Flu Detector: Estimating influenza-like illness rates from online user-generated content

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Abstract

We provide a brief technical description of an online platform for disease monitoring, titled as the **Flu Detector** (`fludetector.cs.ucl.ac.uk`). Flu Detector, in its current version (v.0.5), uses either Twitter or Google search data in conjunction with statistical Natural Language Processing models to estimate the rate of influenza-like illness in the population of England. Its back-end is a live service that collects online data, utilises modern technologies for large-scale text processing, and finally applies statistical inference models that are trained offline. The front-end visualises the various disease rate estimates. Notably, the models based on Google data achieve a high level of accuracy with respect to the most recent four flu seasons in England (2012/13 to 2015/16). This highlighted Flu Detector as having a great potential of becoming a complementary source to the domestic traditional flu surveillance schemes.

1 Introduction

Information epidemiology, or 'infodemiology' (Eysenbach, 2009), is evidently not a hypothesis anymore. Numerous research efforts in recent years have provided proof that user-generated data, especially in the form of search queries or social media, can be used to better understand a multi-faceted collection of health issues. Within this rapidly developing field of research, usually labelled as Computational Health, one of the most prominent examples has been the modelling of influenza-like illness (ILI) rates (Polgreen et al., 2008; Ginsberg et al., 2009; Lampos and Cristianini, 2010; Culotta, 2010; Paul and Dredze, 2011; Signorini et al., 2011). Attempting to translate research results into an actual application, the platform of Google Flu Trends (GFT) was launched in 2008 based on a method proposed by Ginsberg et al. (2009) for mapping the frequency of search queries to ILI rates in the US. In 2010, Lampos et al. developed the first tool that used social media content to estimate ILI rates in the UK (Lampos et al., 2010). The Flu Detector of that era[1] used Twitter posts and basic supervised learning models, such as the 'lasso' (Tibshirani, 1996; Lampos and Cristianini, 2010) or its bootstrapped version (Bach, 2008; Lampos and Cristianini, 2012), operating on Bag-of-Words representations of the data. Naturally, there was space for further improvements, something that has been explored in various follow-up works (e.g. by Lamb et al. (2013) or Preis and Moat (2014) and so on). In late 2015, amidst severe criticism (Olson et al., 2013; Lazer et al., 2014) and bad press due to significant mispredictions in the past flu seasons, the GFT service was unfortunately discontinued.[2]

Advancements in statistical Natural Language Processing (NLP) combined with a better understanding of the problem have recently led to disease models that overcome past deficiencies (Lampos et al., 2015b; Lampos et al., 2015a; Yang et al., 2015). Motivated by this fact, a revamped version of **Flu Detector** (`fludetector.cs.ucl.ac.uk`) that has access to both Twitter and Google search data has been developed and recently launched. Given that GFT never made ILI rate estimates for England (or the UK), Flu Detector embodies the first online tool making ILI rate estimations for England based on Google search data.

To ensure that Flu Detector will not be a one-off scientific outcome, but will have a practi-

[1] Its last working snapshop (circa March 2013) is hosted under `twitter.lampos.net/epidemics`

[2] See `google.org/flutrends`

Figure 1: Flu Detector's weekly ILI estimates for the 2015/16 flu season in England based on Google search data. They are compared to the RCGP ILI rates as released by PHE.

cal impact, the inference accuracy as well as the potential added value of the tool to the current (traditional) health surveillance schemes have been assessed[3] in collaboration with Public Health England (PHE), the leading governmental agency responsible for the national health surveillance schemes.[4] The results of the evaluation are positive, leading to a potential incorporation of Flu Detector's estimates as a complementary indicator in the weekly flu surveillance reports during the coming flu seasons.

This document summarises the main functionalities of Flu Detector. It should be considered as an ongoing reference to the online tool, and as such, it will be updated as new modules are being launched.

2 Data sources

The current version of Flu Detector has access to two online user-generated content sources, namely Twitter and Google search. The supervised models of ILI for England are trained based on syndromic surveillance data.

2.1 Twitter

We collect approximately every exactly geolocated tweet in England using Twitter's Streaming API.[5] By "exact geolocation" we refer to tweets, where the geo-coordinates (latitude and longitude) of the user who posted them, are available. This amounts to an average of approximately 350,000 tweets per day. We note that this number is relatively small as, according to our estimates, it represents only 1%-2% of the entire set of tweets from users in England. Hence, the ILI rate inferences based on Twitter data are inevitably unstable.

2.2 Google search

Flu Detector has access to a non standardised version of the publicly available Google Trends outputs through a private Google Health Trends API.[6] This provides (aggregate and anonymised) normalised frequencies of search queries. More specifically, a query frequency expresses the probability of a short search session for a specific geographical region and temporal resolution, drawn from a uniformly distributed 10%-15% sample of all corresponding search sessions.

2.3 Syndromic surveillance

At the moment, Flu Detector models ILI rates as reported by the Royal College of General Practi-

[3] The evaluation will be published separately.

[4] Public Health England, `gov.uk/government/organisations/public-health-england`

[5] Twitter Streaming API, `dev.twitter.com/streaming/overview`

[6] The Google Health Trends API can only be used for academic research with a health-oriented focus.

tioners (RCGP) and PHE.[7] The estimates represent the number of doctor consultations reporting ILI symptoms per $100{,}000$ people in England.

3 Statistical models and performance evaluation

Supervised learning techniques are used to model flu rates from Twitter or Google search data. A selection of papers has served as motivation for the actual methods that are employed on the website, from early papers on the topic (Ginsberg et al., 2009; Lampos and Cristianini, 2010) to most recent developments (Lampos et al., 2015b; Lampos et al., 2015a; Zou et al., 2016). The applied methods combine these different pieces of knowledge with advancements in statistical NLP (e.g. the use of neural word embeddings (Mikolov et al., 2013a; Mikolov et al., 2013b)) and, at the moment, are being documented.

As a preliminary performance indicator of the Google search based model, the average Mean Absolute Error in year-long weekly ILI rate estimates across four flu seasons (from 2012/13 to 2015/16) is approximately equal to 1.5 (in $100{,}000$ people) compared to the corresponding RCGP ILI rates; the corresponding average Pearson correlation is equal to .95. Extensive performance evaluation will become available in forthcoming publications.

4 Back-end and front-end operations

At the back-end of Flu Detector, there is a software pipeline for data collection, storage and processing. The latter uses standard Python libraries (e.g. `gensim`, `nltk`, `numpy`, `scipy` and so on) and the Apache Hadoop framework[8] for task parallelisation. Textual data can be manually processed in batches (e.g. for model training). In addition, the frequency of the textual variables used in Flu Detector's models is being automatically updated on a daily basis.

The ILI estimation models, which are trained offline, are used to produce daily (over-night) inferences as well as weekly ones. To maintain a consistency with the data distributions during the model training phase, where only weekly ILI rates are available, each estimate on Flu Detector (even the daily ones) uses a week-long set of observations. For example, to estimate the ILI rate of date i, we use the frequencies of textual terms during the dates $\{i, i-1, \ldots, i-6\}$ for the target data set. For Twitter-driven estimates, which are consequently based on a small portion of data, and tend to be noisy, the user of the website can also access smoothed versions of the inferred time series.

The current version of Flu Detector incorporates 5 Twitter-based models, one focusing on England as a whole and the rest in sub-regions ('London', 'North England', 'South England', 'Midlands and East England'). As expected, the regional models are very unstable given the even smaller data ratio that characterises them. Moreover, the platform has a Google search model for England only (regional Google search data have not yet been made available). Given the higher penetration of Google search in the real population as well as the significantly larger sample of searches that are used to compute search query frequencies (10%-15%), the corresponding estimates are much more reliable.

Apart from its public interface, Flu Detector has also an internal one, used for testing new modules and evaluating estimates compared to traditional syndromic surveillance schemes (see Fig. 1).

5 Conclusions and future work

In this brief report, we introduced Flu Detector, an online tool for presenting disease rate estimates based on user-generated content. The current version of Flu Detector uses data from Google search or Twitter and displays ILI rate estimates for England. This report will be updated as new functionalities are being launched.

Future work includes the consideration of different infectious diseases, the incorporation of more data sources as well as the development of unsupervised disease modelling schemes. Stratified disease estimates based on perceived user demographics, e.g. age (Rao et al., 2010), occupation or socioeconomic status (Preoţiuc-Pietro et al., 2015a; Preoţiuc-Pietro et al., 2015b; Lampos et al., 2016), as well as the expansion of models so as to cover different countries are among our priorities.

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[7] See `gov.uk/government/statistics/weekly-national-flu-reports`

[8] Apache Hadoop, `hadoop.apache.org`

[9] EPSRC IRC project i-sense, `i-sense.org.uk`

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