worst transportation and many others health and social issues come which should be not happens with this city because it's now a metropolitan city day by day population of here is going increasing and this city is a big contributor of the whole states budget so why instead of development this government leaders destroying this city time has come to awake this so called netas from their sleeping bed's and let them to know it's not there private assets on which they do as they want .
North & South America	11423510	Ecuador Campaign Update: Indigenous People Take State to Inter-American Court. In 2003, Global Response launched a campaign to protect the Sarayaku people from oil companies CGC of Argentina and Chevron-Texaco from exploration.
Arctic	12172327	The polar bear is a marine mammal because it spends many months of the year at sea.However, it is the only living marine mammal with powerful, large limbs and feet that allow them to cover miles on foot.

APPENDIX C: SAMPLE OF LDA LATENT INTEREST TOPICS FROM USERS TWEETS AT TWITTER

Table C1. Latent Interests of Activists on Twitter

Latent interest	User ID	Tweets sample (with tweet ID)
Animal Rights	(3338860150)	Keep Dogs Off Menu in... #care2 (964506077462237184)
		Save puppies and dogs from hell in South Korea #ShutDogMeatFarms (962045504535216133)
		Stop Killing Homeless Animals in Russia! Stop Bloody FIFA 2018! (961687829632946177)
Pollution	(2736730808)	Fighting #AirPollution 👍 (964201110608236545)
		Air Pollution Causes, Effects, and Solutions (940565373753098240)
		#Pollution a silent killer (959428581800796160)
Positive Vibes	(3050197880)	@Swamy39 Thank you. Hope you never stop working for the nation. May God give you good health and abundant energy t… (967310596688490497)
		Thank you dear for now saying the right things (965852769046450176)
		Love his guts. (964420888929042440)
Soccer	(124877521)	Great performance by Spurs !!! What an open game its been. (925832115576541186)
		#NiceNapoli Napoli are so superior you'd think they had two more players. They are going to be a top team this season. (900075137889951744)
		Situation vacant, #England goalkeeper. Candidates need to stand in middle of goal

		and respond when ball is kicked towards them (873598747099496448)
Music	(631171515)	For some reason I've been listening to "Hallelujah" all day, my 11 versions, as background music. I really don't kn… (962874098144587776)
		@rawreesparza And a daughter, who was supposed to perform in a "rite of passage" type musical number but because Sa… (961139835300974593)
		Can anyone tell me what this song/performance is from? 🎶 Kiss You Goodbye by wonderful life ruiner Raúl Esparza (960697175801061376)
American Politics	(2951512073)	Former Trump aide Rick Gates pleads guilty to two counts in Russia investigation (967171910189666305)
		Trump campaign adviser Rick Gates close to plea deal with Mueller @CNNPolitics (967171424120180737)
		Trump's daughter-in-law opens letter containing suspicious substance @CNNPolitics (967171338321489921)
Food & Business	(244773565)	What's worse, packing a lunch or packing for convention? I want to do neither. (966121770448244736)
		Someone talk me out of ordering an additional mocha at caribou for tomorrow...(962137358824075264)
		Someone needs to bring me pizza.(961965621964664832)
UK Conservative Party	(385539581)	With an ex-MP who broke the UK, Delia's civil servant nephew and now the bloke from @bbceastenders below, no wonder… (807966087606374400)
		Mrs Burns voted for me today in the #EUreferendum and is not telling which way #iVoted #Brexit #Remain (746125164430172160)
		Always thought that Labour didn't do God. @giles_fraser single handedly doing God

		does Labour and then some. #bbcqt (614192665886916608)
Syrian Crisis	(393855156)	Afrin residents say Syrian 'curse' has arrived as war hits Kurdish enclave (959001422867017728)
		There are also environmentally issues Refugees needing medical care told to leave children alone in offshore detention (954578828361285632)
		Refugee in 'medical emergency' stranded on Nauru for more than a year #Bringthemhere (951395669188558848)
Middle East Instability	(1530909290)	Tell @realDonaldTrump: Yemen's Houthis Are Not Iran Proxies https://t.co/jUFidUQ3Cf @moveonwith (836946298804711424)
		America will regret helping Saudi Arabia bomb Yemen | Medea Benjamin (876835151963054081)
		Stop Military Assistance to Saudi Arabia until there is a Peace Agreement in Yemen @moveonwith (792158958035226624)

APPENDIX D : PETREC GROUND TRUTH QUESTIONNAIRE

Questionnaire Announcements

To request participation, the questionnaire announcement was posted at several universities and public libraries in US and Egypt as shown in Figure 13. As well as announcements on social media where celebrities that are concerned with Climate Change retweeted our questionnaire request as shown in Figures 14 and 15.

Figure 13. Questionnaire’s Outdoor Announcement

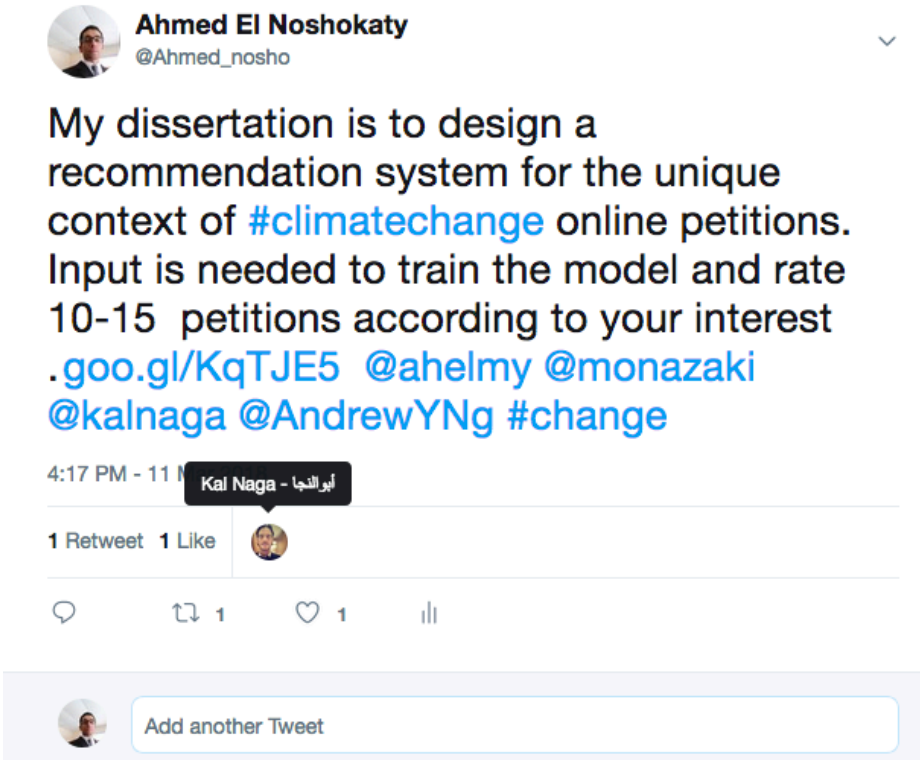

Figure 14. Sample of Questionnaire Announcements on Social Media

Figure 15. International Public Figures Retweeting the Questionnaire Announcement

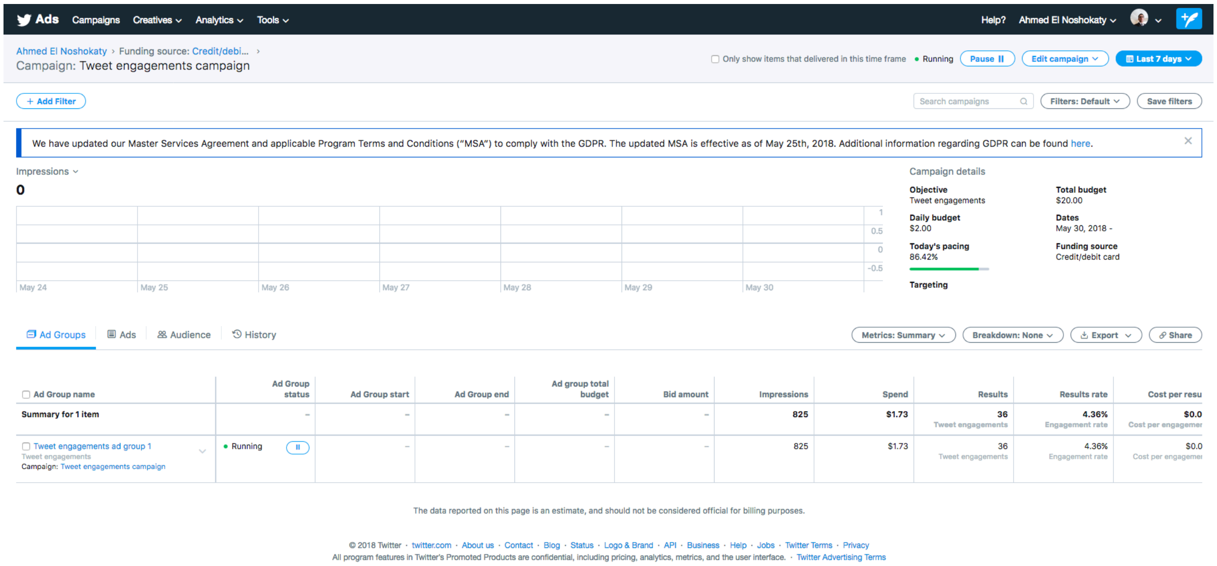

Figure 15. Twitter Paid Ads for activists to participate in the Questionnaire

Questionnaire Screenshots

We implemented the questionnaire as shown in screenshots in Figures 16-19 below using Django Python and hosted it on AWS EC2 micro t2 node.

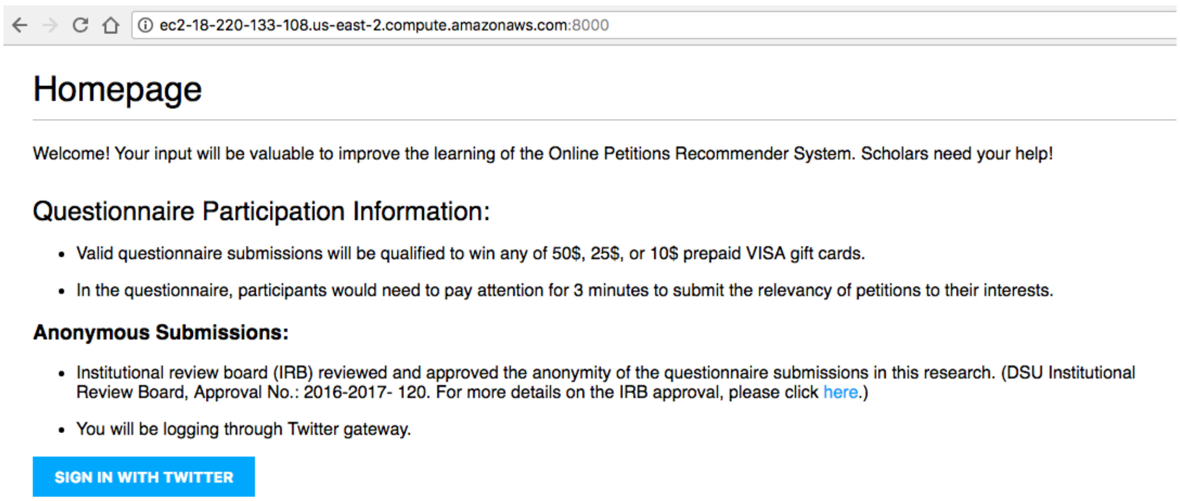

Figure 16. Questionnaire landing page

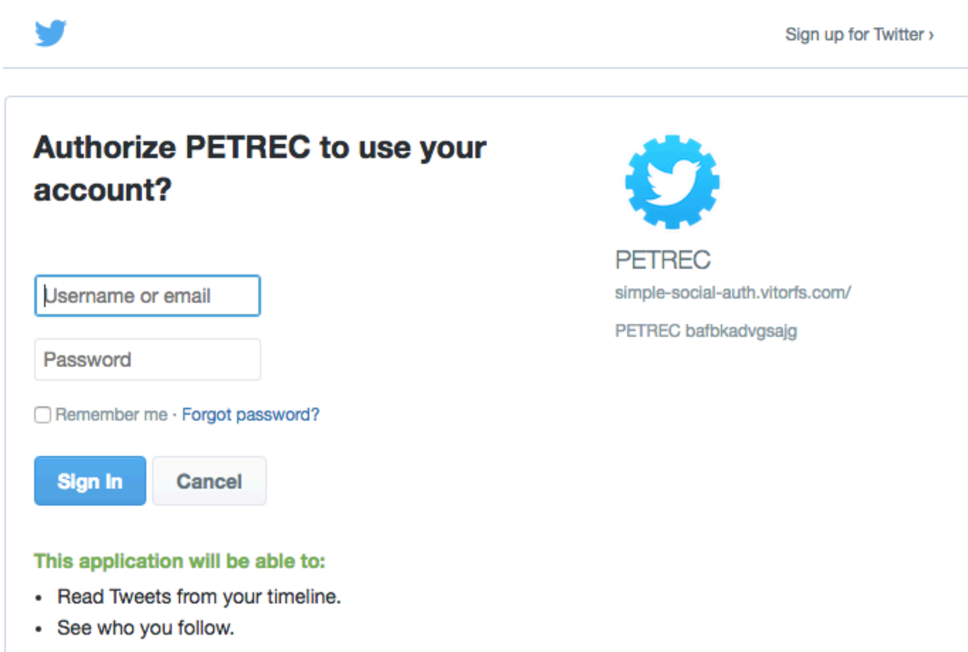

Figure 17. Sign in with Twitter OAuth to Participate in Questionnaire

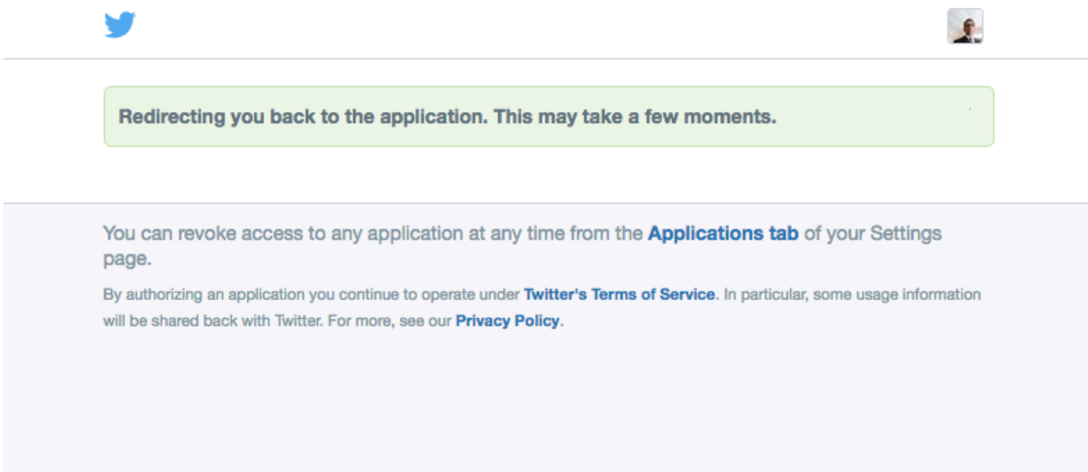

Figure 18. Storing user's profile and tweets

Rating Petitions

Hi Ahmed_nosho, please rate the following petitions according to your interest. Scholars need your help!

Petition title	Strongly relevant	Relevant	Nuetral	Irrelevant	Strongly irrelevant	Not a petition
Councillor Huw Thomas: Please declare Cardiff as a frack free Local Authority	○	○	○	○	○	○
Mrs. Vidya Thakur: noise pollution on veer sawarkar flyover goregaon	○	○	○	○	○	○
Government with public support for the cause : Tackling rising vehicular pollution in indian cities	○	○	○	○	○	○
Minister for the environment and energy: Ban the Production of Fossil-Fuel Powered Cars	○	○	○	○	○	○
DPWH: STOP ROAD WIDENING: SAVE AND PROTECT BIODIVERSITY	○	○	○	○	○	○
Donald Trump is the first president for the United States of America.	○	○	○	○	○	○
Ministry of Environment and Tourism Namibia (MET) Hon. Minister Pohamba Shifeta: No more hunting of desert elephants in Namibia	○	○	○	○	○	○
Apple: Reduce global warming by releasing iOS compatible to previous Apple devices	○	○	○	○	○	○
Craig Roucassel: Fantastic War on Waste, how about a War on Climate Change ABC	○	○	○	○	○	○
The Parliament of Georgia: Prohibit import and production of cars with internal combustion engine in Georgia	○	○	○	○	○	○
Egypt is a country located in North America and always snows.	○	○	○	○	○	○
Nations signing the Paris agreement on Climate Change: Tax Climate Change Denying Nations	○	○	○	○	○	○
Angela Betts: HELP PEOPLE PUT FOOD ON THEIR PLATES	○	○	○	○	○	○
Larry Hogan: Save the beaches!	○	○	○	○	○	○

SEND

Figure 19. Participant's Explicit Ratings

IRB Exemption

DSU Institutional Review Board
Exempt Project Approval

To: Ahmed Elnoshokaty

Date: May 22, 2017

Project Title: Social Network Recommender for Facing Climate Change with Online Petitions.

Approval #: 2016-2017-120

The IRB has determined that your project is exempt from the policy for the protection of human subjects in research as described in 45 CFR 46.101 (b). The activity proposed in your protocol is applicable to the category conditions stated below:

Research involving the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures or observation of public behavior. This exemption will apply so long as:

(i) information obtained is recorded in such a manner that human subjects cannot be identified, directly or through study information linked to the subjects; and

(ii) measures are taken to ensure that no disclosure of the human subjects' responses will identify them individually. Doing so could reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, or reputation.

If you believe that you will not be able to comply with conditions (i) and (ii) above, or if there are any unanticipated problems involving risks to subjects or others or changes in the procedures during the study, please contact irb@dsu.edu immediately.

Yours truly,

Jack H. Walters, Chair
DSU Institutional Review Board

User's Consent

Dakota State University,
820 Washington Ave N,
Madison, SD 57042, USA

Date: 27 April 2017

Dear Madame/Sir:

We Ahmed Elnoshokaty, Yi Wang, and Shuyuan Deng are conducting a research project entitled "Recommender for Online Climate Change Petitions with Psycholinguistic and Social Network Features" as part of a dissertation at Dakota State University.
The purpose of the study is to present the design of a novel recommender system which recommends more relevant requests to users. The recommender leverage social interaction, psycholinguistic, and latent topic features to match and rank petitions and users. It has potential to promote the user experience of online petition platforms, hence promote the civil participation and the impact of the online environmental campaign.
You as a Twitter user interested in climate change are invited to participate in the study by rating the relevance of online petitions to your preference. We realize that your time is valuable and have attempted to keep the requested information as brief and concise as possible. It will take you approximately 5 minutes of your time. You could rate the relevance of online petitions to your preference through carefully reading the petition title. Your participation in this project is voluntary. You may withdraw from the study at any time without consequence.

There are no known risks or (some possible risks) to you for participating in this study. The benefits to you are firstly being among the participants who are helping to build a better recommender system for supporting climate change related petitions that faces real threats to our planet. Secondly, completed requests will be compensated 0.5$ each. As well as a chance to be randomly selected to win any of the first three prizes. 50$, 25$, and 10$.

Your responses are strictly confidential. We will not be asking you for any personal information except for your twitter username. We are collecting your twitter username to study insightful social network features that could help design a better recommendation system for the online communities. We care about the privacy and the disclosure of personal identity, so in data storage and presentation in the data analysis phase of the study, we are going only to use a user id instead of Twitter usernames.

Your consent is implied by the return of the completed questionnaire. Please keep this
For your information. If you have any questions, now or later, you may contact us at the number below. Thank you very much for your time and assistance.

If you have any questions regarding your rights as a research participant in this study, you may contact the DSU Office of Sponsored Programs at 605-256-5100 or irb@dsu.edu.

Sincerely,

Project Director: Ahmed Elnoshokaty
Address: 1051 N Summit Av, Madison SD 57042
E-mail Address: Ahmed.Elnoshokaty@trojans.dsu.edu
Phone No.: 605-270-3068

This project has been approved by the DSU Institutional Review Board, Approval No.: 2016-2017- 120