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Open data visualizations and analytics as tools for policy-making

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ABSTRACT

Government agencies collect large amounts of structured and unstructured data. Although these data can be used to improve services as well as policy processes, it is not always clear how to analyze the data and how to glean insights for policy making, especially when the data includes large volumes of unstructured text data. This article reports opinions found in “We the People” petition data using topic modeling and visual analytics. It provides an assessment of the usability of the visual analytics results for policy making based on interviews with data professionals and policy makers. We found that visual analytics have potentially positive impacts on policy making practices. Experts also articulated potential barriers regarding the adoption of visual analytics tools, and made suggestions. Potential barriers included insufficient resources in government agencies and difficulty integrating analytics with current work practices. The main suggestions involved providing training and interpretation guidelines along with the visual analytics tools. Major contributions of this study include: (1) suggesting viable visualization tools for analyzing textual data for policy making, and (2) suggesting how to lower barriers to adoption by increasing usability.

1. Introduction

Technology developments have been recognized as catalyzers of organizational change and transformation (Bannister & Connolly, 2014; Treacy & O'Sullivan, 2010). The Internet has not been an exception, and it has triggered the development of new business models and service delivery mechanisms both in the public and private sectors (Bergh & Benghiat, 2017; Luna-Reyes & Gil-Garcia, 2014). In the private sector, for example, businesses like Amazon have applied information technologies and data analysis techniques to transform the retail industry (Bergh & Benghiat, 2017). In the public sector, technologies have also promoted change, although research suggests that change has not been transformational, but incremental (Norris & Reddick, 2013). However, recent trends in open data, big data, and data analytics have renewed both the possibility and interest in transforming government activity, particularly in the development of policy (Janssen & Helbig, 2019; Puron-Cid, Gil-Garcia, & Luna-Reyes, 2016).

In particular, some researchers have identified the potential impact of social media data and petitioning systems in the early stages of policy making, contributing to the improvement of problem definition and agenda setting activities (Hagen, Harrison, & Dumas, 2018; Janssen & Helbig, 2019; Luna-Reyes, 2017). More specifically, Janssen and Helbig (In Press) pointed to the need for developing methods to analyze content developed with such platforms as sources of inspiration for policy makers. However, data collected through these platforms poses at least two challenges for its effective use. First, these datasets include large amounts of unstructured textual data that makes manual reading too burdensome to understand the content. Although recent efforts to develop advanced text mining tools have contributed to the first challenge, the use of such tools poses a second challenge given that there is still much to learn in its application and interpretation by policy makers. In this way, it is rare to find empirical examples of textual data being successfully adopted for policy making. However, one of the motivations behind opening data by government is to promote innovations that facilitate the exploitation of these data (Mergel, Kleibrink, & Sörvik, 2018).

Motivated by these challenges, we explore data from the We The People petitioning platform to answer two research questions: (1) what is a potential solution to efficiently extract and effectively present topics expressed in large volumes of textual data?, and (2) to what extent do policy makers consider visual analytics solutions to be usable and useful for policy making?. To answer the first question, we extend previous work on topic modeling (Hagen, 2018) by applying topic modeling for topic extraction and visualization tools such as LDAvis for presenting the extracted topics. Then, to answer the second research question, we test the usability of these possible solutions with policy makers, data

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analysts, and communication specialists to empirically show their perspectives on adopting such visual analytics tools for everyday practices. In this way, this research contributes to the data-driven policy making literature by proposing a framework to facilitate the analysis and visualization of large volumes of text data, and by diagnosing government practitioners' responses and feedback on such visual analytics tools for policy making.

The structure of the paper is as follows: The second section presents background information about “We the People” data. The third section discusses theoretical foundation of value creation through open data and introduces topic modeling and visual analytics research conducted in open data context. The fourth section describes the data and methods, including a potential solution to distill and present representative themes expressed in large volumes of text data. The fifth section presents our key findings from the usability evaluation. The sixth section discusses the main findings in terms of barriers and limitations, and the final section includes conclusion and future research.

2. Background: We the people open data

The US e-petitioning platform “We the People” (WtP) was launched in 2011 as the flagship initiative of the Obama administration to increase public participation in government (The White House, 2015). The data created through e-petitioning includes petition title, petition texts, signatures and their accumulation, some characteristics of petitioners and signers, issue categories and metadata (The White House, 2017). According to the platform rules, petitions that accumulate more than 100,000 signatures in less than 30 days get an official update from the White House. Although not all petitions reach this threshold, data from past petitions are made available to the public for free use, re-use, and distribution as Open Data (Ubaldi, 2013). Datasets are updated about every 6 months by including new data. Following general principles of open data as a source of innovation, the WtP platform provides an API to facilitate data access and manipulation (see https://petitions.whitehouse.gov/developers/get-code). Moreover, the platform provides some analytical tools developed by civic programmers (https://obamawhitehouse.archives.gov/blog/2014/06/03/hackathon-here-white-house). It has been suggested in previous research that open petitioning data are potential sources of policy topics of public interest (Hagen et al., 2018). In this way, open petitioning data becomes the focal point of interest in this research.

WtP open data is unique in three aspects. First, the dataset includes direct expressions of citizen opinion to governments, which is rarely available in traditional information sources such as major news outlets, survey results, or administrative data. Therefore, the petition data can be used to inform public opinion and sentiment regarding policy matters to policy makers. Second, the WtP dataset is a good example of a technically advanced open data set; it is a quality dataset arranged with defined metadata, arranged in a machine-readable format, and is made available through an open API. Third, WtP data is a by-product of a petitioning platform, and governments are flooded with similar types of datasets as the use of social media platforms increases.

The major challenges in using WtP data for creating value for the policy-making process is the volume of data and the unstructured nature of petitions. Use of unstructured data such as abundant text data has been recognized as one of the biggest challenges of big data analytics (Siegel, 2016). While open government and open data initiatives create and share unprecedented amount of text data including citizen expressions, the process of going through them are too time consuming and complicated to be practical, especially if policy makers need to go through large volumes of text (Walters, Aydelotte, & Miller, 2000). These types of big textual data are growing exponentially as the number of government-led platforms and adoption of commercial social media increases. Topic modeling and the recent development of visualization tools may help to reduce cost and time related to the analysis of large volumes of text data.

3. Literature review

3.1. Analytics to create value through open data

Governments around the world have exerted efforts to “create and institutionalize a culture of Open Government” (Nam, 2012, p. 348) by embracing the ideas of transparency, civic engagement in governance, and policy making (Aitamurto, 2012; The White House, 2011). Opening data not only brings changes in government's culture towards “openness, transparency and accountability,” but can also increase public engagement by cultivating a culture of sharing and collaborating through open data (Ubaldi, 2013). These cultural changes and active citizen engagement can create economic innovations (Mergel et al., 2018; Zuiderwijk, Helbig, Gil-Garcia, & Janssen, 2014), improved government performance (Ubaldi, 2013), and increased accountability of elected officials (Sivarajah et al., 2016). Unfortunately, actual creation of value through innovative use of open data has proven to be a difficult task. Despite the increasing initiatives of open data platforms, reported use cases and created value have been lacking (Najafabadi & Luna-Reyes, 2017). For example, out of 183,000 datasets published in data.gov (The United States' open data portal), only 78 apps are made available in the platform as of November 2017.

Data and technology barriers are one of the major obstacles in achieving innovation through open data initiatives (Magalhaes & Roseira, 2017; Toots, McBride, Kalvet, & Krimmer, 2017; Zuiderwijk et al., 2014; Zuiderwijk, Janssen, Choenni, Meijer, & Alibaks, 2012). Early on, scholars stressed the importance of open data technologies—in terms of uniformity and integration of information sources as well as the importance of creating metadata (Dawes, Pardo, & Cresswell, 2004). Later, studies recommended that interactivity and usability are crucial elements to make open platforms available for meaningful citizen engagement (Toots et al., 2017). More recently, open data scholars identified certain technical requirements—such as machine-readable formats, use of APIs, tools for data wrangling, and technical competence of users—are lacking in achieving innovation using open data (Magalhaes & Roseira, 2017; Zuiderwijk et al., 2014).

As scholars commonly have recognized, publishing data is not enough to attain innovation using open data (Janssen, Charalabidis, & Zuiderwijk, 2012). The success of open data depends on active external participation to use the published data (Attard, Orlandi, Scerri, & Auer, 2015). However, for non-technical users, the fundamental lack of expertise and knowledge required for the collection, manipulation, analysis, and interpretability of the data hinders meaningful engagement with open data, and it is a critical problem (Graves & Hendler, 2013). An important portion of open data users may be non-technical users who want to analyze trends over time to understand longitudinal changes but cannot perform required tasks due to a lack of expertise. Recent studies have rightly pointed out lacking capabilities of the supply-side open data platforms for supporting non-technical users (Chatfield & Reddick, 2017) as well as lacking best practices for using the data (Bertot, Butler, & Travis, 2014).

3.2. Visualization of topic modeling

For understanding topics and themes expressed in large volumes of text data, topic modeling has been frequently adopted to automatically discover latent themes in a document collection based on the co-occurrence of words (Blei, 2012). The outcome of topic modeling includes topics (a keyword list sorted by the relevance ranking to the topic) and topic proportions in each document. In general, five to thirty highly ranked keywords are presented as a topic.

Topic modeling is an unsupervised machine learning method that extracts topics without relying on prior human knowledge. So, there are two noticeable issues when applying topic modeling results for policy making. The first issue is *doing it right*. It is important to make proper decisions and care in the process of modeling to produce human interpretable topics (Boyd-Graber, Mimno, & Newman, 2014). Hagen (2018) extracted topics using petitioning data, although this study focus is limited to showing "how to train and evaluate" topic modeling and does not show *how topic modeling results can be presented and utilized for policy making and can be implemented for everyday practices*. Our work extends these efforts to produce interpretable topics that are, therefore, amenable to policy making.

The second issue of topic modeling for policy making resides in how to interpret the meaning of topics and relationship among them (Hagen, 2016; Sievert & Shirley, 2014). Given that topics are extracted based solely on the statistical traits of term co-occurrence, there is no theoretical reason to believe they are easily interpretable by a human (Boyd-Graber et al., 2014). However, some digital government studies have adopted topic modeling to identify and *understand* public opinions expressed in text data. Reddick, Chatfield, and Ojo (2017), for example, extracted topics appearing Facebook posts as an effort to create a social media text analytics framework. Hagen, Uzuner, Kotfila, Harrison, and Lamanna (2015) extracted emerging topics from WtP data using a small set of petitions created in the early years of WtP (initiation to mid-2014). Although both examples are steps in the right direction, these studies only displayed topic words with limited interpretations, and it is still hard to make sense out of the topic modeling results for non-technical readers based solely on the presented topic words. In order to improve interpretability of topic modeling results, more recent studies have adopted visual analytics to present topic modeling results. Cassi, Lahatte, Rafols, Sautier, and de Turckheim (2017) explained the relationships between the ways in which the academic literature and social needs as expressed in discussions among members of the European Parliament approach the topic of obesity. Visual analytics tools were effective in presenting the clear misalignment between academic studies and social needs in terms of the obesity issue.

In addition to an improved interpretability, visual analytics tools enable meaningful engagement of non-technical users. Graves and Hendler (2013) proposed the use of visualization methods to provide simple mechanisms for non-technical users to explore open data. Using over 160 public datasets, Keshif, a visualization tool, "let the user define *what* is being visualized and explored, not *how*" (Yalçın, Elmqvist, & Bederson, 2016). Poucke et al. (2016) demonstrated that researchers can build complex and automated processes with multiple mouse clicks instead of programming codes. Using *rapidminer* (rapidminer, 2017), a big data analytics tool, non-coding scientists can prepare data, train and validate models, and embed analytic results. As such, experts of open data stressed the importance of data analysis and visualization tools to achieve innovation using open data (Toots et al., 2017).

Consumers and end users of open data are diverse (e.g., government employees, innovators, citizens, and journalists/researchers/activists) (Gascó-Hernández, Martin, Reggi, Pyo, & Luna-Reyes, 2018). One of the most popular user groups of open data have been technicians who used open data to develop new tools. Developers and data suppliers (most often using open data) get together through hackathons in order to create new services and products using open data. However, we do not know to what extent these products and services have been used by governments to create value, nor do we have information regarding their influence on actual policy making. Perhaps we can achieve innovation from open data when we make visual analytics tools available on open data platforms alongside open data sets. Moreover, innovative use cases, if provided on open data platforms, can stimulate users' creativity. Further, user-perception on usefulness of a new technology also influences the users' intention to actually use the technology.

4. Methods

4.1. Data

We used data collected through the publicly available White House application program interface (API) that contains all petitions related data appeared on the WtP website between September 22, 2011 (the initiation date), and July 12, 2016. This corpus contained 4985 petition documents. We combined each petition title and its corresponding rationale into one document, which forms the basic unit for this analysis. Fig. 1 is an example of a WtP petition. Available datasets include meta data (including signature counts, user tagging information, the petition creation dates, signature dates and initials of signers).

4.2. Tools for assessing and visualizing data[1]

We collected the WtP OGD data from the WtP API and stored them in a MySQL database (an open source Structured Query Language (SQL) database) (Oracle, 2017). We queried relevant data fields (petition creation date, title, petition body, and signature counts) from the SQL data for the analysis.

After selecting petitions written in English, we converted all texts to lower case, normalized white spaces, eliminated punctuations, non-alphanumeric characters, and removed short words of only one or two characters using R *tm* package. We used an English stopwords dictionary included in the "mallet" package to eliminate less informative words such as "a," "the," and "of," which appear in almost every English documents; "amp" is added in the stopwords dictionary to eliminate "amp" which is a processed version of ampersand (&). We used the R *mallet* package to train Latent Dirichlet Allocation (LDA) topic models (Mimno, 2013). Statistical topic modeling such as LDA (Blei, 2012) extracts a coherent theme, which is a probability distribution over a vocabulary assuming that documents are composed of multiple themes. Each theme (or topic) is generally represented by words (we call this topic words) that appear the most frequently in the relevant documents and also is represented by documents that are the most representative of the theme. In deciding number of topics to produce, we followed suggestions made by Hagen (2018)—30 topics were produced using 3344 petitions and 26 topics are good quality topics for a direct human interpretation, and a manual content analysis result by PEW (2016)—25 issue categories are reported after manual analysis of 4799 WtP petitions. Based on the two studies, it is apparent that about 25 policy issue-dimensions can reasonably reflect the WtP corpus. We decided to produce 30 topics expecting that about 25 topics would be "human interpretable" topics because a small portion of the final topics are likely to be low quality for human interpretation (Boyd-Graber et al., 2014; Hagen, 2016). Using random initiation, we have produced ten sets of 30 topics to reassure random initiation does not influence the stability of the topics. We found that most of the topics (26 out of 30) make sense for human interpretation (Appendix I reports the 30 topics, labels, and quality).

We then developed visualizations for these LDA topics using LDAvis, an open source topic modeling visualization tool (Sievert & Shirley, 2014). We also aggregated available information from the dataset (i.e., signature counts and dates of petition creation) as well as Google Trends for topic interpretation. Fig. 2 shows the framework of the visual analytics using topic modeling.

To help the interpretation and further analyses, we labeled each topic based on the LDAvis visualization results. The topic words were sorted in descending order based on the estimated term frequency within the selected topic (red bars in Fig. 3), which informs topic words that are highly relevant to the specific topic. The relevance of a term to topic is given by a weight parameter λ. Topic words displayed in Fig. 3(a) are acquired using $\lambda = 1$. Topic words displayed in Fig. 3(b) are results from using $\lambda = 0.6$, an optimal value suggested in the literature (Sievert & Shirley, 2014). The width of the blue bar indicates the "corpus-wide frequencies of each term," and the width of the red bar represents "the topic-specific frequencies of each term" (Sievert &

[1] The R script and the data we used for the analysis is available: https://github.com/lonihagen/Topic-Modeling

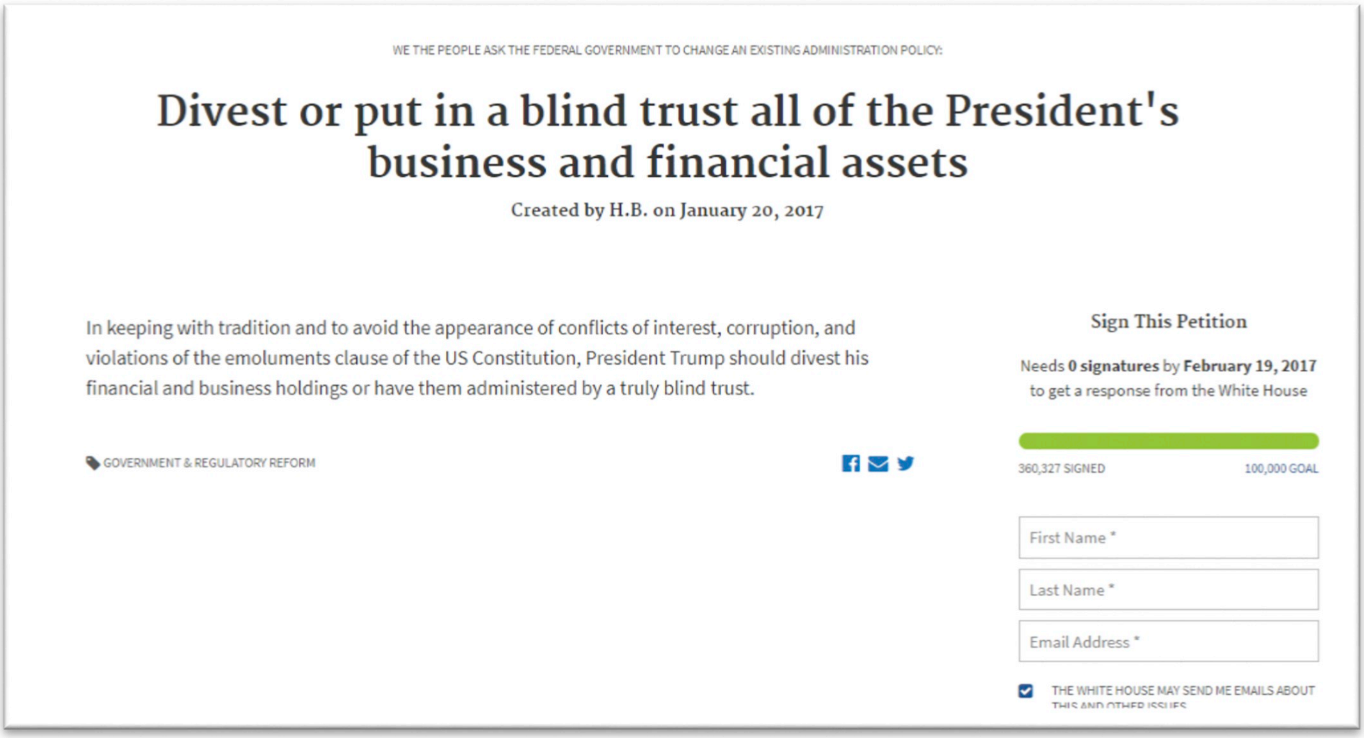

Fig. 1. An example of an WtP petition.
Note: The first two lines (bold and large font) are the title of the petition, and the rest of the text is the rationale of this petition.

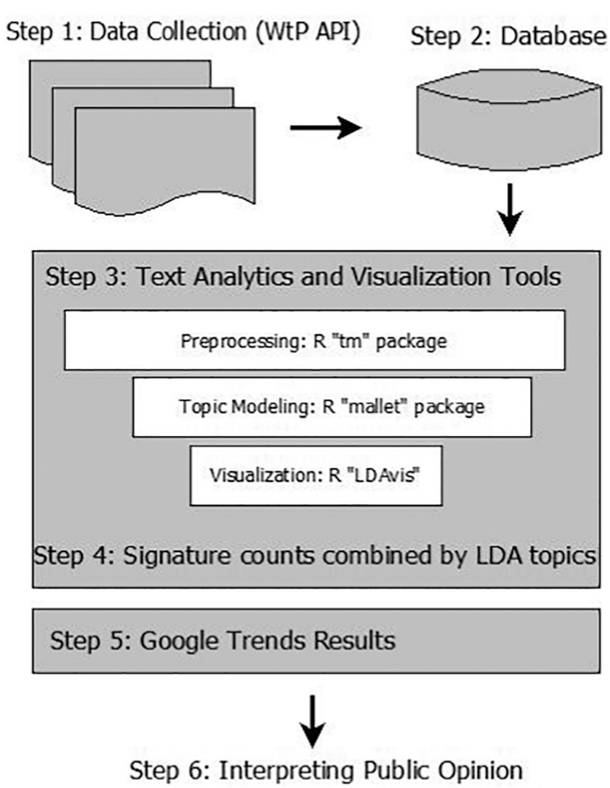

Fig. 2. Framework of the visual analytics of topic modeling.

Shirley, 2014, p. 68). For example, the red bars for "election" and "clinton" are fully red, with no blue bar showing (in Fig. 3(a)), which means that these terms are used exclusively in Topic 5, and thus are highly representative of the Topic 5. When used $\lambda = 0.6$ in Fig. 3(b), these two terms are the first and the second most highly relevant terms representing the Topic 5. After extracting the 30 topics, labels are selected from the top 10 topic words (except Police & BLM) displayed by LDAvis (relevance parameter $\lambda = 0.6$) and by also considering semantic meaningfulness.

The size of circles (on the left side of Fig. 3, which shows the global topic view) "are proportional to the relative prevalence of the topics in the corpus" (Sievert & Shirley, 2014, p. 68). For example, Topic 1 is prevalent in about 20% of the corpus, while Topic 21 is prevalent in about 2% of the corpus according to the circle size displayed in Fig. 3. The biggest topic and the smallest topics tend to be hard to interpret because they often include a mixture of different topics according to a study conducted by Hagen (2016). Also, the distance between topics indicates the semantic distance of topics. For the usability assessment, we created a software package which has interactive features (snapshots of the package is in Figs. 3, 4, and 5).

In addition to the important topic words, the visualization enables the representation of relations between topics, and the prevalence of topics in the entire set of petitions. For example, Fig. 4 shows topic 13, which is a topic about police brutality and the Black Lives Matter (BLM) movement (Rickford, 2016). The left pane of Fig. 4 shows topological positioning of topic 13, which is located close to topics 20 (Http and China—lacking human rights in China), 6 (Prison Sentence topic), 19 (White Genocide) topics. The right-side pane in Fig. 4 shows the most relevant words representing the topic: "police," "officers," "enforcement," "officer," "violence," "black," "shot," "law," "unarmed," "brown," and "killed." In addition, when we click the first topic word "police" for example, we can see other topics that include "police" in their topic words. For example, Fig. 5 shows that topics 6 (Prison Sentence topic) and 7 (Terrorism Syria topic) include the term "police" in topic words. Since the size of topic 6 is bigger in this case, the term "police" plays more important role to form topic 6 (Prison Sentence topic) compared to topic 7 (Terrorism Syria topic).

As such, the LDAvis results show contextual richness of topic modeling results by informing topological position of the topics, and

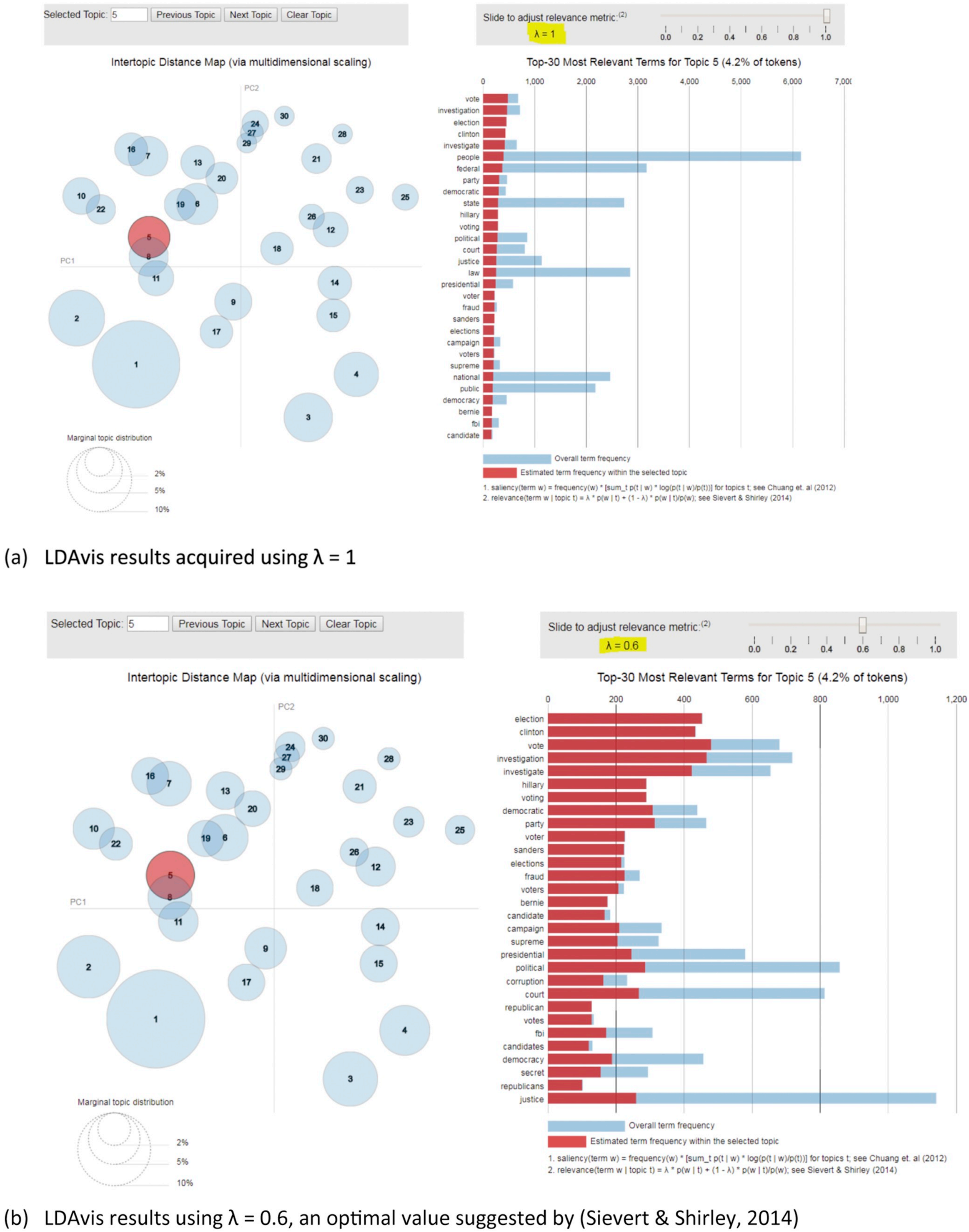

Fig. 3. LDAvis results using λ = 1 (a) and λ = 0.6(b) focused on "clinton" topic.

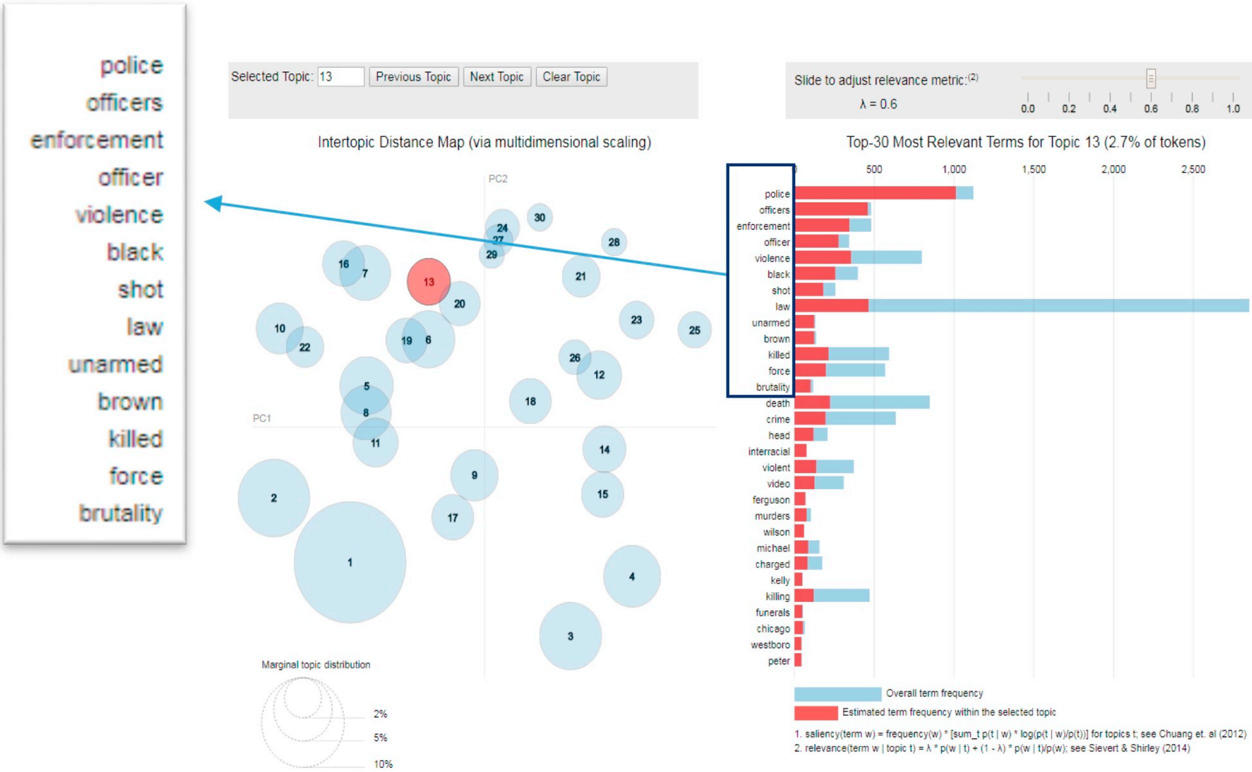

Fig. 4. LDAvis results using λ = 0.6(b) focused on "Police & BLM" topic.

relations of the topic with other closely related topics. Also, the red bar on the right pane shows the level of importance of each term in the topic. These added information provided by LDAvis provides a rich snapshot of public opinions expressed in WtP petitions.

In addition to LDAvis visualizations, we produced two other types of visualizations. As a way of visualizing the popularity of each topic, we decided to show signature counts over time (see Fig. 6). Some topics such as *Election Clinton, Police & BLM,* and *Prison Sentence* topics seem to gain public attention over time. Other topics such as *Food Labeling, Guns Firearms, Marijuana,* and *Secession* topics show overall negative slopes and thus indicate decreasing levels of attention on these topics. Some other topics have different behaviors depending on external events. *Police & BLM* topic, for example, includes topic words such as "police," "law," "officers," "violence," "enforcement," "officer," "black," and "death." The majority of petitions representing the topic are critical of police brutality, especially against African-Americans. Among the top 20 highly relevant petitions to the topic, petitions requesting police officers to wear body cameras were extremely popular, starting on

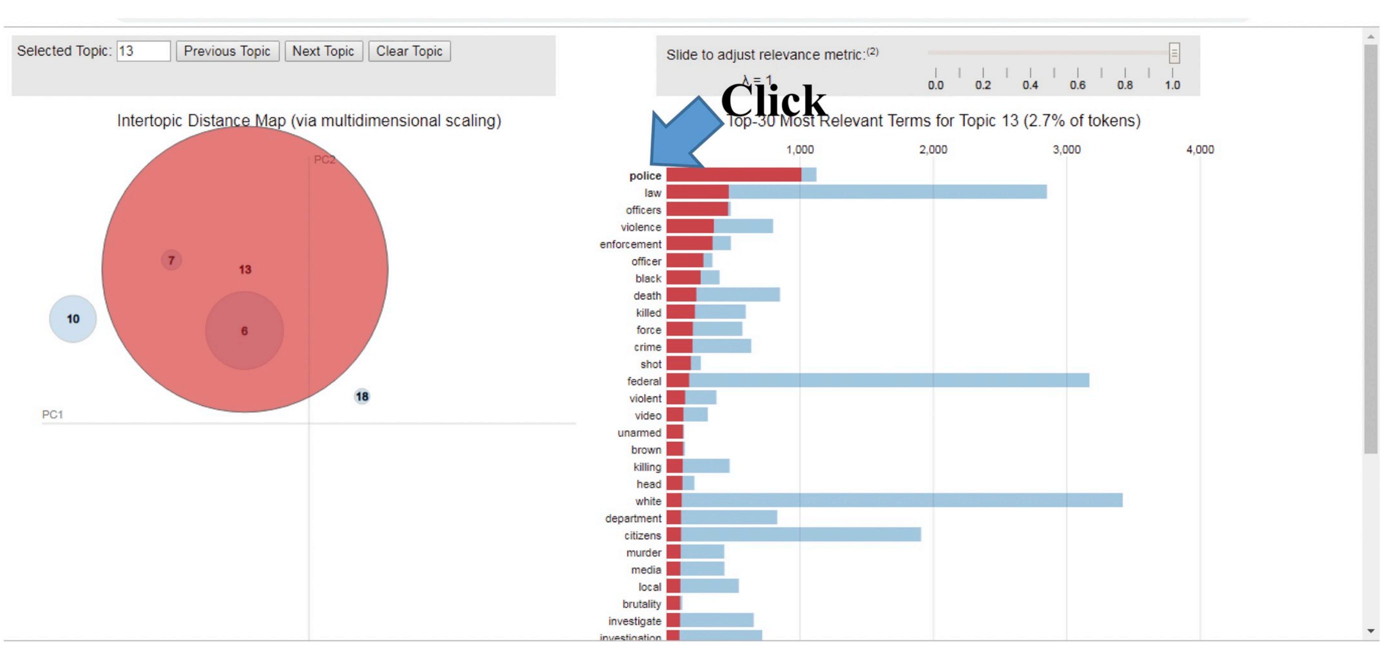

Fig. 5. Topics including "police" in topic words.

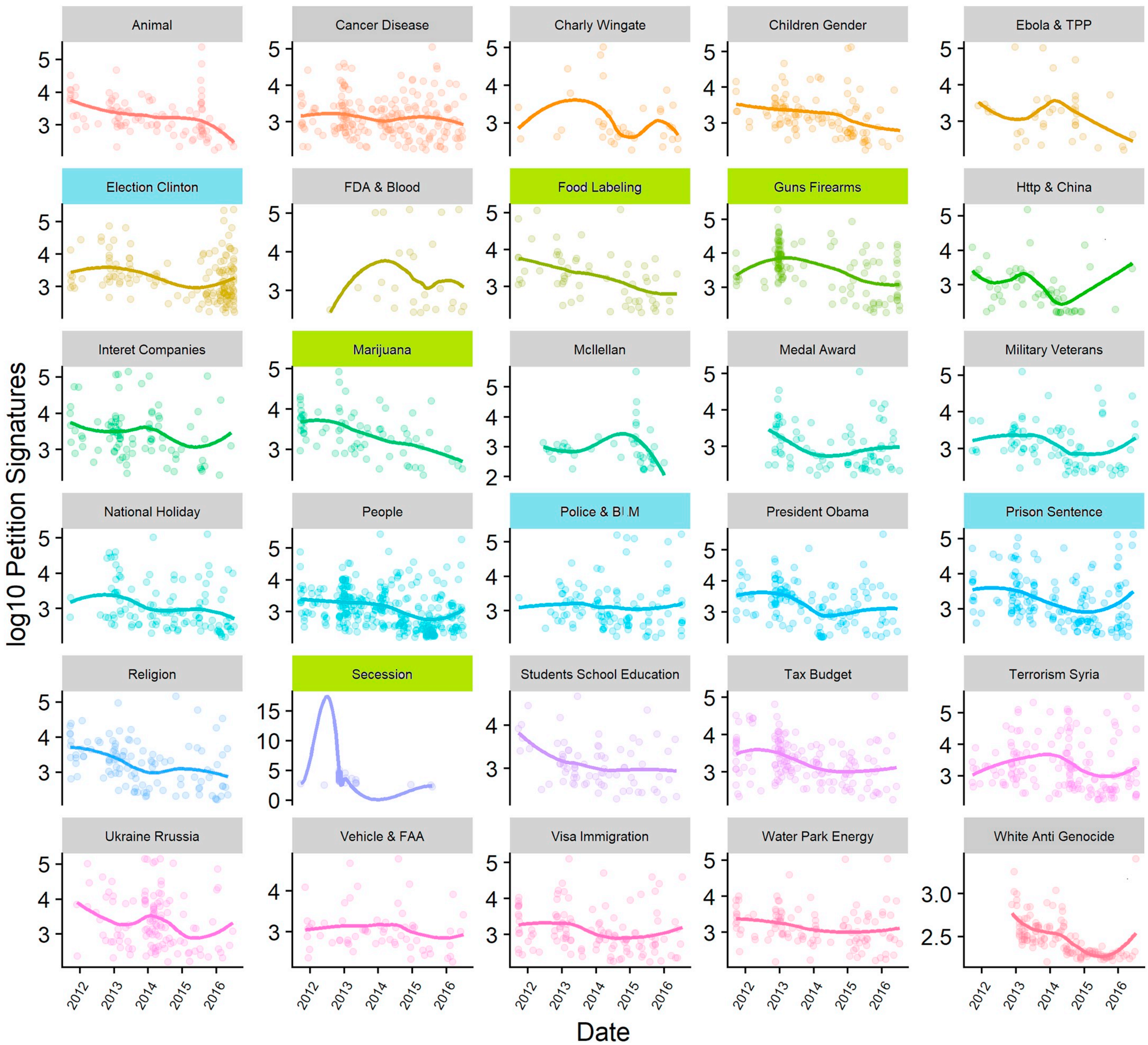

Fig. 6. Changes of number of signatures per topic by time.

August 13, 2014 right after the Michael Brown case, a black male shot by a police officer on August 9, 2014.

Similarly, several petitions under the *Guns Firearms* topic were initiated right after Sandy Hook Elementary School shooting on December 14, 2012, but the level of public attention to the *Guns Firearms* topic (reflected in number of signatures) have been decreasing ever since (see *Guns Firearms* topic in Fig. 6 in the second row).

Other information sources such as Google Trends can be used to compare petition topics and popularities against the keyword search results of Google Trends (see Fig. 7). Google Trends results can be used as a proxy to measure what people are thinking (Stephens-Davidowitz, 2017). We selected relevant topic words from a sample of six topics and searched in Google Trends in the United States (https://trends.google.com/). The Google Trends results are displayed in the left column, in contrast to the WtP topics and signature counts displayed in the right column of Fig. 7.

Some WtP topic popularities seem to correspond to people's thoughts reflected in Google Trends. For example, the attention paid to the topics, *Marijuana, Guns Firearms,* and *Secession*, have decreased since they were peaked in 2012 in both Google Trends and the WtP topics. The *Election Clinton*, and *Police & BLM* topics have gained higher attention in Google Trends as well as in WtP (fourth and fifth rows of Fig. 7). These results indicate that WtP may reflect the public's attention to certain topics, and topic modeling results combined with signature counts can reveal the level of popularity of certain topics. However, due to the platform specific effect, it would be naïve to think that WtP always should correctly reflect the public's attention. For example, the *White Anti Genocide* topic was extremely popular in 2012 and has decreased in popularity on WtP, while making gains in popularity on Google trend (the last row of Fig. 7). During 2012 and 2013 after President Obama's reelection, there were organized activities relating to petition creation and signing on WtP regarding "white genocide" issues (Hagen, 2016), which has gradually decreased since then. Specific groups of people were dedicated to spread out the agenda on WtP. As seen in the Google trend results, the public started paying attention to this topic much later (since mid-2014) than WtP, according to Google

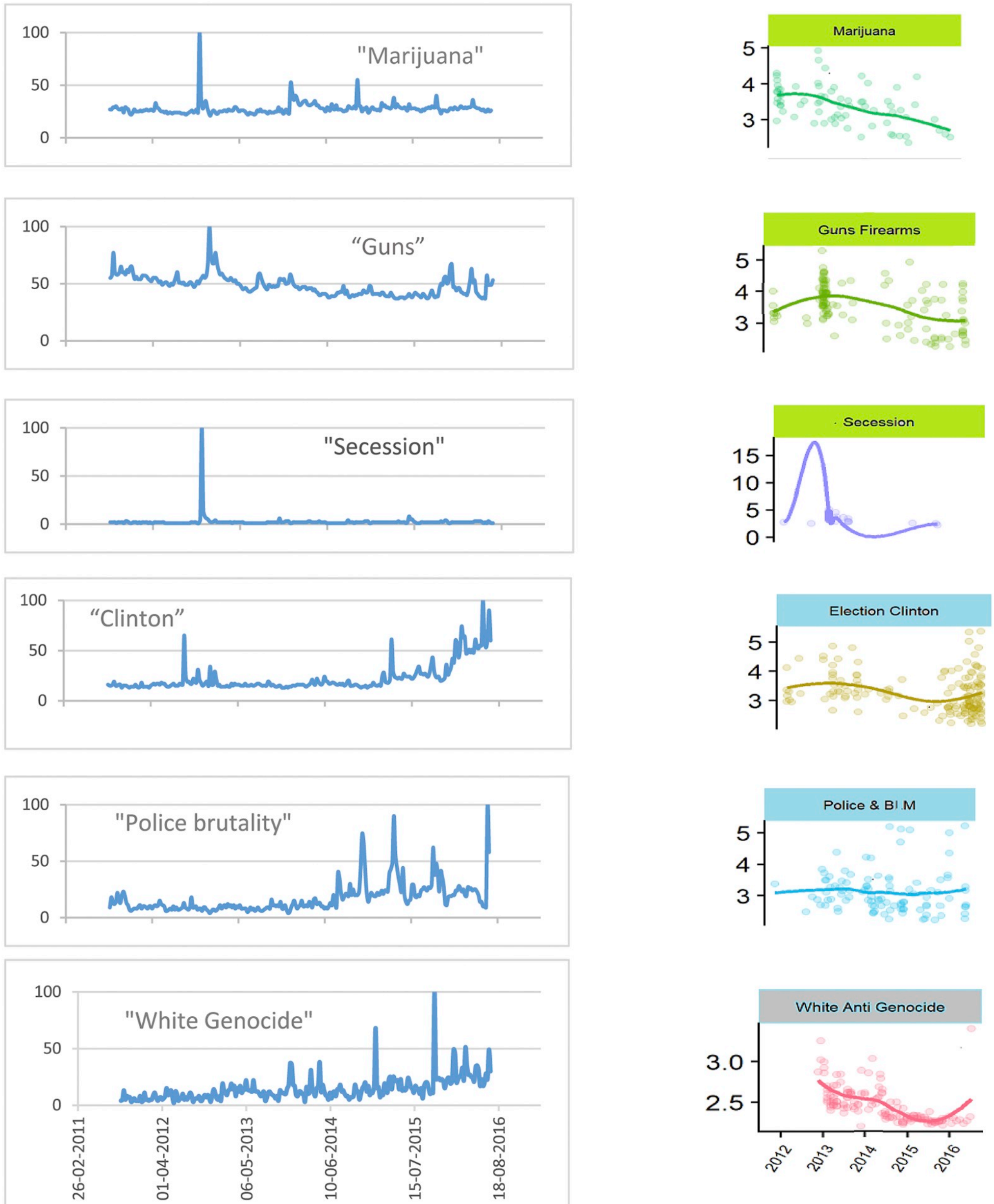

Fig. 7. Google trends and topic popularity.

trends results. These interpretations are merely examples, and were not provided to the experts. If the visual analytics are effective, we expect that policy makers can acquire actionable information and insights that can be used for their policy making.

Note: Y axis of the Google trends results represent search interest relative to the highest point on the chart for the given region (U.S.) and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. Y axis of the topic popularity is log values of signature counts of petitions assigned to the topic.

4.3. Usability assessment

Usability assessments have been used as tools to involve users in the development of technologies to better understand their needs as well as forms in which technology can support their work processes (Howell & Lang, 2017; Rubin, 1994). User-centered approaches to application development involve the use of tools and methods to help software developers and analysts improve the usability of their applications. The International Standard Organization (ISO 9241-11) defines usability as the extent in which a product –in this case a visualization tool—can serve the needs of a specific user group. Usability tests are commonly used to assess information systems. The ISO standard identifies three main indicators for usability, effectiveness, efficiency, and user satisfaction (ISO 9241-11). Effectiveness refers to the extent in which the product features help the user to accomplish the stated goals. Efficiency is related mainly to the extent in which the product helps the user to reach these goals with the least possible effort. Finally, user satisfaction refers to the subjective perception of the user and the interaction with the product. Nielsen (2012) suggests additional indicators such as learnability (how easy is to move around the interface), memorability (how easy is to remember how to use it) and errors (how many errors people make when interacting with the system). The utility of the system –providing the features you need—is closely related to usability. In fact, it is suggested that the usefulness of a system results from considering both usability and utility (Nielsen, 2012).

We adopted a Heuristic Evaluation approach to usability testing

(Nielsen & Molich, 1990), to assess potential ways in which our visualizations may support the process of policy making as well as potential improvements. We were mostly interested in understanding the utility of the visualizations, as well as its learnability and user satisfaction. In this way, we designed a set of questions with these dimensions in mind. We also included questions related to the nature of their expertise and current positions to better understand their responses. Finally, we asked them to give suggestions for improvement and general comments. The interview included 12 questions (see Appendix II). Consistent with the Heuristic Evaluation Approach, we used these questions to explore the expert perspective on the visualizations.

We approached 6 experts who were either policy makers, data analysts, or communications specialists. Although our original plan was to involve only policy and data analysts, one of them suggested the inclusion of a communications specialist. Sample size is consistent with usability testing practices, and experts were selected using a convenience sampling (Rubin, 1994).

Usability tests were conducted with each expert individually during the months of May and June in 2018. Each interview started by asking experts about their background, experience in data analysis, and perception about social media and petitions sites for policy making. Then, we introduced 1) interactive LDAvis interface, snapshots of which are shown in Figs. 3, 4, and 5 2) topics and signature counts by time, shown in Fig. 6, and 3) Google trends and topic popularity, shown in Fig. 7, to the interviewees. It is important to note that some visualizations presented to the interviewees were interactive, allowing them to explore relationships among topics in the computer, and doing some simple analysis with the graphs. Each expert had a chance to interact with the LDAvis interactive visualization tool, as well as the two graphs for 5–10 min. After introducing the visualization tools, we asked experts about their interpretation about the utility, learnability and satisfaction of the visualization tools in their daily job. Each interview had a duration of 45 to 60 min. Five sessions took place in a discussion room on campus reserved by a member of the research team and the other one was conducted at the participant's office.

5. Findings: Usability assessment

In this section of the paper, we include the main findings from the usability assessment of the visualization tools introduced in previous sections of the paper. Data for the assessment comes from the six face-to-face interviews with experts in data analysis, policy making, and communications. Among the experts, three were policy makers from different levels of public sectors of New York State, including institution level, district level, and state level. Only one of them had experience of using data visualizations for policy making. There were two other experts who were data analysts with a background in information science. One of them has significant experience in data analysis, algorithm design, and health informatics, and the other has several years of experience using data visualization for decision making in the private sector. We also interviewed a communication specialist from a public institution, considering her potential in using data visualization for decision making as a criteria for selection. Table 1 presents an overview of main responses from experts in the usability assessment. All experts found at least some topics to be relevant for the policy conversation. Expert 6 suggested that topics in the interface varied in terms of relevance, some of them were more important than others.

We found that experts were able to use the interactive LDAvis interface, and that –in general—their interpretations of the data were consistent among themselves. In general, experts perceived that it was easy to interact with the visualization interface and interpret the results especially with a brief introduction from the interviewer. As it is shown in Table 1, at least two of them found them less intuitive than the other experts and harder to interpret. Some of their reactions included phrases such as “the interface is designed very well, everything is very clear, I feel comfortable interacting with it,” or “your introduction helps a lot… for me to understand the interface and to interpret the visualization.”

They think the tool is potentially helpful for analyzing large amounts of qualitative data through theme generation, and the data visualization provides an easier way to communicate with people possessing different levels of technical proficiency. For example, one mentioned, “couple years ago, we have received a lot of feedback from the residents in our district through the survey we sent out, however, due to a lack of staff and technique, we did not know what to do with it. Now I can see that this tool will be very helpful with analyzing those kind of feedback”. Another one explained, “I think this tool will be very useful to put information into different categories or themes,” and “Data visualization provides summarized results and present it in a very vivid way. It is especially good at presenting the trend and the changes over time.”

Some interviewees without prior experience using visualization, however, conveyed their struggle: “The data visualization catches my eyes but I am not sure whether I understand it correctly. Some of the themes are very self-explanatory, some are not. Maybe because I do not have enough experience, but I think it is very important someone can help people to interpret it in a right way.”

Some experts found visualizations over time (see Fig. 6) particularly interesting, finding different ways of describing them. Some of them described the trends using phrases such as: “It seems that the search interest does not match the signatures over time, I don't know why. Some results are even opposite….” and “Hmmm, it is interesting, the search interest does not necessarily match the signatures overtime, which means that people who are interested in search some topic but may not end up act on it to sign the petition about that topic….”

In addition, most of the experts recognized the utility of LDA tools in analyzing qualitative data in general, and they also pointed out potential areas of improvement and obstacles for them to implement these tools in their own practice. For example:

> Currently, this tool only focuses on topic extraction. However, as a policy maker, when we make decision, we mainly focus on understanding people's opinion, whether they are for or against some issues. We would also be interested to know what specific issues about certain topic that people are interested in. For example, the health care topic, what specific issues people are interested in, do they support or against it?

A couple more shared concerns are associated with a lack of resources and the need for training in the use of this type of tools. For example, one expert stated:

> I am working in the same office with other legislators, and we share one analyst. Most of the time, I will conduct research on my own. For me, I will need some training to be able to use and understand this tool. Also, we have to consider the budget of the department to implement this tool, or even hire some technical person to manage this tool. It is not feasible for my department, at least for now it is not feasible.

Similarly, another expert shared:

> Designing and implementing a visualization tool requires additional funding, staffs with technical skills, data analytical skill, critical thinking, reflective ability, communication skills….Training is necessary, especially for people with no technical background to learn how to use the tool to help with their daily work.

For one, the actual incorporation of the tool into his daily work was unclear: “I rarely use data visualization in my own work, I can see its merit, but I am not sure how to incorporate [it] in my work, maybe in the future, there will be an opportunity for me to do so.”

Experts provided suggestions for the future improvement of the tool. Referring to the LDAvis interface, one of them suggested, “I think in the interface, instead of numbers, adding the labels to each topic will make

Table 1
Overview of main responses from experts.

Topic	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Expert background	Legislative Director (Policy Analyst)	Principal Data Scientist	Former Technology Director at PwC	Trustee for the NYS Higher Education Services analyzing policy impacts	County Legislature Representative	Communications Specialist. User of data in news.
Relevance of the topics	Only the Ukraine Russia, secession topics are relevant.	Some are relevant.	Some are relevant.	Some are relevant.	Many topics are big issues in real life.	Some are more relevant to general public interest than the other.
Interpretability	Visualization of topics over time are more meaningful than a simple topic modeling presentation itself.	Interesting topics. Some topic signatures seem to match the general interest over time, like Clinton & election.	Likes the data visualization of signatures over time, but he would like to see it across longer time frame to get a more information. Some topics are very vague.	Change of the number of the signatures match the change of the public interest in politics in real life.	He felt the results are interesting, but it could have been little confusing without some extra explanations. The search interest do not necessarily align with the number of the signatures.	It catches my eyes, but not very self-explanatory. More interested in the results with big increase or decrease.
Learnability	Very user friendly. If implemented into their domain, only need minor training to use it but need more training to understand the mechanism behind it.	Nice design. Very easy to interact with.	Easy to interact with it but not clear what are the insights that can be drawn from these results.	Easy to understand and interact with the interface.	It will be confusing without explanation.	It is pretty self-explanatory after the introduction. It is easy to interact with the interface.
Utility	Good to analyze feedback from residents automatically. May also be helpful to analyze some controversial issues (only to a certain degree).	It will be useful to track longitudinal change if it can be proved representing general publics.	Data visualization help easily communicate insights with people with different levels of technical backgrounds.	It will be helpful to dealing with large amount of qualitative data. Google trend results may better represent general public interest rather than petition signatures.	Helpful for elected officials and policy makers to get to know the specific people's concern and attitude towards certain issues.	Help interact with data, and easier to extract information from the visualization.
Skills needed to be able to produce or apply these tools	Make sure that the data are from expert sources that can represent the general publics. Need to be trained to understand the mechanics behind the scenes.	Need solid technical skills to put things together. Also need technical training to use the tools.	How to use the tool to effectively communicate with clients and let them understand the information contained in the visualization.	Critical thinking, be reflective, good at math, computer science and technology.	Data analysis skill, programming skills.	Data analytic skill.
Potential of social media to influence policy conversations	Social media and petitions sites definitely play a role, but it cannot represent the general public because of access issues.	Not sure how much it will have impact on legislatures or policy making.	Skeptical because they only represent small groups of people who are either far-left or far-right.	Not sure if social media and petition can represent the general public.	It's good to collect feedback and interact with people. Not sure how it will affect the policy making, may raise awareness.	Petitions won't necessarily lead to any change in policy making. Inappropriate contents of the petitions make people view them as non-high quality reference.

it easier to see which circle represents which topic." Another expert suggested including some measure of people's interest or sentiment analysis, "For me, I would like to see the tool to generate more in-depth analysis on what specific aspects related to each topic that people are interested in, and conduct some sentiment analysis to see what their attitudes towards these aspects are." Finally, another expert suggested including in the visualization information about the validity of the analysis, "Besides the results of the tool, I would be more interested to see how to validate the tool."

Finally, all experts expressed skepticism about how well social media or online petitions reflect the interests of the general public to some extent. For example, one of them mentioned, "In my opinion, online petitions only represent a small group of people who may share a very extreme idea or has strong motivation to express themselves. It is difficult to assess to what extent it represents the more general interest." Another expert also discussed the importance of his local constituents and issues related to online platforms access, "As a policy maker, I care more about the interest and need of the people in my district. In my district, most of the people do not participate in online activities, their opinion may not be shown from these petitions."

6. Discussion

Using topic modeling and visualization tools, we observed that the government experts recognize adopting visual analytics tools as a distant future, rather than current and feasible practices. So, we begin the discussion by deliberating barriers and suggestions for adopting visual analytics tools for policy making based on our interview results.

6.1. Barriers, limitations, and suggestions

All experts thought the tools are potentially helpful for analyzing large amounts of qualitative data by generating themes, and that the data visualization offers an easier way to communicate with people with different technical backgrounds. However, the interview data also identified issues involved with adopting these tools and their corresponding analytics results into their work practices.

Experts stressed that developing "user-centric" tools that support achieving their goals will be crucial. When it comes to "user-centric," previous efforts of providing tools for "users" have mainly assumed users are citizens or developers (Cisco, 2013; Sahuguet, Krauss, Palacios, & Sangokoya, 2014). Efforts to develop tools with government practitioners as "users" have been lacking. Government practitioners are bounded by structure, rules, regulations, and limited resources, which makes tool development and implementation often difficult.

Our tool is specifically designed for government practitioners by adopting no-cost, open source tools in order to address resource constraints issues. Even with the open source tools, the experts identified that a lack of skills are the major barriers for them adopting visual analytics tools. Experts stated that training and some level of guidance on interpreting LDA analytics results will be necessary for them to adopt these results for policy making. In fact, experts stated that the minimal level of introductory training provided to them during the study regarding the LDAvis tool was very helpful in interpreting the LDA results. This is in line with a previous study's findings, which stressed the importance of training to increase confidence of data users (Gascó-Hernández et al., 2018).

Interestingly though, when it comes to implementing the tools in their practices, experts assume that the new tools should work while keeping the current work practices uninterrupted. A policy maker working in the legislative field stated that he relies on document review and door-to-door visits to collect feedback, which information he references for agenda setting activities. And, he stated that new tools such as LDA analytics are not relevant to his work because it does not fit into his current work practice. When it comes to implementing new tools, therefore, it would be helpful to assess current work practices, and to include a feedback loop so that newly adopted tools factor into current practices to bring improvement in work practices, rather than being regarded as a disruption. Ostensibly, this view may vary across levels of government and the perceived access to technology by constituents.

6.2. Higher bars for adopting information acquired by data-driven analysis for policy making

When the visual analytics results were presented (without providing our interpretations), the experts responded with mixed responses in terms of ***interpretability*** of the visual analytics results. While all the experts were able to make sense out of the LDAvis presentations, which we thought was promising, they were split on interpreting the signature trends and the comparison results with Google Trends. This is seemingly because interpretation of these additional visual analysis results requires a technical understanding and contextual knowledge of platform specific effects.

Experts tended to expect that WtP should represent the entire public's opinion to add value to the policy process, and based on this expectation, some of them concluded the analysis was not useful for their decision making because these results cannot be generalizable. Interestingly, when asked about the usual ways of introducing topics into the legislative or policy agenda, experts suggested pathways involving only one or two simple pipelines. Each expert identified only one or two ways that lead to agenda setting in their offices, which are based on letters written by residents, issues people talk about, stakeholder's concern, or reflecting an institution's priorities and subsequent discussions. That means, although experts also depend on a single path to agenda setting, when the analysis results are produced based on one or two platform(s) and computational methods, they raise the bar to conclude the results are not usable for their policy making because the data and analysis results are not generalizable (which we do not claim it can be generalizable).

Considering policy makers' higher expectation for information extracted via a data-driven process, visual analytics should consider including multiple data sources for conducting analyses. This way, diverse pathways can be produced that can be helpful for agenda setting and are not bounded by one specific environment. To clarify, contextual information attached to data are still important for policy making. What we need to be careful about in analytics tool development is understanding the extent we can deliver information by reflecting the contextual basis for that information.

6.3. Implications on tool development

As previous studies have suggested, making good quality open datasets available would be a good start for open data initiatives, but analytics tools provided alongside the datasets help create immediate benefits by extracting useful information from the data. In fact, some U.S. open data sites provide tools for visualization. For example, New York City, San Francisco, and Orlando, among many other major cities, provide interactive visualizations through private vendors. Unfortunately, any analytical tool that also enables textual analysis is not yet available in these platforms.

Our study has implications for tool development so that engineers can develop usable and useful tools for government practitioners using open data. We demonstrated that our topic modeling analytics and visualizations could be useful for policy making when there are large volumes of text data. In order for the LDA results and visualizations to be useful for decision making and agenda setting, government practitioners wanted to see more granular information regarding each topic. Specifically, experts suggested that knowing more granular levels of issues than topic level and public attitude expressed in each topic would be highly valuable for making decisions based on the LDA analytics results. For example, as stated above, one expert suggested that replacing numbers with labels will be more useful for understanding topics at a glance – a move that would make the tool more user-friendly. All in all, the study highlights the importance of user (in this case, government practitioners) engagement in tool development process.

7. Conclusion

In this paper, we extend open data research by suggesting a process to extract and visualize textual big data in order to make sense of it. LDA topic modeling was used to extract emerging topics from petitions, and visualization tools such as LDAvis were used for visual presentations of the topics. Then, we interviewed 6 experts to assess the usability of the prototype visualizations as well as to gather more general impressions of their potential value for policy making.

The interview results of the visual analytics tools show that the experts were positive about the usability of the analytics results and tools regardless of their technical experience. Still, experts had overall high standards for usability and usefulness. While acknowledging the potential of these tools they also desired to maintain their current practices for setting policy agenda. In addition, experts expressed that a lack of resources and training are major barriers for adopting such tools.

Visual analytics tools have evolved so that practitioners, even those who are not big data scientists or engineers, can use these techniques to extract useful and actionable information (Marr, 2018). Our results suggest that achieving tangible benefits from using open data for government policy making through innovative tools and techniques may require overcoming major barriers. Nonetheless, involving policy makers as well as policy analysts in the process of tool building and analytics may provides insights and lessons for the continued adoption of visual analytics for policy making.

This study contributes to the open data literature by producing and testing possible solutions to extract useful information from text data using visual analytics and LDA topic modeling. We expect that these solutions may offer insights to government practitioners as well as scholars of e-government. These possible solutions can be used to convince and motivate other policy makers and to encourage and inspire others to participate in the open data movement. This study also contributes to the policy and data analytics literature by applying topic modeling, an automatic topic extraction method, for policy making. Hagen (2018) demonstrated the process, validity, and evaluation of topic modeling using a WtP data set. Hagen called for more case studies using topic modeling with additional datasets in order to establish the validity of adopting unsupervised learning methods. Compared to Hagen (2018), we produced similar topics using a bigger data set, and captured new topics reflecting important issues during 2015–2016, such as the U.S. Presidential election and the Black Lives Matter movement. Our study also validates the stability of *mallet* topic modeling for extracting interpretable opinions.

Some limitations should be noted. The LDA topic modeling we adopted for the study treats words as discrete entities, which is called bag-of-words representation, which does not capture the full meaning of the text. This is considered as one of the weaknesses of LDA models. More advanced topic modeling methods could potentially increase quality and interpretability of the topics. Studies show that including semantic information in topic modeling can improve topic quality (Batmanghelich, Saeedi, Narasimhan, & Gershman, 2016). Also, putting higher weights on named entities such as person name, location name, and events can improve interpretability and usability of topics (Krasnashchok & Jouili, 2018; Lau, Baldwin, & Newman, 2013). Topic modeling is an unsupervised machine learning methods, which is devised to enhance human decision making. Therefore, rigorous vetting of interpretability and utility are extremely important. So, some recent studies showed that incorporating user feedback in the topic modeling process can improve the interpretability and usefulness of the topics (Feng & Boyd-Graber, 2019; Kumar, Smith-Renner, Findlater, Seppi, & Boyd-Graber, 2019).

In the future, we plan to adopt more advanced topic modeling tools to enhance interpretability of the topics, and also to analyze attitude and sentiment associated with each topic, as the experts suggested. Further, we are also interested in studies on training programs to facilitate open data use for value creation using analytical tools. Future research will benefit from more domain-specific tool development and from including policy makers in the tool development process. In this way, the application will be tailored to the needs of users, and both usability and value will be augmented.

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Appendix I: 30 topics

Table A1
LDA-topics, labels and topic quality.

Topic ID	Label	Topic words
1	People	people time make country american stop government states
2	President Obama**	president obama congress states united petition act administration
3	Tax Budget*	tax federal pay government money dollars budget employees

(*continued on next page*)

Table A1 (*continued*)

Topic ID	Label	Topic words
4	Cancer Disease**	health care cancer disease research medical treatment patients
5	Election Clinton**	vote investigation election clinton investigate people federal party
6	Prison Sentence**	justice years prison case life trial court release
7	Terrorism Syria**	war terrorist people stop government terrorism genocide syria
8	Guns Firearms**	law amendment gun rights states laws ban weapons
9	Children Gender	children child women sex law sexual parents rights
10	Religion*	rights government religious human freedom god religion church
11	National Holiday*	day national american house holiday white awareness world
12	Water Park Energy**	water national energy park land oil areas gas
13	Police & *BLM* **	police law officers violence enforcement officer black death
14	Internet Companies*	internet service information access companies small business government
15	Students School Education**	students school education schools student public children college
16	Ukraine Russia*	ukraine russian russia puerto sanctions japan ukrainian rico
17	Visa Immigration**	visa immigration united states status family green home
18	Military Veterans**	military service members veterans soldiers war army forces
19	White Anti Genocide**	white anti genocide countries whites racist word code
20	Http & China*	http www org chinese people human china world
21	Animal*	animals animal dogs wild hong dog kong horses
22	Secession*	states united government state america people powers nature
23	Vehicle & FAA**	vehicles safety vehicle faa aircraft air cars flight
24	Medal Award*	medal honor freedom award presidential game team american
25	Food Labeling**	food fda products foods health safe labeling ban
26	Marijuana**	marijuana drug cannabis medical schedule hemp states substances
27	Ebola & TPP*	ebola trans media trump trade partnership people protect
28	FDA & Blood	fda blood life india drug sri sikhs drugs
29	Mcllellan	mcclellan act iran veterans toxic nuclear congress health
30	Charly Wingate	charly robbery pardon vietnam max retrial wingate circumcision

Based on the topics and visualization results, human coders put labels following the guideline reported in 3.2 and also judged the quality of each topic. Table A1 shows the label, topic quality (indicated by number of asterisks), and eight topic words for each of the 30 topics extracted from the petition data. Asterisks in the "Label" column in Table A1 indicate topic quality judged by a human annotator; '**' indicates "good quality," '*' indicates "fair quality," and no asterisk indicates "poor quality" topics.

Appendix II: Interview Questions (IRB approved)

Six to eight sampled policy analysts from capital region of New York State will evaluate the practical usefulness of the text mining tools developed by the researchers. We will come to the interviewees' work places and interview them individually. We will prepare three sets of electronic instruments: 1) the interactive software loaded with the visualization results,2) one electronic file containing 30 graphs reflecting topics and petition signatures, and 3) another electronic file containing 12 images showing Google Trends and topics in two columns and six rows. The participants will be instructed about data and data mining tools used to create the visualization and presented images, then will be requested to investigate all of them. Any questions will be answered by the investigator(s). After the participants are finished with the investigation, they will be prompted to answer to the questionnaire. The participants will be given as long as necessary to complete the investigation. The questionnaire includes the following questions:

1. What kind of analysis do you do as everyday practice?
2. How things get into the conversation in regards with legislative or policy agenda?
3. What do you think about using social media and petition sites for possible agenda for legislatures or more in general to establish policy?
4. What is your general perception of the relevance of these topics for current legislative and policy agenda?
5. What is your interpretation of these results?
6. How user friendly are these tools from your point of view and experience?
7. How useful do you think this tool and images would be for your work and practice?
8. What would you do to improve the tool and make it more helpful for your practice?
9. How well do you think that these images and analyses represent the interests of the general public?
10. What do you think about skills needed to be able to produce/apply these tools?
11. Do you feel comfortable about applying similar technologies in your work? What kind of skills would be needed to be able to do this?
12. Is there any other relevant topics you would like to discuss or any other thing you want to mention that was not covered in our questions?

References

Aitamurto, T. (2012). *Crowdsourcing for democracy: A new era in policy-making.* Parliament of Finland.

Attard, J., Orlandi, F., Scerri, S., & Auer, S. (2015). A systematic review of open government data initiatives. *Government Information Quarterly, 32*(4), 399–418. https://doi.org/10.1016/j.giq.2015.07.006.

Bannister, F., & Connolly, R. (2014). ICT, public values and transformative government: A framework and programme for research. *Government Information Quarterly, 31*(1), 119–128. https://doi.org/10.1016/j.giq.2013.06.002.

Batmanghelich, K., Saeedi, A., Narasimhan, K., & Gershman, S. (2016). Nonparametric spherical topic modeling with word Embeddings. *Proceedings of the Conference. Association for Computational Linguistics. Meeting. 2016. Proceedings of the Conference. Association for Computational Linguistics. Meeting* (pp. 537–542). . https://doi.org/10.18653/v1/P16-2087.

Bergh, C., & Benghiat, G. (2017). Analytics at Amazon speed: The new normal. *Business Intelligence Journal, 22*(2), 46–54.

Bertot, J. C., Butler, B. S., & Travis, D. M. (2014). Local big data: The role of libraries in building community data infrastructures. *Proceedings of the 15th annual international conference on digital government research (Dg.o 2014)* (pp. 17–23). . https://doi.org/10.1145/2612733.2612762.

Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM, 55*(4), 77–84.

Boyd-Graber, J., Mimno, D., & Newman, D. (2014). Care and feeding of topic models:

Problems, diagnostics, and improvements. In E. M. Airoldi, D. Blei, E. A. Erosheva, & S. E. Fienberg (Eds.). *Handbook of mixed membership models and their applications* (pp. 225–255). Boca Raton, FL: CRC Press.

Cassi, L., Lahatte, A., Rafols, I., Sautier, P., & de Turckheim, É. (2017). Improving fitness: Mapping research priorities against societal needs on obesity. *Journal of Informetrics, 11*(4), 1095–1113. https://doi.org/10.1016/j.joi.2017.09.010.

Chatfield, A. T., & Reddick, C. G. (2017). A longitudinal cross-sector analysis of open data portal service capability: The case of Australian local governments. *Government Information Quarterly, 34*(2), 231–243. https://doi.org/10.1016/j.giq.2017.02.004.

Cisco. (2013). The internet of everything for cities. Retrieved from https://www.cisco.com/c/dam/en_us/solutions/industries/docs/gov/everything-for-cities. pdf.

Dawes, S. S., Pardo, T. A., & Cresswell, A. M. (2004). Designing electronic government information access programs: A holistic approach. *Government Information Quarterly, 21*(1), 3–23.

Feng, S., & Boyd-Graber, J. (2019). What can AI do for me?: Evaluating machine learning interpretations in cooperative play. *Proceedings of the 24th international conference on intelligent user interfaces - IUI '19* (pp. 229–239). . https://doi.org/10.1145/3301275.3302265.

Gascó-Hernández, M., Martin, E. G., Reggi, L., Pyo, S., & Luna-Reyes, L. F. (2018). Promoting the use of open government data: Cases of training and engagement. *Government Information Quarterly, 35*(2), 233–242. https://doi.org/10.1016/j.giq.2018.01.003.

Graves, A., & Hendler, J. (2013). Visualization tools for open government data. *Proceedings of the 14th annual international conference on digital government research* (pp. 136–145). .

Hagen, L. (2016). *Topic modeling for e-petition analysis: Interpreting petitioners' policy priorities* (Ph.D.)United States – New York: State University of New York at Albany.

Hagen, L. (2018). Content analysis of e-petitions with topic modeling: How to train and evaluate LDA models? *Information Processing and Management, 54*(6), 1292–1307. https://doi.org/10.1016/j.ipm.2018.05.006.

Hagen, L., Harrison, T. M., & Dumas, C. L. (2018). Data analytics for policy informatics: The case of E-petitioning. *Policy analytics, modelling, and informatics* (pp. 205–224). Cham: Springer. https://doi.org/10.1007/978-3-319-61762-6_9.

Hagen, L., Uzuner, O., Kotfila, C., Harrison, T. M., & Lamanna, D. (2015). Understanding Citizens' direct policy suggestions to the Federal Government: A natural language processing and topic modeling approach. *2015 48th Hawaii International Conference on System Sciences (HICSS)* (pp. 2134–2143). . https://doi.org/10.1109/HICSS.2015.257.

Howell, E., & Lang, J. (2017). *Researching UX: User research.* VIC Australia: Sitepoint Pty Ltd.

Janssen, M., Charalabidis, Y., & Zuiderwijk, A. (2012). Benefits, adoption barriers and myths of open data and open government. *Information Systems Management, 29*(4), 258–268. https://doi.org/10.1080/10580530.2012.716740.

Janssen, M., & Helbig, N. (2019). In Press*Innovating and changing the policy-cycle: Policy-makers be prepared!*. Government Information Quarterlyhttps://doi.org/10.1016/j.giq.2015.11.009.

Krasnashchok, K., & Jouili, S. (2018). Improving topic quality by promoting named entities in topic modeling. *Proceedings of the 56th annual meeting of the Association for Computational Linguistics*. *Vol. 2*. *Proceedings of the 56th annual meeting of the Association for Computational Linguistics* (pp. 247–253). . Short Papers. Retrieved from https://www.aclweb.org/anthology/P18-2040.

Kumar, V., Smith-Renner, A., Findlater, L., Seppi, K., & Boyd-Graber, J. (2019). Why Didn't you listen to me? *Comparing user control of human-in-the-loop topic models*. ArXiv:1905.09864 [Cs]. Retrieved from http://arxiv.org/abs/1905.09864.

Lau, J. H., Baldwin, T., & Newman, D. (2013). On collocations and topic models. *ACM Transactions on Speech and Language Processing, 10*(3), 10:1–10:14. https://doi.org/10.1145/2483969.2483972.

Luna-Reyes, L. F. (2017). Opportunities and challenges for digital governance in a world of digital participation. *Information Polity, 22*(2–3), 197–205. https://doi.org/10.3233/IP-170408.

Luna-Reyes, L. F., & Gil-Garcia, J. R. (2014). Digital government transformation and internet portals: The co-evolution of technology, organizations, and institutions. *Government Information Quarterly, 31*(4), 545–555. https://doi.org/10.1016/j.giq.2014.08.001.

Magalhaes, G., & Roseira, C. (2017). Open government data and the private sector: An empirical view on business models and value creation. *Government Information Quarterly*. https://doi.org/10.1016/j.giq.2017.08.004.

Marr, B. (2018, June 20). Comparing data visualization software: Here are the 7 best tools for 2018. *Forbes*. Retrieved from https://www.forbes.com/sites/bernardmarr/2018/06/20/comparing-data-visualization-software-here-are-the-7-best-tools-for-2018/.

Mergel, I., Kleibrink, A., & Sörvik, J. (2018). Open data outcomes: U.S. cities between product and process innovation. *Government Information Quarterly, 35*(4), 622–632. https://doi.org/10.1016/j.giq.2018.09.004.

Mimno, D. (2013). Package "mallet" Retrieved October 9, 2015, from https://cran.r-project.org/web/packages/mallet/mallet.pdf.

Najafabadi, M. M., & Luna-Reyes, L. F. (2017). Open government data ecosystems: A closed-loop perspective. *Proceedings of the 50th Hawaii international conference on system science (HICSS-50)* (pp. 2711–2720). .

Nam, T. (2012). Citizens' attitudes toward Open Government and Government 2.0. *International Review of Administrative Sciences, 78*(2), 346–368. https://doi.org/10.1177/0020852312438783.

Nielsen, J. (2012). Usability 101: Introduction to usability. Nielsen Norman Group. Retrieved from http://www. nngroup.com/articles/usability-101-introduction-to-usability/on 2018-11-20.

Nielsen, J., & Molich, R. (1990). Heuristic evaluation of user interfaces. *CHI '90 proceedings of the SIGCHI conference on human factors in computing systems*https://doi.org/10.1145/97243.97281.

Norris, D. F., & Reddick, C. G. (2013). Local E-Government in the United States: Transformation or incremental change? *Public Administration Review, 73*(1), 165–175. https://doi.org/10.1111/j.1540-6210.2012.02647.x.

Oracle (2017). MySQL. Retrieved November 13, 2017, from https://www.mysql.com/.

Poucke, S. V., Zhang, Z., Schmitz, M., Vukicevic, M., Laenen, M. V., Celi, L. A., & Deyne, C. D. (2016). Scalable predictive analysis in critically ill patients using a visual open data analysis platform. *PLoS One, 11*(1), e0145791. https://doi.org/10.1371/journal.pone.0145791.

Puron-Cid, G., Gil-Garcia, J. R., & Luna-Reyes, L. F. (2016). Opportunities and challenges of policy informatics: Tackling complex problems through the combination of open data, technology and analytics. *International Journal of Public Administration in the Digital Age, 3*(2), 66–85.

rapidminer (2017). Lightning fast unified data science platform. Retrieved November 16, 2017, from https://rapidminer.com/products/.

Reddick, C. G., Chatfield, A. T., & Ojo, A. (2017). A social media text analytics framework for double-loop learning for citizen-centric public services: A case study of a local government Facebook use. *Government Information Quarterly, 34*(1), 110–125. https://doi.org/10.1016/j.giq.2016.11.001.

Rickford, R. (2016). Black lives matter: Toward a modern practice of mass struggle. *New Labor Forum, 25*(1), 34–42. https://doi.org/10.1177/1095796015620171.

Rubin, J. (1994). *Handbook of usability testing: How to plan, design, and conduct effective tests* (1st ed.). Wiley.

Sahuguet, A., Krauss, J., Palacios, L., & Sangokoya, D. (2014). Open civic data: Of the people, for the people, by the people. *IEEE Data Engineering Bulletin, 37*(4), 15–26.

Siegel, E. (2016). *Predictive analytics: The power to predict who will click, buy, lie, or die* (2nd ed.). Wiley.

Sievert, C., & Shirley, K. E. (2014). LDAvis: A method for visualizing and interpreting topics. *Proceedings of the workshop on interactive language learning, visualization, and interfaces* (pp. 63–70). .

Sivarajah, U., Weerakkody, V., Waller, P., Lee, H., Irani, Z., Choi, Y., & Glikman, Y. (2016). The role of e-participation and open data in evidence-based policy decision making in local government. *Journal of Organizational Computing and Electronic Commerce, 26*(1–2), 64–79.

Stephens-Davidowitz, S. (2017). *Everybody lies: Big data, new data, and what the internet can tell us about who we really are.* New York, NY: Dey Street Books.

The White House. (2011). September 20Opening remarks by President Obama on open government partnership. Retrieved May 16, 2015, from https://www.whitehouse.gov/node/78625

The White House (2015). The open government partnership: Third open government National Action Plan for the United States of America. Retrieved from http://www.whitehouse.gov/blog/2013/12/06/united-states-releases-its-second-open-government-national-action-plan.

The White House (2017). *For developers: We the people API.* (Retrieved November 3, 2017, from /developers).

Toots, M., McBride, K., Kalvet, T., & Krimmer, R. (2017). Open data as enabler of public service co-creation: Exploring the drivers and barriers. *2017 Conference for E-Democracy and Open Government (CeDEM)* (pp. 102–112). . https://doi.org/10.1109/CeDEM.2017.12.

Treacy, M., & O'Sullivan, J. (2010). e-Government and organisational transformation – A perspective from the property registration Authority of Ireland. *Presented at the 10th European conference on e-government (ECEG 2010)* (pp. 400–408). .

Ubaldi, B. (2013). *Open government data: Towards empirical analysis of open government data initiatives.* Paris: OECD Working Papers on Public Governance (22) 0_1,1,4-60.

Walters, L. C., Aydelotte, J., & Miller, J. (2000). Putting more public in policy analysis. *Public Administration Review, 60*(4), 349–359. https://doi.org/10.1111/0033-3352.00097.

Yalçın, M. A., Elmqvist, N., & Bederson, B. B. (2016). Keshif: Out-of-the-box visual and interactive data exploration environment - semantic scholar. In: *Proceedings of the IEEE VIS 2016 workshop on visualization in practice: Open source visualization and visual analytics software* (Retrieved from /paper/Keshif-Out-of-the-Box-Visual-and-Interactive-Data-Yalçın-Elmqvist/4364b7bb4f731bef0c9f22067691fefa42d85c93).

Zuiderwijk, A., Helbig, N., Gil-Garcia, R. J., & Janssen, M. (2014). Special issue on innovation through open data - a review of the state-of-the-art and an emerging research agenda: Guest Editors' introduction. *Journal of Theoretical & Applied Electronic Commerce Research, 9*(2), I–XIII. https://doi.org/10.4067/S0718-18762014000200001.

Zuiderwijk, A., Janssen, M., Choenni, S., Meijer, R., & Alibaks, R. S. (2012). Socio-technical impediments of open data. *Electronic Journal of Electronic Government, 10*(2), 156–172.