The CLSA Model: A Novel Framework for Concept-Level Sentiment Analysis

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Abstract. Hitherto, sentiment analysis has been mainly based on algorithms relying on the textual representation of online reviews and microblogging posts. Such algorithms are very good at retrieving texts, splitting them into parts, checking the spelling, and counting their words. But when it comes to interpreting sentences and extracting opinionated information, their capabilities are known to be very limited. Current approaches to sentiment analysis are mainly based on supervised techniques relying on manually labeled samples, such as movie or product reviews, where the overall positive or negative attitude was explicitly indicated. However, opinions do not occur only at document-level, nor they are limited to a single valence or target. Contrary or complementary attitudes toward the same topic or multiple topics can be present across the span of a review. In order to overcome this and many other issues related to sentiment analysis, we propose a novel framework, termed concept-level sentiment analysis (CLSA) model, which takes into account all the natural-language-processing tasks necessary for extracting opinionated information from text, namely: microtext analysis, semantic parsing, subjectivity detection, anaphora resolution, sarcasm detection, topic spotting, aspect extraction, and polarity detection.

1 Introduction

Concept-level sentiment analysis is a natural-language-processing (NLP) task that has recently raised growing interest both within the scientific community, leading to many exciting open challenges, as well as in the business world, due to the remarkable benefits to be had from financial market prediction. The potential applications of concept-level sentiment analysis, in fact, are countless and span interdisciplinary areas such as political forecasting, brand positioning, and human-robot interaction.

For example, Li et al. [54] implemented a generic stock price prediction framework and plugged in six different models with different analyzing approaches. They used Harvard psychological dictionary and Loughran-McDonald financial sentiment dictionary to construct a sentiment space. Textual news articles were then quantitatively measured and projected onto such a sentiment space. The models' prediction accuracy was evaluated on five years historical Hong Kong Stock Exchange prices and news articles and their performance was compared empirically at different market classification levels.

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Rill et al. [90] proposed a system designed to detect emerging political topics in Twitter sooner than other standard information channels. For the analysis, authors collected about 4 million tweets before and during the parliamentary election 2013 in Germany, from April until September 2013. It was found that new topics appearing in Twitter can be detected right after their occurrence. Moreover, authors compared their results to Google Trends, observing that the topics emerged earlier in Twitter than in Google Trends.

Jung and Segev [49] analyzed how communities change over time in the citation network graph without additional external information and based on node and link prediction and community detection. The identified communities were classified using key term labeling. Experiments showed that the proposed methods can identify the changes in citation communities multiple years in the future with performance differing according to the analyzed time span.

Montejo-Raez et al. [66] introduced an approach to sentiment analysis in social media environments. Similar to explicit semantic analysis, microblog posts were indexed by a predefined collection of documents. In the proposed approach, performed by means of latent semantic analysis, these documents were built up from common emotional expressions in social streams.

Bell et al. [5] proposed a novel approach to social data analysis, exploring the use of microblogging to manage interaction between humans and robots, and evaluating an architecture that extends the use of social networks to connect humans and devices. The approach used NLP techniques to extract features of interest from textual data retrieved from a microblogging platform in real-time and, hence, to generate appropriate executable code for the robot. The simple rule-based solution exploited some of the 'natural' constraints imposed by microblogging platforms to manage the potential complexity of the interactions and to create bi-directional communication.

All current approaches to sentiment analysis focus on just a few issues related to processing opinionated text, the most common being polarity detection. However, there are many NLP problems that need to be solved –at the same time– to properly deconstruct opinionated text into polarity values and opinion targets. Detecting a polarity from a document without deconstructing this into specific aspects, for example, is pointless as we may end up averaging positive and negative polarity values associated to different product features. Moreover, we may have the best polarity detection tool on the market but, if this is unable to recognize sarcasm, it could infer a completely wrong polarity.

To this end, we propose the CLSA model (Fig. 1) as reference framework for researchers willing to take a more holistic and semantic-aware approach to sentiment analysis, which also applies to the multimodal realm [82]. The main contributions of the proposed model are that (a) it promotes the analysis of opinionated text at concept-, rather than word-, level and (b) it takes into account all the NLP tasks necessary for extracting opinionated information from text. The rest of the paper consists of an overview of the CLSA model (Section 2), followed by a description of each constituting module of the model, namely: microtext analysis (Section 3), semantic parsing (Section 4), subjectivity detection (Section 5), anaphora resolution (Section 6), sarcasm detection (Section 7), topic spotting (Section 8), aspect extraction (Section 9), and polarity detection (Section 10). Section 11, finally, offers concluding remarks.

2 Model Overview

Sentiment analysis is a ‘suitcase’ research field that contains many different areas, not only related to computer science but also to social sciences, e.g., sociology, psychology, and ethics. The CLSA model focuses on the computational foundations of sentiment analysis research to determine eight key NLP tasks or modules, that are necessary for the correct interpretation of opinionated text, namely:

1. Microtext analysis, for normalizing informal and irregular text (Section 3)
2. Semantic parsing, for deconstructing natural language text into concepts (Section 4)
3. Subjectivity detection, for filtering non-opinionated or neutral text (Section 5)
4. Anaphora resolution, for resolving references in the discourse (Section 6)
5. Sarcasm detection, for detecting sarcastic opinions and flip their polarity (Section 7)
6. Topic spotting, for contextualizing opinions to a specific topic (Section 8)
7. Aspect extraction, for deconstructing text into different opinion targets (Section 9)
8. Polarity detection, for detecting a polarity value for each opinion target (Section 10)

3 Microtext Analysis

Due to the exponential growth of social media, an increasing number of applications, e.g., Web mining, Internet security, cyber-issue detection, and social media marketing, need microtext feature selection and classification.

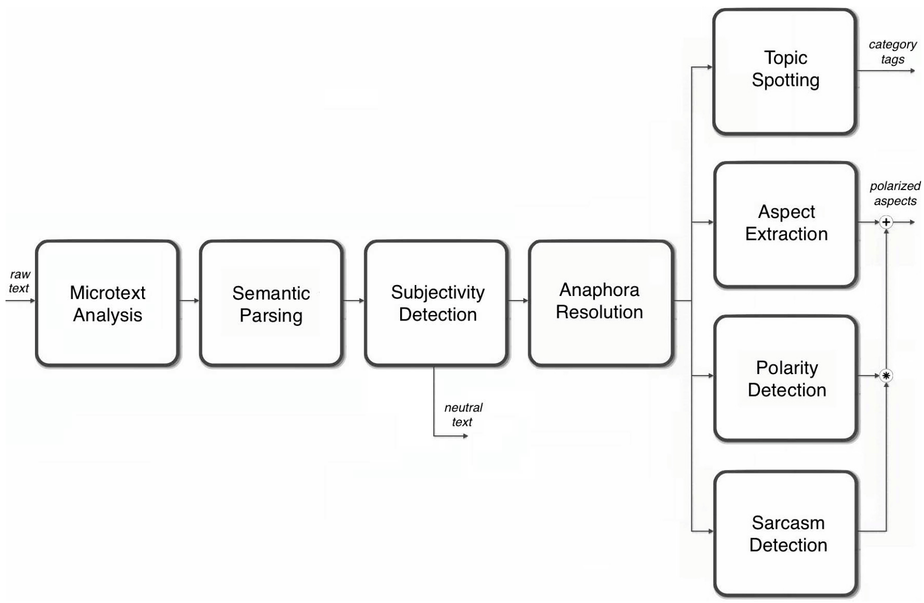

Fig. 1. The CLSA model

Existing sentiment resources developed on non-microblogging data, in fact, turn out to be very inaccurate on informal text [52]. Some of the fundamental characteristics of microtext are a highly relaxed spelling and the reliance on abbreviations, acronyms, and emoticons [89]. This causes problems when trying to apply traditional NLP tools and techniques, e.g., information extraction, automated summarization, and text-to-speech, which have been developed for conventional English text. It could be thought that a simple find-and-replace pre-processing on the microtext would solve that problem. However, the sheer diversity of spelling variations makes this solution impractical; for example, a sampling of Twitter studied in [57] found over 4 million out-of-vocabulary words. Moreover, new spelling variations are created constantly, both voluntarily and accidentally.

The challenge of developing algorithms to correct the non-standard vocabulary found in microtexts is known as text message normalization. The first step in tackling this challenge is to realize that the number of different spelling variations may be massive but they follow a small number of simple basic strategies [57], such as `abbreviation` and `phonetic substitution`. In [111], authors used web blogs to create a corpus for sentimental analysis and exploited emoticons as mood indicators. They used support vector machine (SVM) and conditional random field (CRF) learners to classify sentiments at sentence-level and investigated various strategies to infer the overall sentiment of documents. Later, many other works proposed to do the same using Twitter sentiment [46,72] and buzz [46,74,72]. More recent studies [52,28,65,24] exploit Twitter-specific features such as emoticons, hashtags, URLs, @symbols, capitalizations, and elongations to better detect polarity from microblogging text.

While most of the literature on Twitter sentiment analysis refers to supervised learning, unsupervised approaches [101,75] have recently gained increasing popularity. This is because less number of training data are available for Twitter sentiment analysis and it is practically impossible to train the system every time new data come in. Usually, unsupervised approaches to sentiment analysis involve the creation of a sentiment lexicon in an unsupervised manner first, and then the detection of polarity of unseen text using a function dependent on the number of positive and negative words contained in the input text. [47] proposed an unsupervised graph-based approach to enable target-dependent polarity detection, i.e., the inference of positive or negative polarity associated to a specific target in a query.

4 Semantic Parsing

Concept-level sentiment analysis [12,13,14,85] focuses on the semantic analysis of text [39] through the use of web ontologies or semantic networks, which allow the aggregation of the conceptual and affective information associated with natural language opinions. By relying on large semantic knowledge bases, such approaches step away from the blind use of keywords and word co-occurrence count, but rather rely on the implicit features associated with natural language concepts. Unlike purely syntactical techniques, concept-based approaches are able to detect also sentiments that are expressed in a subtle manner, e.g., through the analysis of concepts that do not explicitly convey any emotion, but which are implicitly linked to other concepts that do so.

The bag-of-concepts model can represent semantics associated with natural language much better than bags-of-words [17]. In the bag-of-words model, in fact, a concept such as `cloud computing` would be split into two separate words, disrupting the semantics of the input sentence (in which, for example, the word `cloud` could wrongly activate concepts related to `weather`). Concept extraction is one of the key steps of automatic concept-level text analysis. [19] used domain specific ontologies to acquire knowledge from text. Using such ontologies, the authors extracted 1.1 million common-sense knowledge assertions.

Concept mining is useful for tasks such as information retrieval [87], opinion mining [16], text classification [112]. State-of-the-art approaches mainly exploit term extraction methods to obtain concepts from text. These approaches can be classified into two main categories: linguistic rules [22] and statistical approaches [114,1]. [114] used term frequency and word location and, hence, employed a non-linear function to calculate term weighting. [1] mined concepts from the Web by using webpages to construct topic signatures of concepts and, hence, built hierarchical clusters of such concepts (word senses) that lexicalize a given word. [32] and [103] combined linguistic rules and statistical approaches to enhance the concept extraction process.

Other relevant works in concept mining focus on concept extraction from documents. Gelfand et al. [35] have developed a method based on the Semantic Relation Graph to extract concepts from a whole document. They used the relationship between words, extracted from a lexical database, to form concepts. Nakata [70] has described a collaborative method to index important concepts described in a collection of documents. [81] proposed an approach that uses dependency-based semantic relationships between words. [86] used a knowledge-based concept extraction method relying on a parse graph and a common-sense knowledge base, coupled with a semantic similarity detection technique allowing additional matches to be found for specific concepts not present in the knowledge base.

Lexico-syntactic pattern matching is also a popular technique for concept extraction. [40] extracted hyponomy relations from text from Grolier's Encyclopedia by matching four given lexico-syntactic patterns. Her theory explored a new direction in the field of concept mining. She claimed that existing hyponomy relations can be used to extract new lexical syntactic patterns. [58] and [59] used the "is-a" pattern to extract Chinese hyponymy relations from unstructured Web corpora and obtained promising results.

5 Subjectivity Detection

Subjectivity detection aims to automatically categorize text into subjective or opinionated (i.e., positive or negative) versus objective or neutral and is hence useful to analysts in government, commercial and political domains who need to determine the response of the people to different events [98,9]. Linguistic pre-processing can be used to identify assertive sentences that are objectively presented and remove sentences that are mere speculations and, hence, lack sentiments [69]. This is particularly useful in multi-perspective question-answering summarization systems that need to summarize different opinions and perspectives and present multiple answers to the user based on opinions derived from different sources.

Previous methods used well established general subjectivity clues to generate training data from un-annotated text [91]. In addition, features such as pronouns, modals, adjectives, cardinal numbers, and adverbs have shown to be effective in subjectivity classification. Some existing resources contain lists of subjective words, and some empirical methods in NLP have automatically identified adjectives, verbs, and N-grams that are statistically associated with subjective language. However, several subjective words such as 'unseemingly' occur infrequently, consequently a large training dataset is necessary to build a broad and comprehensive subjectivity detection system.

While there are several datasets with document and chunk labels available, there is a need to better capture sentiment from short comments, such as Twitter data, which provide less overall signal per document. Hence, in [91], authors used extraction pattern learning to automatically generate linguistic structures that represent subjective expressions. For example, the pattern 'hijacking' of $< x >$, looks for the noun 'hijacking' and the object of the preposition $< x >$. Extracted features are used to train state-of-the-art classifiers such as SVM and Naïve Bayes that assume that the class of a particular feature is independent of the class of other features given the training data [108].

Sentence-level subjectivity detection was integrated into document-level sentiment detection using minimum cuts in graphs where each node is a sentence. The graph cuts try to minimize the classification error of a baseline classifier, e.g., Naïve Bayes, over sentences. The contextual constraints between sentences in a graph could lead to significant improvement in polarity classification [76]. On the other hand, bag-of-words classifiers represent a document as a multi set of its words disregarding grammar and word order. They can work well on long documents by relying on a few words with strong sentiments like 'awesome'. However, distributional similarities of words, such as co-occurrence matrix and context information, are unable to capture differences in antonyms. This is a problem typical of sentiment analysis, as semantic similarity and affective similarity are often different from each other, e.g., `happy` and `sad` are two similar concepts in a semantic sense (as they are both emotions) but they are very different in an affective sense as they bear opposite polarities.

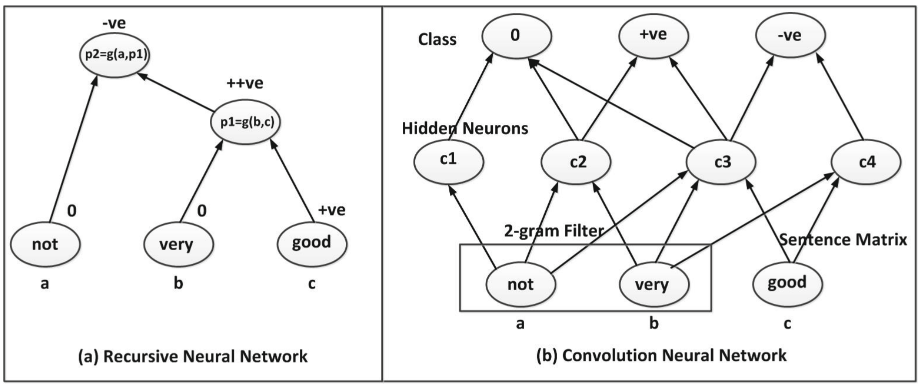

Fig. 2. Example of subjectivity detection using (a) Recursive NN (b) Convolution NN

Several works have explored sentiment compositionality through careful engineering of features or polarity shifting rules on syntactic structures. However, sentiment accuracies for binary positive/negative classification for single sentences has not exceeded 80% for several years. When including a third 'neutral' class, the accuracy falls down to only 60%. It can be seen that many short n-grams are neutral while longer phrases are well distributed among positive and negative subjective sentence classes. Therefore, matrix representations for long phrases and matrix multiplication to model composition are being used to evaluate sentiment.

In such models, sentence composition is modeled using deep neural networks such as recursive auto-associated memories [50,36]. Recursive neural networks (RNN) predict the sentiment class at each node in the parse tree and try to capture the negation and its scope in the entire sentence. In the standard recursive neural network, each word is represented as a vector and it is first determined which parent already has all its children computed. Next, the parent is computed via a composition function over child nodes. In the RNN matrix, the composition function for long phrases depends on the words being combined and hence is linguistically motivated.

However, the number of possible composition functions is exponential. Hence, [93] introduced a recursive neural tensor network that uses a single tensor composition function to define multiple bilinear dependencies between words. Fig. 2 (a) illustrates the state space of a recursive neural network. Parent feature vectors are computed in a bottom-up manner by combining child nodes using composition function g. The polarity at each node is determined using its feature vector and a baseline classifier. Fig. 2 (b) illustrates the state space of a convolution neural network, where the input are feature vectors of words and the hidden neurons use convolution filters to detect patterns. Each neuron in the output layer corresponds to a single polarity type.

6 Anaphora Resolution

Anaphora can be defined as the presupposition that points back to some previous item. The pointing back reference is called anaphor and the entity to which it refers is its antecedent. The process of determining the antecedent of an anaphor is called anaphora resolution. Anaphora resolution is an open NLP challenge that needs to be tackled in many domains, including machine translation, summarization, question-answering systems and sentiment analysis. In machine translation, for example, anaphora must be resolved to disambiguate pronouns and develop a reliable machine translation algorithm. Current machine translation systems usually do not go beyond sentence level, thus failing a complete discourse understanding. Automatic text summarization systems, instead, need anaphora resolution for the selection of meaningful sentences in text. Because such systems often select salient sentences based on the words or concepts these contain, in fact, they may miss key sentences that use anaphoric expressions to provide important information about previously mentioned topics.

There are various types of anaphora. The most widespread ones are: pronominal anaphora, which is realized by anaphoric pronouns; adjectival anaphora, realized by anaphoric possessive adjectives; and one-anaphora, the anaphoric expression is realized by a "one" noun phrase (Fig. 3).

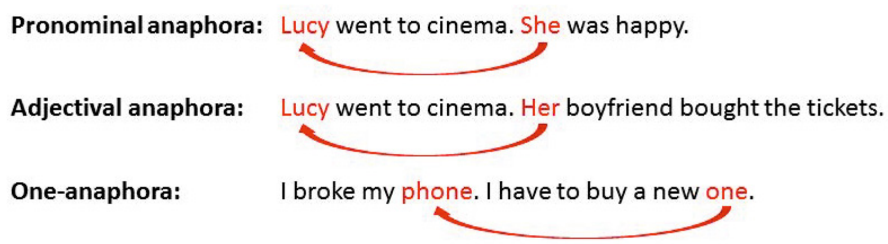

Fig. 3. Different types of anaphora

When resolving anaphora, some constraints must be respected:

- Number agreement: it is necessary to distinguish between singular and plural references.
- Gender agreement: it is necessary to distinguish between male, female, and neutral genders.
- Semantic consistency: it is assumed that both the antecedent clause and the one containing the anaphora are semantically consistent.

Grammatical, syntactic or pragmatic rules have been widely used in the literature to identify the antecedent of an anaphor. Hobbs' algorithm [41] searches parse trees (i.e., basic syntactic trees) for antecedents of a pronoun. After searching the trees, it checks the number and gender agreement between a specified pronoun and its antecedent candidates. The method proposed by Lappin and Leass [53], termed Resolution of Anaphora Procedure (RAP), is a discourse model in which potential referents have degrees of salience. In particular, authors try to solve pronoun references by finding highly salient referents compatible with pronoun agreement features. [51] proposed a modified version, which is based on part-of-speech tagging with a shallow syntactic parse indicating grammatical rules. The centering theory [11] is based on the presence and the consequent searching of a focus, or center, of the discourse and on the assumption that subsequent pronouns have the strong tendency to refer to it. In [20], a distance metric function is introduced to calculate the similarity between two noun phrases.

The Anaphora Matcher proposed by [30] embeds semantic knowledge in anaphora resolution, by means of the lexical database WordNet, used to acquire semantic information about words in sentences. However, the algorithm still focuses on words and not on concepts, thus losing the possibility to connect a pronoun to a general, multi-word concept (e.g., 'Lucy went to cinema. It was amazing', the concept `go to the cinema` cannot be related to the pronoun using only words). An alternative to the syntactical constraints is represented by the statistical approach introduced by [26]. In order to match the anaphor, the model uses the statistical information represented by the frequencies of patterns obtained from a selected corpus to find the antecedent candidate with the highest frequency. CogNIAC (COGnition eNIAC) [3] solves the association of pronouns with limited knowledge and linguistic resources. It achieves high precision for some pronouns.

In [63], the input is checked against agreement and for a number of so-called antecedent indicators. Candidates are assigned scores by each indicator and the candidate with the highest score is returned as the antecedent. [4] offers an evaluation environment for comparing anaphora resolution algorithms. [64] presents the system MARS, which operates in fully automatic mode and employs genetic algorithms to achieve optimal performance. In [55], the resolution of anaphora is achieved by employing both the WordNet ontology and heuristic rules. The percentage of correctly resolved anaphors reaches almost 80%.

7 Sarcasm Detection

Sarcasm is always directed at someone or something. A target of sarcasm is the person or object against whom or which the ironic utterance is directed. Targets can be the sender himself, the addressee or a third party (or a combination of the three). The presence of sarcastic sentences may completely change the meaning of the whole review, therefore misleading the interpretation of the review itself.

While the use of irony and sarcasm is well studied from its linguistic and psychologic aspects, sarcasm detection is still represented by very few works in the computational literature. [79] suggested a theoretical framework in which the context of sentiment words shifts the valence of the expressed sentiment. This is made on the assumption that, though most salient clues about attitude are provided by the lexical choice of the writer, the organization of the text also provides relevant information for assessing attitude. To this end, authors described how the base attitudinal valence of a lexical item is modified by lexical and discourse context and propose a simple implementation for some contextual shifters. In [100], a semi-supervised algorithm for sarcasm identification in product reviews is proposed. The authors proposed a set of pattern-based features to characterize sarcastic utterances, combined with some punctuation-based features. The experiments were performed on a dataset of about 66,000 Amazon reviews, and a precision of 77% and recall of 83.1% were obtained in the identification of sarcastic sentences. [29] extended this approach to a collection of 5.9 million tweets and 66,000 product reviews from Amazon, obtaining F-scores of 0.78 and 0.83, respectively.

Their algorithmic methodology is based on patterns. In order to extract such patterns automatically, they classified words into high-frequency words and content words. After filtering these patterns, other generic features are added: sentence length in words, number of “!” and "?" characters in the sentence, number of quotes in the sentence, and number of capitals words in the sentence. Then, they employed a k-nearest neighbors (kNN)-like strategy for the classification task. In [56], a classifier is trained for the detection of Dutch tweets, by exploiting the use of intensifiers such as hyperbolic words, which are able to strengthen the sarcastic utterance. [38] proposed a method for the identification of sarcasm in Twitter, where each message is codified based on lexical and pragmatic factors, the former including unigrams and dictionary-based factors, the latter combining positive and negative emoticons and tweet replies. The authors then employed and compared performances of SVM and logistic-regression machines used for the classification task.

8 Topic Spotting

Topic spotting or auto-categorization is about classifying or tagging a piece of text with one or more category labels. Unlike topic modeling, topic spotting does not focus on clustering the words of a large text corpus into set of topics but rather giving a context to the input text. In other words, topic spotting is more similar to short text conceptualization than topic modeling (which is inapplicable to short texts). Let us consider the multi-word statement `score grand slam`, taken as an unit, it is obviously related to tennis, however word-by-word passes on very surprising semantics. Correspondingly, in a bag-of-words model, the expression `get withdrawn` would not convey the meaning `withdraw from a bank`. Psychologist Gregory Murphy began his highly acclaimed book [68] with the statement "Concepts are the glue that holds our mental world together". Still, Nature magazine book review calls it an understatement because "Without concepts, there would be no mental world in the first place"[8].

Undoubtedly, the ability to conceptualize is a defining characteristic of humanity. We focus on conceptualizing from texts or words. For example, given the word "India," a person will form in his mind concept such as a country or region. Given two words, "India" and "China," the top concepts may shift to an Asian country or a developing country, etc. Given yet another word, "Brazil," the top concept may change to BRIC or an emerging market and so forth (Fig. 4). Besides generalizing from instances to concepts, human beings also form concepts from descriptions. For example, given the words 'body', 'smell' and 'color', the concept 'wine' comes to our mind. Certainly, instances and descriptions may get mixed up, for example, we conceptualize 'apple' and 'headquarters' to a company but 'apple', 'smell' and 'color' to a fruit.

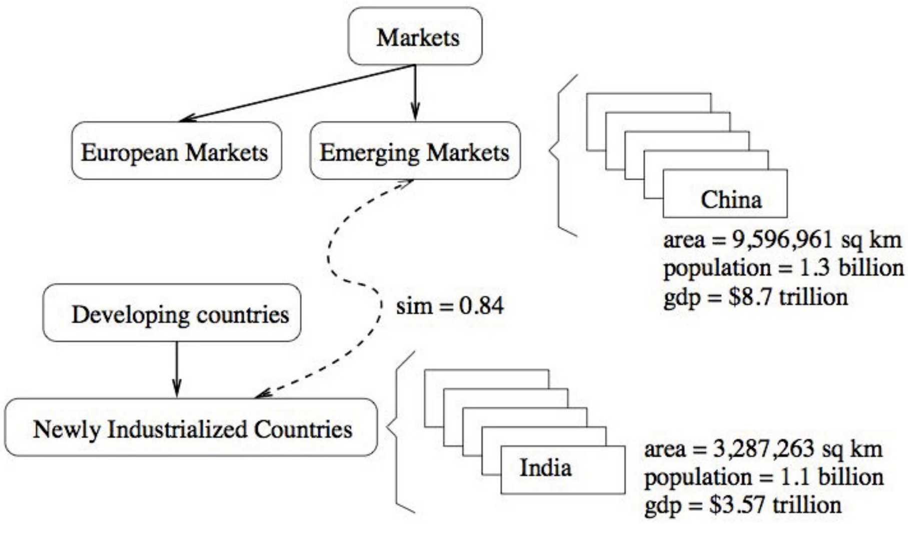

Fig. 4. Context-based short text conceptualization

The question is whether machines can do it. Much work has been devoted to the topic discovery from a text. The task of classifying the textual data that has been culled from sites on the World Wide Web is both difficult and intensively studied [25,48,71]. [96] proposed a bag-of-words model to classify tweets into set of generic classes. As classification classes they considered "News", "Events", "Opinions", "Deals", and "Private Messages". Though their method does not deal with topic spotting, the classification method is surely helpful to spot topics in tweets. An unsupervised method was proposed by [21] to leverage topics at multiple granularity. In [27], broad and generic Twitter categories based on the topics are described. All of these approaches, however, are only good at classifying tweets within some limited, generic and pre-defined topics.

In order to accurately detect topics from tweets, a concept-based approach is necessary. Recently, Wang et al. [105] presented a novel framework to classify any given short text to general categories. The method relies on a bag-of-concept model and a large taxonomy, it learns a concept model for each category, and conceptualizes short text to a set of relevant concepts. Similar approaches were proposed by [95], who used a large probabilistic knowledge base and Bayesian inference mechanism to conceptualize words in short text, and [18], who merged common and common-sense knowledge for topic spotting in the context of open-domain sentiment analysis.

9 Aspect Extraction

In opinion mining, different levels of analysis granularity have been proposed, each one having its advantages and drawbacks. Aspect-based opinion mining [43,31] focuses on the relations between aspects and document polarity. Aspects are opinion targets, i.e., the specific features of a product or service that users like or dislike. For example, the sentence “The screen of my phone is really nice and its resolution is superb” expresses a positive polarity about the phone under review. More specifically, the opinion holder is expressing a positive polarity about its *screen* and *resolution*; these concepts are thus called opinion targets, or aspects. It is important to identify aspects because reviewers may express opposite polarities about different aspects in the same sentence. Without such an identification, sentences like “I love the touchscreen of iPhone6 but the battery lasts too little” may be categorized as neutral because the average polarity is null when, in fact, the reviewer is very positive about one aspect but very negative about another.

The task of identifying aspects in a given opinion is called aspect extraction. Aspect extraction from opinions was first studied by Hu and Liu [43]. They introduced the distinction between explicit and implicit aspects, but only dealt with the former. They used a set of rules based on statistical observations. Hu and Liu’s method was later improved by Popescu and Etzioni [80] and by Blair-Goldensonh [6]. [80] assumes the product class is known in advance. Their algorithm detects whether a noun or noun phrase is a product feature by computing PMI between the noun phrase and the product class. Poria et al. [83] proposed a set of linguistic rules to extract aspect terms, e.g., `speaker` and employed a knowledge base technique to extract the aspect category, e.g., `sound`. Scaffidi et al. [92] presented a method that uses language model to identify product features, under the assumption that product features are more frequent in product reviews than in general natural language text.

Topic modeling has been widely used as a basis to perform extraction and grouping of aspects [44,23]. In the literature, two models have been considered: pLSA [42] and LDA [7]. Both models introduce a latent variable 'topic' between the observed variables 'document' and 'word' to analyze the semantic topic distribution of documents. In topic models, each document is represented as a random mixture over latent topics, where each topic is characterized by a distribution over words. The LDA model defines a Dirichlet probabilistic generative process for document-topic distribution; in each document, a latent aspect is chosen according to a multinomial distribution, controlled by a Dirichlet prior α. Then, given an aspect, a word is extracted according to another multinomial distribution, controlled by another Dirichlet prior β.

Some existing works employing these models include the extraction of global aspects (such as the brand of a product) and local aspects (such as the property of a product) [99], the extraction of key phrases [10], the rating of multi-aspects [106] and the summarization of aspects and sentiments [61]. [113] employed Maximum-Entropy to train a switch variable based on POS tags of words and use it to separate aspect and sentiment words. [62] added user feedback into LDA as a response variable connected to each document. In [60], a semi-supervised model was proposed. DF-LDA [2] also represents a semi-supervised model, which allows the user to set must-link and cannot-link constraints. A must-link means that two terms must be in the same topic, while a cannot-link means that two terms cannot be in the same topic.

[107] proposed two semi-supervised models for product aspect extraction, based on the use of seeding aspects. Within the category of supervised methods, [45] employed seed words to guide topic models to learn topics of specific interest to a user, while [106] and [67] employed seeding words to extract related product aspects from product reviews.

10 Polarity Detection

Polarity detection is the most popular sentiment analysis task. In fact, many research works even use the terms 'polarity detection' and 'sentiment analysis' interchangeably. This is due to the definition of sentiment analysis as the NLP task that aims to classify a piece of text as positive or negative. As discussed before, however, there are several other tasks that need to be taken into account in order to correctly infer the polarity associated with one or more opinion targets in informal short text. Existing approaches to polarity detection can be grouped into four main categories: keyword spotting, lexical affinity, statistical methods, and concept-level approaches.

Keyword spotting is the most naïve approach and probably also the most popular because of its accessibility and economy. Polarity is inferred after classifying text into affect categories based on the presence of fairly unambiguous affect words like 'happy', 'sad', 'afraid', and 'bored'. Elliott's Affective Reasoner [33], for example, watches for 198 affect keywords, e.g., 'distressed' and 'enraged', plus affect intensity modifiers, e.g., 'extremely', 'somewhat', and 'mildly'. Other popular sources of affect words are Ortony's Affective Lexicon [73], which groups terms into affective categories, and Wiebe's linguistic annotation scheme [109].

Lexical affinity is slightly more sophisticated than keyword spotting as, rather than simply detecting obvious affect words, it assigns arbitrary words a probabilistic 'affinity' for a particular emotion. For example, 'accident' might be assigned a 75% probability of being indicating a negative affect, as in 'car accident' or 'hurt by accident'. These probabilities are usually trained from linguistic corpora [110,97,94,88].

Statistical methods, such as latent semantic analysis (LSA) and SVM, have been popular for polarity detection from text and have been used by researchers on projects such as Goertzel's Webmind [37], Pang's movie review classifier [78], and many others [77,102,104]. By feeding a machine learning algorithm a large training corpus of affectively annotated texts, it is possible for the systems to not only learn the affective valence of affect keywords, but such a system can also take into account the valence of other arbitrary keywords (like lexical affinity), punctuation, and word co-occurrence frequencies. However, statistical methods are generally semantically weak, meaning that, with the exception of obvious affect keywords, other lexical or co-occurrence elements in a statistical model have little predictive value individually. As a result, statistical classifiers only work with acceptable accuracy when given a sufficiently large text input. So, while these methods may be able to detect polarity on the page or paragraph level, they do not work well on smaller text units such as sentences.

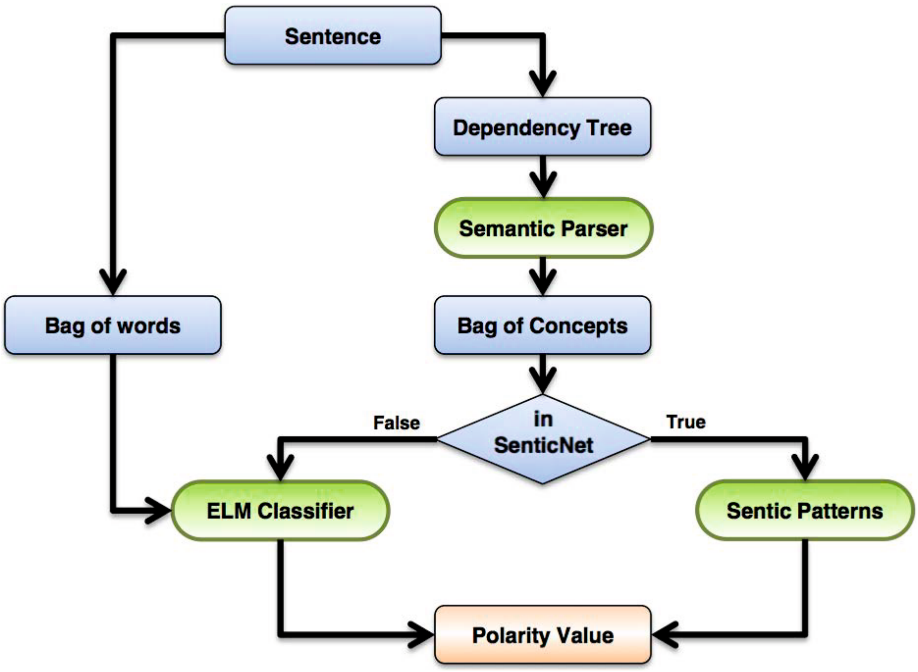

Fig. 5. Sentic patterns

Concept-based approaches focus on a semantic analysis of text through the use of web ontologies [34] or semantic networks [15], which allow grasping the conceptual and affective information associated with natural language opinions. By relying on large semantic knowledge bases, such approaches step away from the blind use of keywords and word co-occurrence count, but rather rely on the implicit meaning/features associated with natural language concepts. Unlike purely syntactical techniques, concept-based approaches are able to detect also sentiments that are expressed in a subtle manner, e.g., through the analysis of concepts that do not explicitly convey any emotion, but which are implicitly linked to other concepts that do so.

Besides these four categories, there are hybrid frameworks for polarity detection that propose an ensemble of two (or more) of the above-mentioned approaches, e.g., sentic patterns [84], which employ both statistical methods and concept-based techniques to infer the polarity of short texts (Fig. 5).

11 Conclusion

Sentiment analysis is a research field germane to NLP that has recently raised growing interest both within the scientific community, leading to many exciting open challenges, as well as in the business world, due to the remarkable benefits to be had from financial market prediction.

While the high availability of dynamic social data is extremely beneficial for tasks such as branding, product positioning, and social media marketing, the timely distillation of useful information from the huge amount of constantly produced unstructured information is a very challenging task. The two main issues associated with sentiment analysis research today are that (a) most techniques focus on the syntactic representation of text, rather than on semantics, and (b) most works only focus on one or two aspects of the problem, rather than taking a holistic approach to it.

To this end, we proposed the CLSA model, a novel framework for concept-level sentiment analysis that takes into account all the NLP tasks necessary for extracting opinionated information from text, namely: microtext analysis, for normalizing informal and irregular text; semantic parsing, for deconstructing natural language text into concepts; subjectivity detection, for filtering non-opinionated or neutral text; anaphora resolution, for resolving references in the discourse; sarcasm detection, for detecting sarcastic opinions and flip their polarity; topic spotting, for contextualizing opinions to a specific topic; aspect extraction, for deconstructing text into different opinion targets; finally, polarity detection, for detecting a polarity value for each opinion target.

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