Detecting Influenza Epidemics on Twitter

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Abstract

This paper presents a predictive model for Influenza-Like-Illness, based on Twitter traffic. We gather data from Twitter based on a set of keywords used in the Influenza wikipedia page, and perform feature selection over all words used in 3 years worth of tweets, using real ILI data from the Greek CDC. We select a small set of words with high correlation to the ILI score, and train a regression model to predict the ILI score cases from the word features. We deploy this model on a streaming application and feed the resulting time-series to FluHMM, an existing prediction model for the phases of the epidemic. We find that Twitter traffic offers a good source of information and can generate early warnings compared to the existing sentinel protocol using a set of associated physicians all over Greece.

1 Introduction

We aim to estimate the probability of a future Influenza or Influenza Like Illness (ILI)[4] epidemic using a stream of Twitter posts. Monitoring and detecting an epidemic and its diffusion is a task of great importance. It can help authorities and health experts plan their responses, such as preparing specific Anti-Influenza drugs in advance, or issue a warning towards vulnerable groups. As crucial as monitoring is, it can be very challenging. Information gathered from the general public, such absences recorded in schools and work environments, search engine queries about symptoms [7], or actual patient reports from health practitioners, are often either inconclusive (one could be missing work due to having the flu, or for another reason), or delayed (processing and submitting such accumulated information takes time).

Twitter [3] is a micro-blogging service that can serve as a valuable information resource in this process of epidemic surveillance. As shown by Lampos et

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1This work was performed in 2018 and 2019, and has now been made obsolete by the COVID-19 pandemic, as any word-trained predictive model does not apply, since the pandemic-related twitter traffic dominates any other ILI-related traffic.
al. [8, 9], Aramaki et al. [6], Lee et al. [10], and Achrekar et al. [5], monitoring user posts (tweets) offers a direct and real-time perspective to current events, including Influenza symptoms or possible cases. The continuous growth of its community, along with the immediacy and the convenience it offers users in expressing their thoughts and updating their statuses, renders Twitter a timely, accurate and effective tool for health research and surveillance.

In this paper we focus on the Greek-speaking twitter community and influenza cases in Greece. We integrate data from the twitter stream into FluHMM [11], an open source R package for seasonal influenza (ILI) sentinel surveillance that performs fitting of a Bayesian HMM (Hidden Markov Model) to data. Traditionally, FluHMM uses patient reports of health practitioners and can calculate the posterior probability of the next ILI epidemic phase. In order to reduce processing times, we use FluHMM with input from Twitter (since tweets can be accurate indications of the real situations), resulting in a more time-efficient predicting model. To do this, we use a large corpus of offline twitter data to select a set of words which have a high correlation with actual ILI recorded cases, using 3 years' worth of historical ILI data from Greece. We then train a predictive model based on the selected set of word features and deploy it on a current stream of Twitter traffic.

2 Implementation

2.1 Offline Twitter data

Using twAwler [12], a lightweight twitter crawler that can run on a single machine, we were able to obtain Greek-language tweets containing keywords that are related to Influenza and express either illness symptoms or describe the infection itself. Weekly aggregated Twitter data from 2013 to 2015, along with the actual ILI patient scores for the same time, were used to select the ILI keywords we will be monitoring for our current approach.

2.2 Feature Selection

We used the greek Wikipedia [1, 2] page about Influenza to obtain a large set of flu related terms, by eliminating stopwords in the entire page, and keeping the rest. Then, a medical expert hand picked the most relevant words out of those. We crawled all related tweets and counted all instances of the selected terms for three years. To decide on the most relevant ILI terms, we calculate each term’s correlation to the actual ILI score presented by the country’s health organisation for those past years. The terms with the highest Pearson’s correlation coefficient (Pearson’s R), and therefore the ones most strongly related to ILI, along with their coefficients, are presented in Table 1.

Clearly, a user tweeting one or more of the above words does not necessarily indicates a person affected with the flu. However, an increase in overall occurrence is correlated with ILI cases, over the 3-year period studied. We trained
Table 1: All keywords with the higher correlation to ILI, along with their Pearson’s coefficients.

| Keyword     | Pearson’s R |
|-------------|-------------|
| γριπη       | 0.4675661553|
| γριπης      | 0.3207126142|
| κρυολογηµατα | 0.309322553 |
| κρυωµα      | 0.3719017249|
| ωση         | 0.3671084547|
| ωσεις       | 0.3933606774|
| βηχας       | 0.3303753935|
| βηχα       | 0.3868373845|
| βηχω        | 0.3269930131|
| βηχεις      | 0.2838413272|

2.3 Collecting Tweets
To apply the model trained on historic data and monitor the diffusion of the disease, we collect a continuous stream of tweets created by Greek users, which contain one or more ILI related terms. More specifically, we expand our set of keywords to contain many versions of each term, using combinations of capital letters, noun declinations and verb conjugations, and accents. This generates a streaming flow of matching tweets, which however is not of huge volume, as most of Twitter traffic is not illness-related.

This way we can obtain a list of public tweets (including their actual content, along with the time they were posted, the user who posted them and the location of the user) containing one or more of our assigned keywords, the moment they are posted. To evaluate the application, we monitored the stream every day for one month (30 days), resulting in an estimated number of ILI cases, by applying the trained model to the daily twitter features.

2.4 Hidden Markov Model for influenza surveillance
FluHMM is an open source R package for seasonal influenza ILI sentinel surveillance that performs fitting of a Bayesian HMM (Hidden Markov Model) to data. FluHMM constructs an inference model based on the assumptions of a Markov process. Traditionally, FluHMM uses surveillance data (number of patients recorded) collected from a network of primary-care physicians, monitored by the Greek CDC, in order to partition the surveillance period into five phases (pre ILI epidemic, epidemic growth, epidemic plateau, epidemic decline and post-epidemic phase) and determine the weekly posterior probability of each
phase. While accurate, FluHMM results can be delayed, since processing patient reports can take time, along with manually processing them, calculating ILI scores and fitting weekly scores.

In our approach, instead of the number of actual patients, we produce an estimated number of actual patients based on our aggregated Twitter data, using a linear regression model trained on historical data. Tweets correspond to real time events and there is no delay or processing time. This can be crucial in cases of epidemic growth, since authorities and health experts need to be alert in advance, and the sooner we have results the better.

More specifically, after we have calculated the total of ILI-related tweets per day and performed linear regression to calculate a daily estimated ILI score, we pass an array of ILI scores as input and proceed to aggregate the scores per week. Then we start fitting the model on a vector of integers (one for each week), performing 5000 iterations. After the initial sampling is complete, the model proceeds to check for initial convergence, and if it is not reached, it starts updating in increments of 5000 iterations until convergence is reached. Once convergence is reached, an object of class FluHMM is created, containing the fitted model, which can then be plotted to show each week’s epidemic probability.

We show graphic representations of the results of fitting the second semester of 2013 and the entirety of the year 2015, below. Figure 1 and Figure 3 show the actual ILI patient numbers for the years 2013 and 2015 respectively, compared to the fitting of aggregated tweet count of ILI terms for the same periods shown in Figure 2 and Figure 4. The posterior probabilities of the five epidemic phases per week (pre-epidemic, epidemic growth, epidemic plateau, epidemic decline, and post-epidemic) are displayed with colored bars on the top of the plot and also as a vertical stack of numbers. Note that both the tweet count and the actual patient count have a blue bar above the fourteen first weeks displayed, which means both show that the first fourteen weeks (June to mid September) are pre-epidemic. Additionally, each column of numbers above every week indicates the percentage of each phase probability.

In the real ILI patient graph shown in Figure 1, weeks 1 to 13 have more than 80 percent pre epidemic probability, whereas weeks 14 to 17 have up to 98 percent chance of epidemic growth probability (meaning people are starting to contract the flu) and weeks 18 to 26 (last two months of 2013) are divided
between epidemic plateau, with percentages from 63 percent to 72 percent, and epidemic growth (15 to 35 percent).

Similarly, in the twitter data graph shown in Figure 2, the first 13 weeks display a 83 to 100 percent pre epidemic probability, while weeks 14 to 17 have a 57 to 64 epidemic growth probability, and weeks 18 to 26 are divided between epidemic plateau and epidemic decline.

In the real ILI score of the entire year of 2015, shown in Figure 3, week 4 marks the beginning of epidemic growth, with 100% posterior probability, while week 6 has a 98% probability of epidemic plateau.

Figure 2: A FluHMM fitted model for ILI related tweets of June to December 2013

Figure 3: A FluHMM fitted model for real ILI patients of the year 2015

Figure 4: A FluHMM fitted model for ILI related tweets of the year 2015
In the graph for the ILI related tweets of 2015 shown in Figure 4, week 4 is also marked with epidemic plateau, and week 6 beginning of the epidemic plateau phase, in accordance with the real ILI patient reports of the same time. Therefore, fitting the real patient report numbers, and the estimated ILI scores calculated from tweets, gives similar results to FluHMM, with an average deviation of one week. Note that the training data and evaluation data overlap in this case, as the ILI score prediction model was trained using the shown datasets. To further evaluate its use, we perform additional evaluation using a real-time stream of Tweets, presented below.

2.5 Live stream results

We summarize and graphically plot our live data, to gain a collected and better understanding of our findings, and also test how the trained model can be applied in practice. That applies both to the raw Twitter counters shown in Figure 5 and the FluHMM results, shown in Figure 6.

Figure 5 shows a sample representation of our collected testing data. It shows the amount of Tweets posted containing any of the selected ILI terms per day, from August 23 to September 12, 2019, showing how many people tweeted ILI related posts on a span of three weeks, as well as which specific term they mentioned. The Figure legend uses transliterations of the Greek words in the Latin alphabet.

Figure 6 is a plot of our currently gathered data. Note that the first two weeks (from August 23 to September 5) are 100 percent in the pre epidemic
phase, while the third week is starting to get in the epidemic growth phase with a posterior probability of 56 percent.

3 Conclusions

Monitoring an Influenza epidemic is a vital task that can reduce response times from authorities and health facilities, as well as help vulnerable groups be alert and safe. Traditional ways of ILI surveillance are often delayed due to processing times. Twitter is an ever growing microblogging service that can aid in monitoring the diffusion of an epidemic, as it allows users to share their current status and situation, such as being sick with the flu, instantly. We use a filtered Twitter stream based on selected word features and find users that talk about Influenza daily, including one or more of our selected ILI related terms in their posts. We then use weekly counters to fit a Bayesian HMM (Hidden Markov Model) and calculate the probability of an ILI epidemic for the following week, based on the current week’s situation. Though this model normally takes input from health practitioners’ reports on real ILI patients, when presented with input from Twitter we can see very similar results, with probability percentages having an average deviation of a week or less, as shown in the 2013 and 2015 graphs. Therefore the approach of substituting real ILI numbers with estimated ILI scores based on counts of ILI related tweets, achieves a satisfactory sensitivity and timeliness, thereby demonstrating its usefulness.

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