A Sentiment Analysis Approach for supporting Blended Learning Process

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Abstract— E-Learning is one of the most widely used training approaches in recent years. Numerous universities and training institutions adopt this approach to deliver courses or support the students in their training process. In particular, the blended E-Learning is a useful approach for supporting students and better understanding their learning issues. The possibility of using collaborative tools and interacting with other students allows the student to share doubts on certain topics. The teacher often remains outside of this dynamic and does not understand the learning problems that characterize the class. A possible solution, which ensures the privacy of communication between students, is the Sentiment Analysis. The computational study of opinions, feelings and emotions expressed in a text often relates to the identification of agreement or disagreement with statements, contained in comments that convey positive or negative feelings. In this paper, we investigate the adoption of a probabilistic approach based on the Latent Dirichlet Allocation (LDA) as Sentiment Grabber. Through this approach, for a set of documents belonging to a same knowledge domain, a graph, the Mixed Graph of Terms, can be automatically extracted. The paper shows how this graph contains a set of weighted word pairs, which are discriminative for sentiment classification. In this way, the system can detect the feeling of students on some topics and teacher can better tune his/her teaching approach. In fact, the proposed method has been tested in real cases with effective and satisfactory results.

Keywords-Sentiment Analysis; e-Learning; Collaborative Learning Approach; Blended Approach.

I. INTRODUCTION

Our society is living a transformation, maybe the most important of the latest years, which, through the strong diffusion of the new information technologies, is radically modifying the nature of the relationships among countries, markets, people and cultures. This technological revolution has clearly facilitated the process of globalization, Internet well represents the concept of global village, and the information exchange [28][29].

Information can be considered as an economic good whose value is tightly linked to the amount of knowledge that can give to its users. Gaining new knowledge, competences or skills has determined the need for a continuous update by the actors of the supply chain of the new economy. In fact, in this context, a fundamental service is the life-long learning, or permanent training, which continues all along life and aims at promoting people’s fulfilment both at personal and social level. In the learning society, keeping continuously up-to-date is the essential condition to live in it and follow the changes of our times. In this scenario, the information technologies, the languages, the business management are among the sectors that depend more and more on the on-line training services [36] [37] [38].

For about twenty years, the ‘E-Learning’ phenomenon has largely spread itself in the distance-learning panorama. This reality reverses the paradigm of the old distance education experiences representing the evolution through the technological platforms. These use the Internet and/or the web and the user’s monitoring and tracking procedures perfectly integrating the pedagogical and technological aspect for a dynamic learning [30] [33] [34].

Employing the new tools offered by the Web 2.0, the E-Learning gives innovative services that make possible the realization of typical aspects of the ‘collaborative learning’ and allow the users to have an efficient on-line ‘conversation’. The students can leave the old role of users who received information with a top-down approach, to assume a new position of talkers, of people who interact among them creating and exchanging culture [31][32].

Recent studies showed that emotions can affect the E-Learning experience. [1] What are emotions? A general definition for emotions could be the following: emotions are complex psychophysical processes that evoke positive or negative psychological responses (or both) and physical expressions, often involuntary. Emotions are often related to feelings, perceptions or beliefs about elements, objects or relations between them, in reality or in the imagination. They typically arise spontaneously, rather than through conscious effort. An emotion (reaction or state) is often differentiated from a feeling (sensation or impression), although the word “feeling” is used as a synonym for “emotion” in some contexts. Obviously, the topic of emotions goes far beyond this simple definition and it is especially hard to detect in an e-learning environment [35]. In a face-to-face class, instructors can detect facial expressions of students but, in an online environment, students need to establish an online presence and the instructors need to be able to notice this [2]. In this scenario, a promising approach is the sentiment analysis: the computational study of opinions, sentiments and emotions expressed in a text [3]. Its main aim is the identification of agreement or disagreement statements to capture positive or negative feelings in comments or reviews. Many scholars are investigating the adoption of Sentiment Analysis in E-Learning field [6]. An introduction to an opinion mining framework that can be manipulated to work in an e-learning system was presented by [7]. A promising
approach uses Conditional Random Fields for identifying and extracting the opinions; it considers the negative sentences and degree adverbs in sentiment processing [8]. The experiment has proved that it is with high analysis precision and accuracy on opinions’ extraction and sentiment analysis are helpful to the e-learning system. Another interesting approach is in [9] where a HMM and SVM-based hybrid learning sentiment classification algorithm has been introduced to classify the learner opinion regarding the e-learning system service to improve its performance. In [10] different possibilities aimed at automatically extracting emotions from texts have been explored: twelve essays written by a fresher student along her first semester in college are analyzed and investigated. The results support the idea of using non-intrusive emotion detection for providing feedback to students. In this paper, an approach for detecting the emotions of students in an e-learning environment by the use of the sentiment analysis is proposed. In particular, we investigate the adoption of an approach to sentiment analysis based on the Latent Dirichlet Allocation (LDA). In LDA, each document may be viewed as composed by a mixture of various topics. This is similar to probabilistic latent semantic analysis (pLSA), except that in LDA the topic distribution is assumed to have a Dirichlet prior. By the use of the LDA approach on a set of documents belonging to a same knowledge domain, a Mixed Graph of Terms can be automatically extracted [11][12]. Such a graph contains a set of weighted word pairs, which we demonstrate to be discriminative for sentiment classification. The proposed approach has been applied to a real case: the blended course of Software Technologies for the Web held in the University of Salerno’s Computer Science School. The organization of this paper is the following: in section 2 related works on sentiment analysis are discussed; section 3 discusses briefly the extraction of a Mixed Graphs of Terms from a document corpus and main features. Section 4 introduces the proposed approach while section 5 discusses experimental results.

II. RELATED WORKS

In literature, there are many approaches related to the sentiment analysis [4][5][25][24][23]. In particular, some approaches attempt to classify the sentiment at a document level. In [22] authors introduce an approach based on the algebraic sum of the orientation terms (positive or negative) for document classification. Starting from this approach other techniques have been developed [21]. Baroni [20] proposed to rank a large list of adjectives according to a subjectivity score by employing a small set of manually selected adjectives and computing the mutual information of pairs of them using frequency and co-occurrence frequency counts on the web. Starting from this approach many researchers developed "sentiment" lexicon. The work of Turney [19] proposes an approach to measure the semantic orientation of a given word based on the strength of its association with a set of context insensitive positive words minus the strength of its association with a set of negative words. By this approach sentiment lexicon can be built and a sentiment polarity score can be assigned to each word [18][17]. Artificial intelligence and probabilistic approaches have been adopted for the sentiment mining. In [16] three machine learning approaches (Naive Bayes, Maximum Entropy and Support Vector Machines) have been adopted to label the polarity of movie reviews. A promising approach has been developed in [15] where a novel methodology has been obtained by the combination of rule-based classification, supervised learning and machine learning. Another interesting approach is in [14] where a probabilistic model, the Sentiment Probabilistic Latent Semantic Analysis (S-PLSA), has been adopted [13]. The S-PLSA is an extension of the PLSA where it is assumed that there are a set of hidden semantic factors or aspects in the documents related to each other according to a probabilistic framework. In this paper the adopted approach is the one introduced in [4]. In the next paragraph the proposed approach will be described.

III. WHAT IS MIXED GRAPH OF TERMS?

In this section we explain how a Mixed Graph of Terms can be extracted from a corpus of documents. The Feature Extraction module (FE) is represented in Fig. 1. The input of the system is a set of documents.

After the pre-processing phase, which involves tokenization, stop words filtering and stemming, a Term Document Matrix is built to feed the Latent Dirichlet Allocation (LDA) [27] module. The LDA algorithm, assuming that each document is a mixture of a small number of latent topics and each word’s creation is attributable to one of the document’s topics, provides as output two matrices - and which express probabilistic relations between topic-document and word-topic respectively. Under particular assumptions [26], LDA module’s results can be used to determine: the probability for each word $v_i$ to occur in the corpus ($W_A$); the conditional probability between word pairs ($W_C$); the joint probability between word pairs ($W_l$). Details on LDA and probability computation can be found on [26]. Defining Aggregate roots (AR) as the words whose occurrence is most implied by the occurrence of other words of the corpus, a set of H aggregate root $r=(r_1,\ldots, r_H)$ can be determined in the following way:

$$r_i = \arg \max_{v_j} \prod_{j \neq i} P(v_i|v_j)$$  \hspace{1cm} (1)

This phase is referred as Root Selection (RS) in Fig. 1. A weight $\psi_{ij}$ can be defined as a degree of probabilistic correlation between AR pairs $\psi_{ij} = P(r_i, r_j)$. We define an aggregate as word $v_a$ having a high conditional dependency with an aggregate root $r_i$. Such a dependency can be expressed through the probabilistic weight $\rho_{ia} = P(r_i|v_a)$. Therefore, for each aggregate root, a set of aggregates can be selected according to the highest weight values. As result of the Root-Word level selection (RWS), an initial mGT structure, composed by H aggregate roots $R_l$ linked to all possible aggregates $W_l$ is obtained. An optimization phase allows neglecting weakly related pairs according to fitness function [26]. In particular, the proposed algorithm, given the number of aggregate roots $H$ and the desired max number of pairs as constraints, chooses the best parameter settings $\mathbf{T}$ and $\mu = (\mu_1,\ldots,\mu_H)$, defined as follows:

- $\mathbf{T}$: the threshold that establishes the number of aggregate root/aggregate root pairs. A relationship
between the aggregate root \( r_i \) and aggregate root \( r_j \) is relevant if \( \psi_{ij} \geq \tau \).

- \( \mu_i \): the threshold that establishes, for each aggregate root \( U_i \), the number of aggregate root/word pairs. A relationship between the word \( U_k \) and the aggregate root \( r_l \) is relevant if \( \rho_{kl} \geq \mu_i \).

A mixed graph of terms is then built from several clusters, each containing a set of words \( U_k \) (aggregates) related to an aggregate root \( r_l \), the centroid of the cluster. Some aggregate roots are also linked together building a centroids subgraph.

Figure 1. \textit{mGT Feature Extraction Module}

IV. SEARCHING THE SENTIMENT BY THE USE OF THE MIXED GRAPH OF TERMS

As described in the previous section, a Mixed Graph of Terms gives a compact representation of a set of documents related to a well-defined knowledge domain. In this way the obtained graph can be considered as a filter to be employed in document classification problems. The main aim of this paper is to show how mGT can be effectively applied for sentiment mining from texts: the proposed method can be used to build a sentiment detector able to label a document according its sentiment. Our system is composed by the following modules:

- **Mixed Graph of Terms building module**: this module builds a mixed graph of terms starting from a set of documents belonging to a well-defined knowledge domain and previously labeled according the sentiment expressed in them. In this way the obtained mixed graph of terms contains information about the words and their co-occurrences so representing a certain sentiment in a well-defined knowledge domain. As described in section 3 thanks to the LDA approach such a graph can be obtained by the use of a set of few documents. In figure 2 the module architecture and its main functional steps are depicted. The output of this module is a mixed graph of terms representing the documents and their sentiment. By feeding this module with positive or negative training sets, it will be possible to build mixed graphs of terms for documents that express positive or negative sentiment in a well-defined domain.

- **Sentiment Mining Module**: this module extracts the sentiment from a document thanks to the use of the Mixed Graph of Terms as a sentiment filter. The input of this module is a generic document, the mixed graph of terms representing positive and negative sentiment in a knowledge domain and the output is the sentiment detected in the input document.

Figure 2. \textit{Sentiment Analysis System Architecture mGT}

The sentiment extraction is obtained by a comparison between document and the mixed graph of terms according to the following algorithm:

\textbf{Sentiment Mining Algorithm}

**Input**: \( W = \{w_1, w_2, \ldots, w_N\} \) the words that are in a Document D belonging a knowledge domain K; the mixed graph of terms mGT, and mGT obtained analyzing documents related to the knowledge domain K expressing positive and negative sentiment; \( RW_+ = \{rw_1, rw_2, \ldots, rw_t\} \) the aggregator words that are in mGT; \( AW_+ = \{aw_1, aw_2, \ldots, aw_m\} \) the aggregated words that are in mGT; \( RW_- = \{rw_1, rw_2, \ldots, rw_n\} \) the aggregator words that are in mGT; \( AW_- = \{aw_1, aw_2, \ldots, aw_p\} \) the aggregated words that are in mGT, \( L \) an annotated lexicon

**Output**: Sentiment\(_D\) = \{Positive, Negative, Neutral\} the sentiment expressed in the document D

**Algorithm Description**

\[ f_p = 0; \quad f_n = 0; \]

**Determining the synonyms for each word belonging to the vector W**

for \( i = 0 \) -> Length\([W]\)

\[ WS = WS + \text{Synset}[L, W[i]]; \]
end for
W=W+WS

**Mining the sentiment from the document**

for i=0 -> Length[W]
    for k=0 -> Length[RW.]
        if(RW. [k] == W[i])
            f_p = f_p + 2;
        end if
    end for
    for k=0 -> Length[RW.]
        if(RW. [k] == W[i])
            v_f_n = f_n + 2;
        end if
    end for
    for k=0 -> Length[AW.]
        if(AW. [k] == W[i])
            f_p = f_p + 1;
        end if
    end for
    for k=0 -> Length[AW.]
        if(AW. [k] == W[i])
            f_n = f_n + 1;
        end if
    end for
end for

**Determining the Sentiment**

if f_p / f_n > 1.5
   Sentiment_D = Positive
else
   if f_n / f_p > 1.5
      Sentiment_D = Negative
   else
      Sentiment_D = Neutral
   end if
end if

The proposed algorithm requires the use of an annotated lexicon, as for example WordNet or ItalWordNet, for the retrieval of synonyms of the words contained in the document D and not included in the reference mGT. The retrieved synonyms are added to the vector W and analyzed according to the classification strategy. The proposed approach is effective in an asynchronous sentiment classification, but can work also in a synchronous way. In figure 3 the synchronous sentiment real time classificatory architecture is depicted. For real time working two new modules have been introduced:

- **Document Grabber.** This module aims to collect documents from web sources (social networks, blogs and so on). These documents can be collected both for updating the training set and for their classification according to the sentiment. The training set update is an important feature of the proposed approach. In this way, in fact, the various mGTs can be continuously updated and improve their discriminating power introducing new words and relations and deleting inconsistent ones.

- **Document Sentiment Classification.** The new documents inserted into the training set have to be classified by the support of an expert. The aim of this module is to provide a user friendly environment for the classification, according to their sentiment, of the retrieved documents.

![Figure 3. System Architecture for Synchronous Classification](image)

V. EXPERIMENTAL RESULTS

The evaluation of the proposed method has been conducted through two steps. Firstly the proposed approach has been applied on a standard dataset: the Movie Reviews Dataset [16]. The main aim of this experimentation was to evaluate method’s performance and make a comparison with the other approaches well known in literature. The experimentation has been conducted considering the 25% of the dataset as training set and the remaining 75% as test set. The obtained results and their comparison with other approaches are depicted in table 1. From the table 1 it can be observed that the proposed approach shows the best results from the point of view of accuracy.

<table>
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<tr>
<th>Reference</th>
<th>Methodology</th>
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The second experimental phase has been carried out using three different datasets. The experimental scenario involved the analysis of posts collected from the popular e-learning platform Moodle. In particular, the courses of Web Software Technologies (Period: September – December 2016, Number of Students: 63), Computer Networks (Period: March – July
2017, Number of Students: 27) and Introduction to Computer Science (Period: September – December 2016, Number of Students: 126) has been held by the use of a blended approach.

The courses has been organized in the following topics:

**Web Software Technologies**
- Apache Technologies
- XML Language
- HTML Language
- Servlet and JSP
- PHP Language
- Ajax

**Computer Networks**
- Introduction to Computer Networks
- Application Layer
- Transport Layer
- Network Layer
- Data-Link Layer
- Cyber Security

**Introduction to Computer Science**
- Introduction to Computer Architecture
- Operating Systems Architecture
- Algorithm
- C Language

For each topic a final test has been submitted to the students. The traditional lectures have been supported by the use of additional learning contents distributed by the use of Moodle. Chat and forum enhanced the collaborative approach of the course. Some twitter hashtags supported the courses. The contents exchanged by the use of forum and chat have been set not visible for the teacher and this policy was known by students. A Sentiment Analysis Module has been used for grabbing the mood of each student during the various lectures related to the various topics. The real time analysis of the comments furnished a sort of thermometer of the mood of classroom regarding to the various topics. In table 2 the number of the posts collected from the chat and the forum for each topic has been reported. Also the relative retrieved sentiment has been reported in terms of positive and negative percentage. The observation period expresses the length of the course’s section dedicated to a certain topic.

It is interesting to notice the increasing trend of the positive sentiment during the observation time. The reason of this trend is almost clear: at the beginning of each topic students showed a natural disorientation that is greater for topics related to new technologies or concepts. After these first phases teacher updated his teaching style according to the sentiment of the students giving them more contents or introducing more examples or exercises. For example, in the case of PHP language teacher introduced a series of solved exercises and this kind of support had a positive effect on the students. The same approach worked well in the case of C Language. The evaluation of sentiment, furthermore, can highlight the topics which are more complex for the students. In this way, at the end of the course teacher can improve the teaching approach. In general, teachers appreciated the Sentiment Grabber tool above all for the opportunity to manage the mood of the class without the filter of the relationship teacher – student.

**VI. Conclusions**

This paper proposes the use of the mixed graph of terms, obtained by the use of Latent Dirichlet Allocation approach, as tool for the sentiment classification of documents. The method relies on building the reference mGTs from documents labeled according their sentiment. The classification of a document can be conducted by using the reference nrGTs. The proposed method has been applied in the e-learning field for measuring the mood of a classroom towards some topics. Further development of this approach will include the introduction of annotated lexicon, as SentiWordnet, for a better sentiment evaluation of the words and the sentence structures.

**References**


**Figure 4.** Obtained Results. The Sentiment has been measured three times: at the beginning of a new topic, at the middle and at the end. The system measured Positive, Negative and Neutral mood. In the figure there are the percentage of Positive and Negative comments.

### Web Software Technologies

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<th>% Negative Mood</th>
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### Introduction to Computer Science

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