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Uncovering Wireless Blackspots using Twitter Data

Weisi Guo, Jie Zhang

Blackspots are areas of poor signal coverage or service delivery that leads to customer complaints and loss in business revenue. Understanding their spatial-temporal patterns at a high resolution is important for interventions. Conventional methods such as customer helplines, drive-by testing, and network analysis tools often lack the real-time capability and spatial accuracy required. In this paper, we investigate the potential of utilizing geo-tagged Twitter data to uncover blackspots. Here, we apply lexicon and machine-learning natural language processing techniques to over 1.4 million Tweets in London to uncover blackspots for both pre-4G (2012) and post-4G (2016) roll out. It was found that long-term poor signal complaints make up the majority of complaints (86%) pre-4G roll out, but short-term network failure was responsible for most complaints (66%) post-4G roll out.

***Introduction**:* An important component in modern business is the mining and analysis of data obtained from the customer base. In the past 5 years, the proliferation of Online Social Networks (OSN) platforms (i.e., Twitter) has led to the development of new social media analytics tools. In the context of mobile network operators, investment in both small-cell deployments have been widely recognised as a cornerstone of current 4G LTE and future 5G networks [1]. Yet, current small-cells are often deployed without high resolution traffic and QoE knowledge, leading to potentially poor profit returns. Existing practices of using long-term statistical traffic data from macro-base stations (BSs) have poor spatial resolution and lacks end-user context.

In recent years, a number of enterprises have already been using OSN data and mobile application data [2] to act as a proxy for high resolution spatial-temporal traffic patterns with the purpose of guiding small-cell deployment. Recent research by ourselves used geo-tagged Tweets to show that Twitter data is an accurate proxy for 3G data demand [3]. Other related research have examined the opportunity to use geo-tagged OSN data to add spatial analysis to QoE complaints [4] and detect core network problems [5]. Yet, most current research in wireless engineering have not exploited the unstructured information in Tweets, which have the potential to uncover the sentiment towards specific topic areas and understand the perceived Quality-of-Experience (QoE).

In this paper, the data comes from 0.4 million (**pre-4G roll-out in 2012**) and 1.0 million (**post-4G roll-out in 2016**) geo-tagged Twitter data, covering a 2 week period in the aforementioned years. Each Tweet consists of full structured and unstructured data fields, including the user name, registration details, Tweet text data and hashtag, Tweet time stamp, geo-location, and approximate regional location. We first apply natural language processing (NLP) techniques for cellular network QoE keywords, and we use OpenSignal database to validate some of the results. This study has the potential to help operators to deploy small-cells and integrate the real time analytics with self organising network functions.

***Methodology**:* Natural language processing revolves around mining text and classifying it for topic and sentiment analysis [6]. The sentiment to be identified typically range from three basic sentiments (positive, negative, neutral) to six emotion categories (i.e., Ekman universal categories).

A general flow model for the NLP algorithm and a lexicon based example is given in Fig. 1. We first filter all Tweets and identify ones which are relevant to the topic domain (QoE for cellular networks). After which, we classify each Tweet complaint with sentiment labels to infer polarity of the filtered Tweets. To assign each tweet with a sentiment score we first apply tokenization pre-filtering to remove language noise and transform all text to a common lower case format with no punctuations. We then extract single word unigram features independently to determine the orientation of the tweet.

Method 1: Opinion Lexicon

First, a dictionary of words is obtained through a bootstrapping process using WordNet, which offers semantic relations among words [7]. It is built utilizing the adjectives synonym set and antonym set available in WordNet to predict the semantic orientations of text used in tweet sentence. This method enables us to find the average semantic orientation of tweets in simplistic ways of independent of the context of the text under analysis. The algorithm then calculates the score of each tweet by simply subtracting the number of occurrences of negative words from the number of positive occurrences for each tweet. A threshold is usually implemented before classification in order to reduce the number of false positive opinion results.

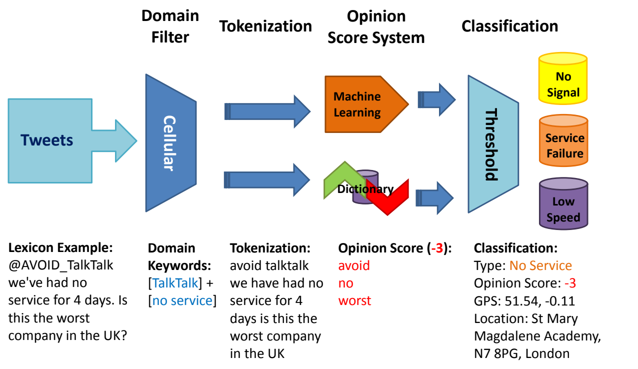


Fig. 1: Lexicon and Machine-Learning based NLP algorithm with filtering, tokenization, and opinion score classification.

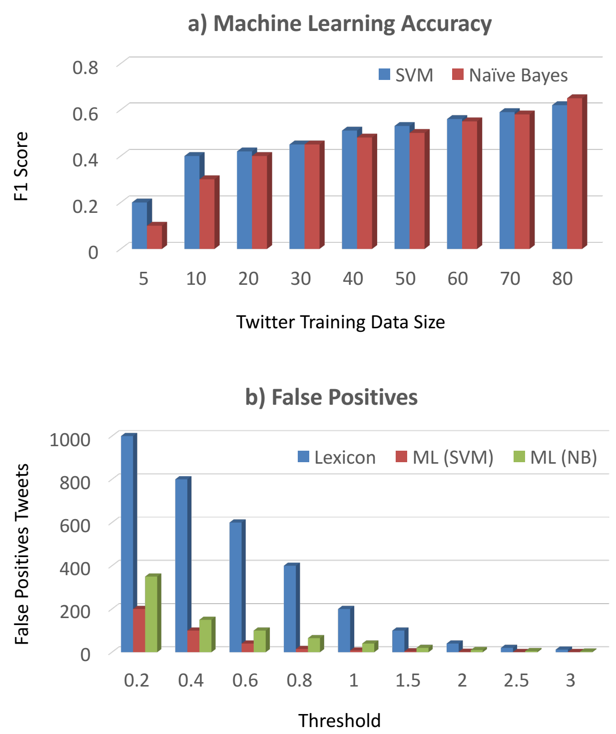
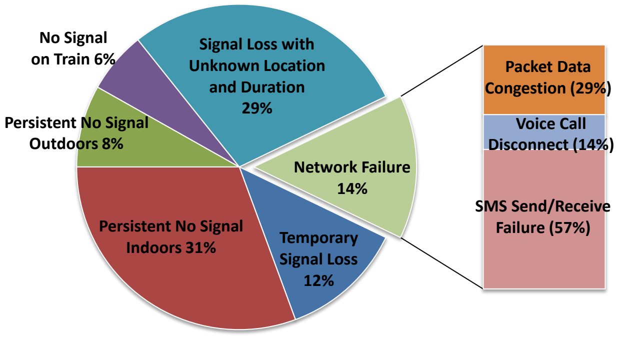


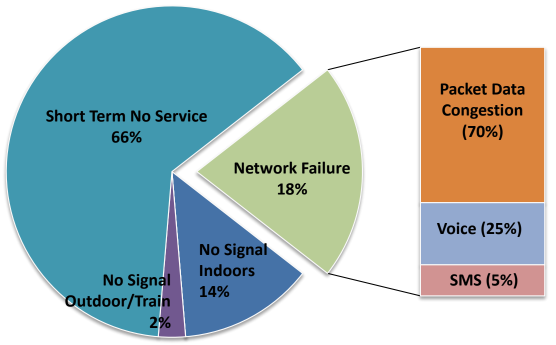
Fig. 2: Machine-Learning based NLP algorithm with a) F1 score vs. Twitter training data size, and b) False positive vs. Threshold.

Method 2: Machine Learning

We consider 2 techniques: Support Vector Machine (SVM) with a Gaussian kernel and Naive Bayes (NB). Both techniques depend on the volume of training data, which is manually annotated by the authors, of which 80 representative example texts were available from existing complaint data on Twitter. In considering the accuracy performance of machine learning approaches, the $F1$ score is often used, which considers both the precision and the recall statistics. Precision p is the number of correct positive results divided by the number of all positive results, and r is the number of correct positive results divided by the number of positive results that should have been returned. The $F1$ score is the harmonic mean of precision and recall $F1 = 2\frac{pr}{p+r}$. The accuracy results in Fig. 2**a** show that SVM with Gaussian kernel has a similar F1 score performance to Naive Bayes, superseding it for low sample sizes. It is worth noting



(a) 2012 (Pre-4G) QoE Problems Classification in Greater London



(b) 2016 (Post-4G) QoE Problems Classification in Greater London

Fig. 3: Text Analysis of Tweets: results show the customer complaints for pre-4G roll out in 2012 and post-4G roll out in 2016.

that the training data size for more complex complaints is usually orders of magnitude higher, but for simpler Tweets with a limited number of keywords, the sample required is quite small.

Commonly occurring **false positives** are removed from the data (i.e., poor train signal). It is worth noting that filtering by operator names or the operator's official Hashtag is not useful in most cases, as most complaints do not use the associated name or Hashtag of the operator. The results in Fig. 2**b** compares the threshold size and the false positive Tweet number for Lexicon and ML techniques using the full training data set. The results clearly demonstrate the superior performance of ML techniques over Lexicon based techniques, especially for SVM.

Characterizing Blackspots*:* By using the previously mentioned NLP techniques, we were able to show that the majority of customer complaints were a result of poor signal (86%) before 4G roll out in 2012 - see Figure 3**a**. By checking against keywords related to indoor areas, it was found that many (36%) of these cases are persistent. After 4G roll out in 2016 - see Figure 3**b**, the complaints were mainly (66%) of service failures that span from a few hours to several days. This may indicates problem related to operating the 4G network. Signal complaints (especially in indoor and for on trains) were lower both proportionally and in absolute numbers.

Several QoE complaint areas were identified. These are plotted as star symbols in Figure 4**a**. Figure 4**b** shows an example area centred on London Bridge Station. There are numerous QoE complaints inside the station (black star), despite several macro-BSs nearby yielding excellent outdoor signal. Therefore, this presents small-cell operators with an opportunity to both target the persistent poor QoE blackspot inside the station (black circular zone), as well as several Twitter hotspots near the station (red circular zones). The authors also use OpenSignal to reveal poor signal measurement reports in this area with a spatial resolution of (60m). These are represented by blue stars with a blue circular zone. The overlapping circular zones represent an opportunity to address one or more of the following: i) high traffic demand (inferred from Twitter intensity); ii) poor signal strength (measurement reports from OpenSignal); and iii) poor QoE (data mined from Twitter).

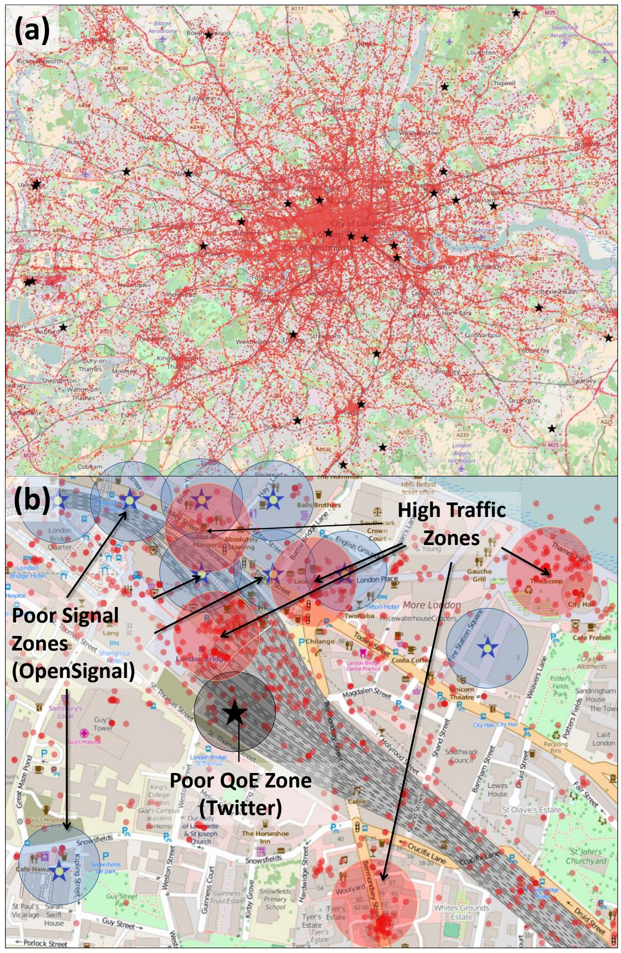


Fig. 4: (a) identified poor QoE blackspots, (b) case study of London Bridge showing both high traffic hotspots and poor signal (OpenSignal data) and poor QoE (Twitter data) blackspots.

Conclusions*:* Social media data presents us with a new opportunity to better understand end user consumption and experience patterns. In this paper, we have shown that the Twitter data allows for a scalable way to create accurate maps of quality of experience. As a result, we are able to identify blackspots using natural language processing techniques. To demonstrate applicability, a case study is conducted for the London Bridge Station area, and small-cell deployment recommendations are presented.

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