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Traffic Events Detection from Status Updated Messages of Twitter

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ABSTRACT

Now Days the Social networks are also used as a source of information for events detection, with particular position to road traffic details etc. In this paper, we present a real-time monitoring system for traffic event detection from Twitter stream analysis. The system fetches tweets from Twitter according to several search criteria; processes tweets, by applying text-mining techniques; and finally performs the classification of tweets. The aim is to assign the suitable class label to each tweet, as related to a traffic event or not. The traffic detection system was employed for real-time monitoring of several areas of the road network, allowing for detection of traffic events almost in real time, often before online traffic news web sites. We employed the support vector machine as a classification model, and we achieved an accuracy value by solving a binary classification problem (traffic versus nontraffic tweets).
Keywords : Traffic Event Detection, Tweet Classification, Text Mining, Social Sensing.

I. INTRODUCTION

Due to huge usage of SOCIAL network sites, these are new kind of information channel. Their popularity stems from the characteristics of portability thanks to several social networks applications for smartphones and tablets, easiness of use, and real-time nature [1], [2]. People intensely use social networks to report (personal or public) real life events happening around them or simply to express their opinion on a given topic, through a public message. Social networks allow people to create an identity and let them share it in order to build a community. The resulting social network is then a basis for maintaining social relationships, users with similar interests, and locating content and knowledge entered by other users [3]. The users are sharing the messages in social networks is called Status Update Message (SUM), and it may contain, apart from the text, meta-information such as timestamp, geographic coordinates (latitude and longitude), name of the user, links to other resources, hash tags, and mentions. Several SUMs referring to a certain topic or related to a limited geographic area may provide, if correctly analysed, great deal of valuable information about an event or a topic. In fact, we may regard social network users as social sensors [4], [5], and SUMs as sensor information [6], as it happens with traditional sensors. Now a Days the Social networks are also used as a source of information for events detection, with particular position to road traffic details and accidents , natural disasters (earthquakes, storms, fires, etc.), or other events. An event can be defined as a real-world occurrence that happens in a specific time and space [1], [7]. In particular, regarding traffic related events, people often share by means of an SUM information about the current traffic situation around them while driving. For this reason, event detection from social networks is used with Intelligent Transportation Systems (ITSs). An ITS is an infrastructure which, by integrating ICTs (Information and Communication Technologies) with transport networks, vehicles and users, allows improving safety and management of transport networks. ITSsprovide, e.g.,realtime information about weather, traffic or plan efficient (e.g., shortest, fast driving, least polluting) routes [4], [6], [8]–[14]. However, event detection from social networks analysis is a more challenging problem than event detection from traditional media like blogs, emails, etc., where texts are well formatted [2]. In fact, SUMs are unstructured and irregular texts, they contain informal or abbreviated words, misspellings or grammatical errors [1]. Due to their nature, they are usually very brief, thus becoming an incomplete source of information [2]. Furthermore, SUMs contain a huge amount of not useful or meaningless information [15], which has to be filtered. For all of these reasons, in order to analyse the information coming from social networks, we exploit text mining techniques [17], which employ methods from the fields of data mining, machine learning, statistics, and Natural Language Processing (NLP) to extract meaningful information [18]. More in detail, text mining refers to the process of automatic extraction of meaningful information and knowledge from unstructured text. The main difficulty encountered in dealing with problems of text mining is caused by the vagueness of natural language. In fact, people, unlike computers, are perfectly able to understand idioms, grammatical variations, slang expressions, or to contextualize a given word. On the contrary, computers have the ability, lacking in humans, to quickly process large amounts of information [19], [20]. The text mining process is summarized in the following. First, the information content of the document is converted into a structured form (vector space representation). In fact, most of text mining techniques are based on the idea that a document can be faithfully represented by the set of words contained in it (bag-of-words representation [21]). Regarding the aim of this paper, Twitter has several advantages over the similar micro-blogging services. First, tweets are up to 140 characters, enhancing the real-time and news-oriented nature of the platform. In fact, the life-time of tweets is usually very short, thus Twitter is the social network platform that is best suited to study SUMs related to real-time events [22]. Second, each tweet can be directly associated with meta-information that constitutes additional information. Third, Twitter messages are public, i.e., they are directly available with no privacy limitations. For all of these reasons, Twitter is a good source of information for real-time event detection and analysis. In this paper, we present an intelligent system, based on text mining and machine learning algorithms, for real-time detection of traffic events from Twitter stream analysis. The system, after a feasibility study, has been designed and developed from the ground as an event-driven infrastructure, built on a Service Oriented Architecture (SOA) [23]. The system exploits available technologies based on state-of-the-art techniques for text analysis and pattern classification. These technologies and techniques have been analyzed, tuned, adapted, and integrated in order to build the intelligent system.

II. METHODS AND MATERIAL

Related Work

The current methods for using social media to extract useful information for event detection, we need to distinguish between small-scale events and large-scale events. Small-scale events (e.g., traffic, car crashes, fires, or local manifestations) usually have a small number of SUMs related to them, belong to a detailed geographic location, and are concentrated in a small time interval. On the other hand, large scale events e.g., earthquakes, tornados, or the election of a prime minister) are characterized by a huge number of SUMs, and by a wider temporal and geographic coverage [24]. Consequently, due to the smaller number of SUMs related to small-scale events, small-scale event detection is a non-trivial task.

In this paper, we focus on a particular small-scale event, i.e., road traffic, and we aim to detect and analyze traffic events by processing users' SUMs belonging to a certain area and written in the Italian language. To this aim, we propose a system able to fetch, elaborate, and classify SUMs as related to a road traffic event or not. To the best of our knowledge, few papers have been proposed for traffic detection using Twitter stream analysis. However, with respect to our work, all of them focus on languages different from Italian, employ different input features and/or feature selection algorithms, and consider only binary classifications. In addition, a few works employ machine learning algorithms [9], [24], while the others rely on NLP techniques only. The proposed system may approach both binary and multi-class classification problems. As regards binary classification, we consider traffic-related tweets, and tweets not related with traffic. As regards multi-class classification, we split the traffic-related class into two classes, namely traffic congestion or crash, and traffic due to external event. In this paper, with external event we refer to a scheduled event (e.g., a football match, a concert), or to an unexpected event (e.g., a flash-mob, a political demonstration, a fire). In this way we aim to support traffic and city administrations for managing scheduled or unexpected events in the city. Moreover, the proposed system could work together with other traffic sensors (e.g., loop detectors, cameras, infrared cameras) and ITS monitoring systems for the detection of traffic difficulties, providing a low-cost wide coverage of the road. network, especially in those areas (e.g., urban and suburban) where traditional traffic sensors are missing. Concluding, the proposed ITS is characterized by the following strengths with respect to the current research aimed at detecting traffic events from social networks:

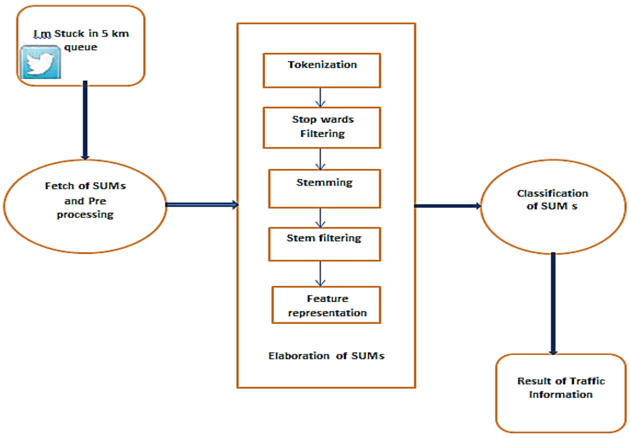

Figure 1. System architecture for traffic detection from Twitter

i)it performs a multi-class classification, which recognizes non-traffic, traffic due to congestion or crash, and traffic due to external events; ii) it detects the traffic events in real-time; and iii) it is developed as an event-driven infrastructure, built on an SOA architecture. As regards the first strength, the proposed ITS could be a valuable tool for traffic and city administrations to regulate traffic and vehicular mobility, and to improve the management of scheduled or unexpected events. For what concerns the second strength, the real-time detection capability allows obtaining reliable information about traffic events in a very short time, often before online news web sites and local newspapers. As far as the third strength is concerned, with the chosen architecture, we are able to directly notify the traffic event occurrence to the drivers registered to the system, without the need for them to access of- facial news websites or radio traffic news channels, to get traffic information. In addition, the SOA architecture permits to exploit two important peculiarities, i.e., scalability of the service (e.g., by using a dedicated server for each geographic area), and easy integration with other services (e.g., other ITS services).

III. RESULTS AND DISCUSSION

Architecture of the Traffic Detection System

In this section, our traffic detection system based on Twitter streams analysis is presented. The system architecture is service-oriented and event-driven, and is composed of three main modules, namely: i) "Fetch of SUMs and Pre-processing", ii) "Elaboration of SUMs", iii) "Classification of SUMs". The purpose of the proposed system is to fetch SUMs from Twitter, to process SUMs by applying a few text-mining steps, and to assign the appropriate class label to each SUM. Finally, as shown in Fig. 1, by analysing the classified SUMs, the system is able to notify the presence of a traffic event. The main tools we have exploited for developing the system are:

1) Twitter's API,which provides direct access to the public stream of tweets;
2) Twitter, a Java library that we used as a wrapper for Twitter's API;
3) The Java API provided by Weka (Waikato Environment for Knowledge Analysis) [32], which we mainly employed for data pre-processing and text mining elaboration. We recall that both the "Elaboration of SUMs" and the "Classification of SUMs" modules require setting the optimal values of a few specific parameters, by means of a supervised learning stage. To this aim, we exploited a training set composed by a set of SUMs previously collected, elaborated, and manually labeled.

A. Fetch of SUMs and Pre-Processing

The first module, "Fetch of SUMs and Pre-processing", extracts raw tweets from the Twitter stream, based on one or more search criteria (e.g., geographic coordinates, keywords appearing in the text of the tweet). Each fetched raw tweet contains: the user id, the timestamp, the geographic coordinates, a retweet flag, and the text of the tweet. The text may contain additional information, such as hashtags, links, mentions, and special characters. In this paper, we considered only Italian language tweets. However, the system can be easily adapted to cope with different languages. After the SUMs have been fetched according to the specific search criteria, SUMs are pre-processed. In order to extract only the text of each raw tweet and remove all meta-information associated with it, a Regular Expression filter [33] is applied. More in detail, the meta-information discarded are: user id, timestamp, geographic coordinates hashtags, links, mentions, and special characters. Finally, a case-folding operation is applied to the texts, in order to convert all characters to lower case. At the end of this elaboration, each fetched SUM appears as a string, i.e., a sequence of characters.

B. Elaboration of SUMs

The second processing module, "Elaboration of SUMs", is devoted to transforming the set of pre-processed SUMs, i.e., a set of strings, in a set of numeric vectors to be elaborated by the "Classification of SUMs" module. To this aim, some text mining techniques are applied in sequence to the pre-processed SUMs. In the following, the text mining steps performed in this module are described in detail: a) tokenization is typically the first step of the text mining process, and consists in transforming a stream of characters into a stream of processing units called tokens (e.g., syllables, words, or phrases). During this step, other operations are usually performed, such as removal of punctua- tion and other non-text characters [18], and normalization of symbols (e.g., accents, apostrophes, hyphens, tabs and spaces). In the proposed system, the tokenizer removes all punctuation marks and splits each SUM into tokens corresponding to words (bag-of-words representation). At the end of this step, each SUMj is represented as the sequence of words contained in it.

C. Stop-Word filtering

It consists in eliminating stop-words, i.e., words which provide little or no information to the text analysis. Common stop-words are articles, conjunctions, prepositions, pronouns, etc. Other stop-words are those having no statistical significance, that is, those that typically appear very often in sentences of the considered language (language-specific stop-words), or in the set of textsbeing analyzed (domain-specific stop-words), and can therefore be considered as noise [34].

D. Stemming

It is the process of reducing each word (i.e., token) to its stem or root form, by removing its suffix. The purpose of this step is to group words with the same theme having closely related semantics. In the proposed system, the stemmer exploits the Snowball Tartarus Stemmer7 for the Italian language, based on the Porter's algorithm [36]. Hence, at the end of this step each SUM is represented as a sequence of stems extracted from the tokens contained in it. We denote the jth stemmed

E. Stem filtering

It consists in reducing the number of stems of each SUM. In particular, each SUM is filtered by removing from the set of stems the ones not belonging to the set of relevant stems. At the end of this step, each SUM is represented as a sequence of relevant stems.

Actually, it was really difficult to find realistic data to test the proposed system, basically for two reasons: on the one hand, we have realized that real traffic events are not always notified in official news channels; on the other hand, situations of traffic slowdown may be detected by traditional traffic sensors but, at the same time, may not give rise to tweets. In particular, in relation to this latter reason, it is well known that drivers usually share a tweet about a traffic event only when the event is unexpected and really serious, i.e., it forces to stop the car. So, for instance, they do not share a tweet in case of road works, minor traffic difficulties, or usual traffic jams (same place and same time). In fact, in correspondence to minor traffic jams we rarely find tweets coming from the affected area.

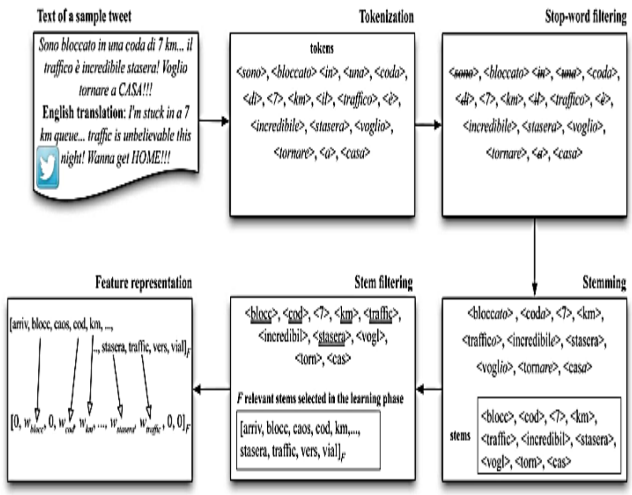

Figure 2. Steps of the text mining elaboration applied to a sample tweet.

F. Feature Representation

It consists in building, for each SUM, the corresponding vector of numeric features. Indeed, in order to classify the SUMs, we have to represent them in the same feature space. In Fig. 2, we summarize all the steps applied to a sample tweet by the "Elaboration of SUMs" module.

IV. CONCLUSION

In this paper, we have proposed a system for real-time detection of traffic-related events from Twitter stream analysis. The system, built on a SOA, is able to fetch and classify streams of tweets and to notify the users of the presence of traffic events. Furthermore, the system is also able to discriminate if a traffic event is due to an external cause, such as football match, procession and manifestation, or not. We have exploited available software packages and state-ofthe-art techniques for text analysis and pattern classification. These technologies and techniques have been analyzed, tuned, adapted and integrated in order to build the overall system for traffic event detection. Among the analyzed classifiers, we have shown the superiority of the SVMs, which have achieved accuracy of 95.75%, for the 2-class problem, and of 88.89% for the 3-class problem, in which we have also considered the traffic due to external event class. The best classification model has been employed for realtime monitoring of several areas of the Italian road network. We have shown the results of a monitoring campaign, performed in September and early October 2014. We have discussed the capability of the system of detecting traffic events almost in realtime, often before online news web sites and local newspapers.

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