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Preface

Computational approaches to subjectivity and sentiment analysis: Present and envisaged methods and applications

Abstract

Recent years have witnessed a surge of interest in computational methods for affect, ranging from opinion mining, to subjectivity detection, to sentiment and emotion analysis. This article presents a brief overview of the latest trends in the field and describes the manner in which the articles contained in the special issue contribute to the advancement of the area. Finally, we comment on the current challenges and envisaged developments of the subjectivity and sentiment analysis fields, as well as their application to other Natural Language Processing tasks and related domains.

Keywords: Subjectivity analysis; Sentiment analysis; Multilingual resources; Social Media mining; Chat analysis

1. Introduction

Recent years have witnessed a surge of interest in computational methods for affect, ranging from opinion mining, to subjectivity detection, to sentiment and emotion analysis. These methods typically focus on the identification of private states, such as opinions, emotions, sentiments, evaluations, beliefs, and speculations in natural language. While subjectivity classification labels text as either subjective or objective, sentiment classification adds an additional level of granularity by further classifying subjective text as either positive, negative or neutral, which is then further refined by emotion analysis by identifying the presence of emotions such as joy, anger, or fear.

In computational linguistics, the automatic detection of affect in texts is becoming increasingly important from an applicative point of view. Consider for example the tasks of opinion mining, market analysis, or natural language interfaces such as e-learning environments or educational/edutainment games. For instance, the following represent examples of applicative scenarios in which affective computing could make valuable and interesting contributions:

- *Sentiment analysis*. Text categorization according to affective relevance, opinion exploration for market analysis, etc., are examples of applications of these techniques. While positive/negative valence annotation is an active area in sentiment analysis, a fine-grained emotion annotation could also contribute to the effectiveness of these applications.
- *Computer assisted creativity* The automated generation of evaluative expressions with a bias on certain polarity orientation is a key component in automatic personalized advertisement and persuasive communication.
- *Verbal expressivity in human–computer interaction* Future human–computer interaction is expected to emphasize naturalness and effectiveness, and hence the integration of models of possibly many human cognitive capabilities, including affective analysis and generation. For example, the expression of emotions by synthetic characters (e.g., embodied conversational agents) is now considered a key element for their believability. Affective words selection and understanding is crucial for realizing appropriate and expressive conversations.

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The articles contained in this special issue are in their majority the extended versions of the best articles (as reviewed by the Program Committee) that have been presented at the 3rd Workshop on Computational Approaches to Subjectivity and Sentiment Analysis (WASSA 2012) – http://gplsi.dlsi.ua.es/congresos/wassa2012/. The event was organized in conjunction to the 50th Annual Meeting of the Association for Computational Linguistics, on July 12, 2012, in Jeju, Republic of Korea.

This edition has again shown that both the academic, as well as the industry communities have a great interest in the topics covered by the workshop. The large number of submissions and the tough review process ensured a high quality of the papers selected for presentation at the event. As such, the articles that are contained in this special issue regard important challenges in subjectivity and sentiment analysis areas, advancing the state of the art in these fields. They cover topics such as: multilingual sense subjectivity, multilingual sentiment analysis, lexicon and corpora building for subjectivity and sentiment analysis, emotion detection and contextuality and the applications of subjectivity and sentiment analysis to the detection of social and psychological phenomena. The types of texts on which the analysis is done vary from newspaper articles, to blogs and Social Media messages, thus exploring also the challenges posed by the structure of each of these text types.

In the following section, we present some of the most relevant work that has been recently conducted in subjectivity and sentiment analysis and describe the research trends in this field.

2. Recent trends in subjectivity and sentiment analysis

Subjectivity and sentiment analysis have been very active research topics in the past decade. Different authors have proposed methods to tackle the tasks from various types of texts and with diverse applications. Although much has been achieved in the field, some aspects still require additional tackling and further efforts are needed to expand the results to the multilingual and cross-lingual settings and new, informal types of texts. The articles contained in this special issue represent an advancement to the state of the art in this sense, as they deal with approaches to the above-mentioned issues. Their efforts are inscribed in the recent trends in the field, represented by related work described in the following subsections.

2.1. Multilingual subjectivity and sentiment analysis

The first aspect on which subjectivity and sentiment analysis (SSA) requires further efforts is related to the analysis of multilingual texts. The manual annotation of resources is a tedious and costly task, therefore very few task-specific corpora and dictionaries for SSA exist. In order to overcome this problem, researchers have proposed methods to adapt existing resources and tools for sentiment analysis developed for English to build resources in other languages. In this sense, lexicons, annotation schemes and annotated corpora were transferred to new languages using bilingual dictionaries, monolingual and multilingual bootstrapping or machine translation.

Existing English subjectivity and sentiment lexicons were transferred into Chinese (Ku et al., 2006), Romanian (Mihalcea et al., 2007), and Italian (Esuli and Sebastiani, 2011). In an early work, Kim and Hovy (2006) use a machine translation system and subsequently employ a subjectivity analysis system that was developed for English to create subjectivity analysis resources in other languages. Ahmad et al. (2007) use the topical distributions in different languages to detect important sentiment phrases in a multilingual setting, starting from the idea that words with a lower frequency are more representative of the topic and searching for sentiment-related terms around those. Inui and Yamamoto (2011) employ machine translation and, subsequently, sentence filtering to eliminate the noise obtained in the translation process, based on the idea that sentences that are translations of each other should contain sentiment-bearing words that have the same polarity. Mihalcea et al. (2007) propose a method to learn multilingual subjective language via cross-language projections. They use the Opinion Finder lexicon (Wilson et al., 2005) and use two bilingual English-Romanian dictionaries to translate the words in the lexicon. Another approach was proposed by Banea et al. (2008). To this aim, the authors perform three different experiments – translating the annotations of the MPQA corpus, using the automatically translated entries in the Opinion Finder lexicon and the third, validating the data by reversing the direction of translation. In a further approach, Banea et al. (2008) apply bootstrapping to build a subjectivity lexicon for Romanian, starting with a set of 60 words which they translate and subsequently filter using a measure of similarity to the original words, based on Latent Semantic Analysis (LSA) Deerwester et al. (1990) scores. Yet another approach to mapping subjectivity lexicons to other languages is proposed by Xiaojun (2009), who uses co-training to classify un-annotated Chinese reviews using a corpus of annotated English reviews. He first translates the English reviews into Chinese and subsequently back to English. He then performs co-training using all generated corpora. Kim et al. (2010) create a number of systems consisting of different subsystems, each classifying the subjectivity of texts in a different language. They translate a corpus annotated for subjectivity analysis (MPQA), the subjectivity clues (Opinion Finder) lexicon and re-train a Naïve Bayes classifier that is implemented in the Opinion Finder system using the newly generated resources for all the languages considered. Banea et al. (2010) translate the MPQA corpus into five other languages (some with a similar ethimology, others with a very different structure). Subsequently, they expand the feature space used in a Naïve Bayes classifier using the same data translated to 2 or 3 other languages. Another type of approach was proposed by Bader et al. (2011), who use Latent Semantic Indexing as a manner to bridge between the concepts in different languages. Finally, Steinberger et al. (2011a,b) create sentiment dictionaries in other languages using a method called "triangulation". They translate the data, in parallel, from English and Spanish to other languages and obtain dictionaries from the intersection of these two translations.

2.2. Subjectivity and sentiment analysis in Social Media

The second important aspect which challenges SSA applications is the type of texts for which they are designed. In the past years, the influence of Social Media sites such as Twitter or Facebook has constantly grown. These platforms, with millions of active users, are employed as a manner to convey short messages with comments on present events, preferences, opinions, emotions, etc. As such, they are very useful at the time of obtaining unbiased, real-time opinions about different topics ranging from politics, to economics and everyday life. Thus, the automatic analysis of the opinions conveyed in these social platform has become an important direction for the research in SSA. One of the first studies on the classification of polarity in tweets was done by Go et al. (2009). The authors conducted a supervised classification study on tweets in English, using the emoticons (e.g. ":)", ":(", etc.) as markers of positive and negative tweets. Read (2005) employed this method to generate a corpus of positive tweets, with positive emoticons ":)", and negative tweets with negative emoticons ":(". Subsequently, they employ different supervised approaches (SVM, Naïve Bayes and Maximum Entropy) and various sets of features and conclude that the simple use of unigrams leads to good results, but it can be slightly improved by the combination of unigrams and bigrams. In the same line of thinking, Pak and Paroubek (2010) also generated a corpus of tweets for sentiment analysis, by selecting positive and negative tweets based on the presence of specific emoticons. Subsequently, they compare different supervised approaches with n-gram features and obtain the best results using Naïve Bayes with unigrams and part-of-speech tags.

Another approach on sentiment analysis in tweet is that of Zhang et al. (2011). Here, the authors employ a hybrid approach, combining supervised learning with the knowledge on sentiment-bearing words, which they extract from the DAL sentiment dictionary (Whissell, 1989). Their pre-processing stage includes the removal of retweets, translation of abbreviations into original terms and deleting of links, a tokenization process, and part-of-speech tagging. They employ various supervised learning algorithms to classify tweets into positive and negative, using n-gram features with SVM and syntactic features with Partial Tree Kernels, combined with the knowledge on the polarity of the words appearing in the tweets. The authors conclude that the most important features are those corresponding to sentiment-bearing words. Finally, Jiang et al. (2011) classify sentiment expressed on previously given "targets" in tweets. They add information on the context of the tweet to its text (e.g. the event that it is related to). Subsequently, they employ SVM and General Inquirer and perform a three-way classification (positive, negative, neutral).

3. Special issue articles and their contribution to advancing research in subjectivity and sentiment analysis

In the following paragraphs, we briefly describe the ideas and contributions to the advancements of the state of the art brought by each of the articles included in the special issue:

- The first article is entitled "Sense-level Subjectivity in a Multilingual Setting", and is authored by Carmen Banea, Rada Mihalcea and Janyce Wiebe. This contribution deals with the issue of subjectivity classification in a multilingual setting. Particularly, the authors start from findings that subjectivity is a property that is better captured at the level of word senses and study whether this property can be transferred across different languages, in an automatic manner. Following an initial study on aligned word senses in WordNet, in which this hypothesis was confirmed, the authors design different learning mechanisms to exploit multilingual data to predict the subjectivity of a word sense.

The results of the evaluations show that learning from multilingual data improves the performance of subjectivity classification when compared to monolingual baselines.

- The second contribution of the special issue is "SAMAR: Subjectivity and Sentiment Analysis for Arabic Social Media" – Muhammad Abdul-Mageed, Mona Diab, Sandra Kuebler. The paper describes a system for subjectivity and sentiment analysis for Arabic – a language with a very rich morphology. The aim is to study how to represent lexical information in such a language and to adapt the features that are currently being used on English data. Additionally, the authors explore the issue of adapting the proposed method to existing dialects and various textual genres. Their extensive evaluations show that in the case of rich morphology languages, the use of lemmatization and POS-tagging is a necessary step and that dealing with different text types requires significant adaptations.
- The paper by Michal Ptaszynski, Rafal Rzepka, Kenji Araki and Yoshio Momouchi, entitled "Automatically Annotating a Five-Billion-Word Corpus of Japanese Blogs for Sentiment and Affect Analysis" deals with the issue of annotating large corpora with subjectivity, sentiment polarity and emotion information. In the present study, a five-billion word corpus is annotated at the word and sentence levels of granularity. The authors choose a large existing corpus and apply an existing sentiment and emotion classification system – ML-Ask, and an emotion detection system based on emoticons – CAO. These systems have been previously evaluated and were shown to have a high precision. In large annotated corpora, precision is more important than recall. The corpus thus obtained is evaluated in different contexts: emotion annotation, comparisons to other annotated corpora and emotion ontology generation to retrieve moral consequences of actions. The high level of performance obtained in these evaluations show that this is a useful and reliable resource.
- Following the efforts to develop and apply multilingual sentiment analysis systems, Alexandra Balahur and Marco Turchi perform "Comparative Experiments Using Supervised Learning and Machine Translation for Multilingual Sentiment Analysis". The paper describes experiments to use machine translation to obtain multilingual data and supervised learning to classify sentiment. The authors quantify the effect of translation quality on the performance of the sentiment classification, using three different machine translation systems and various features, algorithms and meta-classifiers for polarity detection. The evaluations show that machine translation systems are mature enough to be employed as a means to obtain quality multilingual data for sentiment analysis.
- The fifth contribution to the special issue is the article "Prior and Contextual Emotion of Words in Sentential Context", by Diman Ghazi, Diana Inkpen and Stan Szpakowicz. In this article, the authors explore the issue of assigning words with prior or contextual emotion labels and subsequently classify sentences into Ekman's 6 classes of emotions. They explore different types of features: dictionaries of words with assigned emotion and polarity values, part-of-speech features and syntactic dependency features. Following experiments employing the different features separately and jointly, the authors show that emotion detection can be best performed combining all considered features, although good results are also obtained using combinations thereof.
- The next paper describes a "Ranked WordNet Graph for Sentiment Polarity Classification in Twitter" (Arturo Montejo-Ráez, Eugenio Martínez-Cámara, M. Teresa Martín-Valdivia, L. Alfonso Ureña-López). The method proposed combines SentiWordNet scores with a random walk analysis of the concepts found in the text over the WordNet graph. The approach is compared with simple scoring of sentences based on the values assigned to individual concepts in SentiWordNet and also with supervised learning using Support Vector Machines. They show that such an unsupervised approach can obtain similar results to SVM, without requiring annotated training corpora and being applicable to any domain.
- Finally, the article by Dasha Bogdanova, Paolo Rosso and Thamar Solorio, entitled "Exploring High-Level Features for Detecting Cyberpedophilia" presents an application of sentiment analysis to the present challenge of minors' safety in virtual environments: on-line chats and their misuse by paedophiles. The authors propose the use of specific emotion indicators pinpointed by correlated research in the psychology of individuals with paedophile inclinations and show that features tailored taking these aspects into account can more precisely identify abuse in chats.

4. Challenges and envisaged developments

Although much work has been carried out in the field of subjectivity and sentiment analysis, there are still many challenges to be overcome. First of all, as the papers in this special issue have shown, the approaches proposed in the field still require adaptation and much work to be done in order to be employed to other languages. Secondly, as new text types appear on the Social Web, the techniques to pre-process, as well as to tackle their informal style must be adapted, so as to obtain acceptable levels of performance of the subjectivity and sentiment analysis systems. Finally, given that these systems have been shown to be of real use to existing NLP, but also other types of social and economic applications, further challenges are posed by their adaptation from academic applications to industrial ones.

In the near future, we envisage that apart from the technical improvements brought by the creation of new resources and more powerful supervised algorithms, the field will also englobe more of the existing research in the affective computing, linguistic theory, psychology and neuroscience fields, converging together to a unified methodology to tackle automatic human affect detection and simulation.

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