Understanding and Visualizing Flu Vaccination Behaviors in Social Media

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Abstract

Traditional research methods of influenza vaccination has several limitations: high cost, limited coverage of underrepresented groups, and low sensitivity to emerging public health issues. Social media, such as Twitter, provides an alternative means of understanding a populations vaccination-related opinions and behaviors. In this work, we built a prototype visualization system to monitor and analyze people's vaccination behaviors. Additionally, to interpret how machine learning processes human language, we built a visualization of the processed tweets from machine learning perspective.

Index Terms: K.6.1 [Management of Computing and Information Systems]: Project and People Management—Life Cycle; K.7.m [The Computing Profession]: Miscellaneous—Ethics

1 Introduction

The U.S. Center for Disease Control and Prevention (CDC) conducts interviews and surveys annually to measure the coverage of flu vaccination services using this data for future decision making of health services. The CDC hopes to improve the vaccination coverage from 40% to 70% in the next few years [2]. Though periodic interviews provide concrete results, they are expensive and inefficient, and might lose coverage of underrepresented groups, preventing them making accurate decisions. For example, the results of survey and interview are generated a year before, which cause the high-latency issue of the analysis [2]. In contrast, social media data, specifically from Twitter provides an alternative to surveys or interviews. This user-generated content provides a unique opportunity to observe flu vaccination related behaviors in a more naturalistic setting. Additionally, the data in Twitter is free and easily obtained. By additionally breaking down tweets by topic, this method allows for qualitative analysis of sentiment toward vaccination.

2 Related Works

A number of works have been done in utilizing data from social media, like Twitter, to mining and understand public health issues [1,11]. Ji et al. employs Twitter data, combined with sentiment classification to obtain some analysis about public opinion about different diseases' outbreaks. Similar to our work, this work addresses the benefits of low cost opinion aggregation and analysis for health sentiment [8]. Work such as Wu et al. 2014 deals with visualizing opinion based on classification of twitter data [14]. This work classifies tweets into topics and analyzes how sentiment toward those topics changes over time. Chaney et al. addresses the issue of visualizing complex topics generated by machine learning classification, giving a high level overview of a topic based on its constituent descriptors [3].

However, less work has been done in using social media to visualize and understand people's opinions of vaccination services, some researchers used Twitter data to analyze sentiment toward vaccination [4, 6, 12, 13]. But our research focus is on visualization of the opinions towards influenza vaccination services. In this paper, we extend our work based on previous system [7] in three aspects: we build our analyzing system based on Deep Learning; a prototype of visualization system is developed to mining insights of the opinions; a demo of model analysis is developed to understand how machine learning understand human languages.

3 Design and Implementation

We designed a visualization dashboard to represent pre-processed data–tweets between 2013 and 2016 matching one the words ”flu”, ”influenza”, ”vaccination” or ”vaccine”. There are two main parts: visualization of classified results; visualization of classifier.

3.1 Visualization of Classified Results

One view shows a visualization of the results of the classification. In this view, two side-by-side graphics represent six different views of online vaccination behaviors, which are shown in Figure 1.

Intention vs. Other Mention Trends. We used our well-trained Convolutional Neural Network classifier to classify 1 million tweets into two categories: Intention/Receipt, Other Mentions. Compared to CDC data, which can only show monthly trends, our visualization can show both monthly and weekly trends. The visualization allows user to select and deselect each category. This trends might be also meaningful that its peaks might indicate the break of flu seasons in October each year.

Intention rates in each state of U.S.. We inferred the US state for tweets using the Carmen geolocation system [5]. We combined intentions and geolocation to visualize people's intentions rate in each state of U.S. It might be useful for the government make decision of which states should improve their services of flu vaccinations.

Monthly Language Usage in Intention and Other Mention. We generated the monthly top ranked words by computing TF-IDF score for each word. We picked top 10 words for each period. To visualize the model of deciding whether a tweet indicates intent to receive a vaccination, we showed the text of a tweet, adjusting the colors and sizes of the words to show whether the word skews the tweet in the positive or negative direction. The tweet is then summarized by a percentage to indicate confidence that the tweet shows positive or negative sentiment toward vaccination. So, it might be helpful for public health experts to interpret how opinion changes overtime. For example, the highest score word in May, 2016 is “biases”, which might show the people encounter biases during their health services.

Gender information in Intention and Other Mention. We inferred the gender of each Twitter user in the dataset using the Demographer tool[1] [9]. We summarize how female and male hold different opinions toward flu vaccination services. From our visualization, it seems there are more females took or plan to take the flu vaccination than males do.

Monthly topic trends & **Top words in each topic**. Though a classified tweet could be as simple as ”receiving a vaccination” or ”how much the shot hurts”, the user's generated contents are complex, and to describe them, we used Mallet [10] to build Topic Model on our dataset. We set 10 topics and 1500 iterations and other parameters as default values during experiments. We accumulated and averaged topic distributions in each period. We picked the top

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[1]https://bitbucket.org/mdredze/demographer

20 topic words in each topic, and visualized them as word cloud. This might be helpful if linguistic experts could identify the theme for each topic, and we can track the trends of the corresponding topic overtime. For example, most of the words in Figure 1f are negative words, and thus, we may view this topic as negative sentiments towards vaccination services. We can track the negative sentiment trends by the corresponding line chart.

3.2 Interpretable Machine Learning

To interpret how the machine learning algorithms understand human languages, we visualized the weights of words, shown in Figure 2. We assign negative weights as "green" color and positive weights as "red" color. The font size is readjusted to larger if the word has a weight score. We visualized the prediction probabilities for each category and the labels of tweets as cute emoji. If the tweet is intention/receipt, its emoji will be a happy face. If the tweet is other mentions, its emoji will be a angry face. If the prediction contradicts with the true label, its emoji will be a question face, which might be useful for error analysis.

4 Conclusion

Social media sentiment analysis is an alternative to delivering expensive surveys to the public. Our visualization provides some insight into peoples' opinions about flu vaccination by depicting topics visually, showing how different groupings affect opinion, and visualizing breakdown of individual tweets. For future work, we hope to iterate on initial feedback including a sensible implementation of language usage bubbles and usability fixes. We hope to test our visualization tool for discovery among domain experts and average users.

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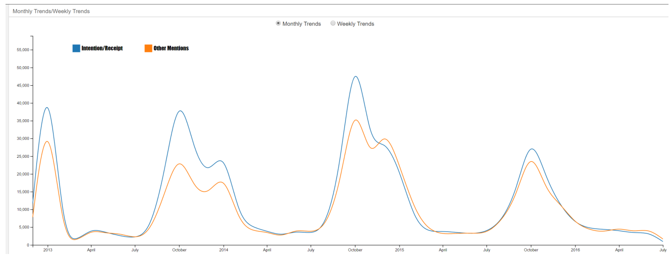
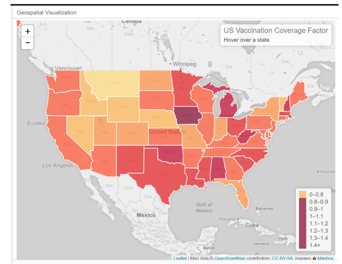
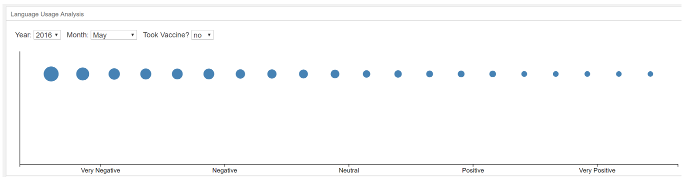


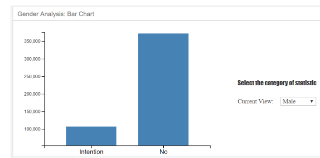
(a) Intention vs. Other Mention Trends



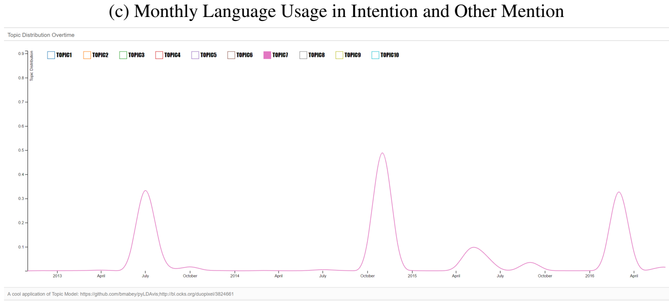
(b) Intention rates in each state of U.S.



(c) Monthly Language Usage in Intention and Other Mention



(d) Gender information in Intention and Other Mention



(e) Monthly topic trends

(f) Top words in each topic

Figure 1: Dashboard of classified results. Six different views of online vaccination behaviors.

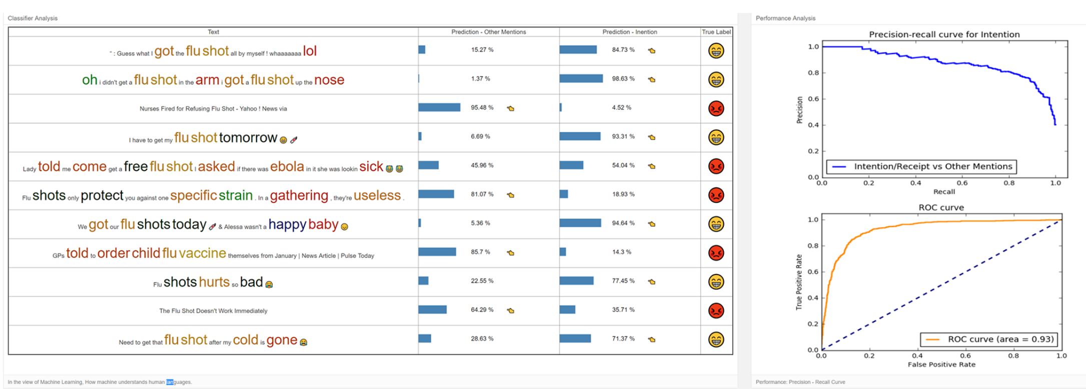


Figure 2: Visualization Dashboard, the last figure is visualization of machine learning and the rest figures are visualization of the classified results.