Analysis of complex sentiment on social networks

Seminar I

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Abstract

The main goal of sentiment analysis (also known as opinion mining) on social networks is to analyze and determine sentiment of the author publishing on social networks using text mining and machine learning technologies. Although basic sentiment (positive, negative, neutral) analysis is an interesting and important topic and well covered in research, complex sentiment analysis, like detection of sarcasm, judgement, aggression or disappointment, still poses a research challenge from linguistic and technical point of view. Another topic of our interest, which is also challenging, is detection and analysis of sentiment changes in time. This paper presents an overview of recent research on complex sentiment analysis and sentiment dynamics analysis problems. Past work is critically evaluated and recommendations for future research is proposed.

Keywords: complex sentiment analysis, social networks, sentiment change analysis, text mining, machine learning, natural language processing
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1. INTRODUCTION

Rapid development of social media, which we have observed in recent years, has drastically transformed the way in which people communicate, obtain information and express their opinion. Social media has become ubiquitous and plays an increasingly important role in today’s business, political and social spheres. Many economic and political entities use social media platforms such as Facebook or Twitter to promote their services, products or ideas on one hand and to interact with customers, voters or followers on the other hand. As a result of these interactions, a large quantity of user generated content is available on social media sites and the growth in the quantity of subjective, opinionated information has led to changes in the economic, political and social spheres. The extensiveness of this phenomenon, the velocity with which opinions are created and spread has brought about a growing need to develop systems that automatically detect and classify opinions, sentiments and attitudes in these texts, as Balahur et al. [1] explain.

Sentiment analysis is defined [2] as an interdisciplinary area which comprises of natural language processing, text analytics and computational linguistics to identify the sentiment expressed in text. Further definitions of sentiment analysis provided by Pang et al. [3] might also use the terms opinion mining and/or subjectivity analysis, however recent research in the area of sentiment analysis focus on the specific application of classifying text as to their polarity (either positive, negative or neutral). Complex sentiment analysis or fine-grained sentiment analysis as mentioned by Pang et al. [3] extends beyond detection of polarity and deals with deep sentiment analysis that measures the causal relationships between author’s attitudes, value structures and personality as proposed by Jang et al. [4] and might include detection of emotions and polarity change over time.

In the following sections we will present an overview of recent research on complex sentiment analysis and sentiment dynamics analysis problems. Past work will be critically evaluated and recommendations for future research will be proposed.
2. RESEARCH OVERVIEW

2.1. Sentiment analysis process

Sentiment analysis can be considered a classification process as described by Medhat et al. [5]. A general approach to a process flow of this kind is illustrated in Figure 1:

![Sentiment analysis process diagram](image)

Figure 1: Sentiment analysis process
Adopted from [5]

Although the process in Figure 1 is applied in the field of product reviews by Medhat et al. [5], basic idea and approach still holds when applied in other fields and more complex sentiment analysis beyond identification of sentiment polarity. The first step in sentiment classification problem is to extract and select text features. Some of the important features are [5]:

- **Terms presence and frequency**: these features are individual words or word n-grams and their frequency counts. It either gives the words binary weighting or uses term frequency weights to indicate relative importance of features.
- **Parts of speech**: finding verbs, nouns and adjectives, as they are important indicators of opinion
- **Opinion words and phrases**: these are words commonly used to express opinions including *good or bad, like or hate*. On the other hand, some phrases express opinions without using opinion words, for example: *cost me an arm and a leg*.
- **Negations**: the appearance of negative words may change the opinion orientation, for example: *not good* is equivalent to *bad*.

Feature selection methods attempt to reduce the dimensionality of the data by picking from the original set of attributes.
2.2. Feature selection methods

The whole process involves several steps: online text cleaning, white space removal, expanding abbreviations, stemming, stop words removal, negation handling and finally feature selection.

Feature selection methods can be divided into lexicon-based methods that need human annotation, and statistical methods which are automatic methods that are more frequently used. Lexicon-based approaches usually begin with a small set of seed words. Then they bootstrap this set trough synonym detection or on-line resources to obtain a larger lexicon. Whitelaw et al. [6] reported many difficulties when using this approach for the purpose of fine-grained sentiment analysis. Statistical approaches, on the other hand, are fully automatic.

The feature selection techniques treat the documents either as group of words (Bag of Words, BOW), or as a string which retains the sequence of words in documents. BOW is used more often because of its simplicity for the classification process.

Medhat et al. [5] describe the most frequently used statistical methods in feature selection, among other Point-wise Mutual Information (PMI), Chi-square and Latent Semantic Indexing (LSI).

The Point-wise Mutual Information (PMI) $M_i(w)$ between the word $w$ and class $i$ is defined on the basis of the level of co-occurrence between the class $i$ and word $w$. The word $w$ is positively correlated to the class $i$, when $M_i(w)$ is greater than 0. The word $w$ is negatively correlated to the class $i$ when $M_i(w)$ is less than 0. Yu et al. [7] have extended the basic PMI by developing a contextual entropy model to expand a set of seed words generated from a small corpus of stock market news articles. Their contextual entropy model measures the similarity between two words by comparing their contextual distributions using an entropy measure, allowing for the discovery of words similar to the seed words. Once the seed words have been expanded, both the seed words and expanded words are used to classify the sentiment of the news articles. Their results showed that their method can discover more useful emotion words, and their corresponding intensity improves their classification performance. Their method outperformed the (PMI)-based expansion methods as they consider both co-occurrence strength and contextual distribution, thus acquiring more useful emotion words and fewer noisy words. Chi-square and PMI are two different ways of measuring the correlation between terms and categories, but Chi-square is normalized value and therefore more comparable across terms in the same category.

Feature transformation methods create a smaller set of features as a function of the original set of features. LSI method transforms the text space to a new axis system which is a linear combination of the original word features. Principal Component Analysis (PCA) techniques are used to achieve this goal. The main disadvantage of LSI is that it is an unsupervised technique which is blind to the underlying class-distribution. Therefore, the features found by LSI are not necessarily the directions along which the class-distribution of the underlying documents can be best separated [5].

Other statistical approaches which could be used in feature selection include Hidden Markov Model (HMM) and Latent Dirichlet Allocation (LDA). They were used by Duric and Song [8] to separate entities in a review document from the subjective expressions that describe those entities in terms of polarities. LDA are generative models that allow documents to be explained by unobserved (latent) topics. HMM-
LDA is a topic model that simultaneously models topics and syntactic structures in a collection of documents. There are several ways to assess the importance of each feature by attaching a certain weight in the text. The most popular ones are: Feature Frequency (FF), Term Frequency Inverse Document Frequency (TF-IDF) and Feature Presence (FP). Kira and Rendell [27] proposed Relief as feature selection method in binary classification problems and Kononenko [28] proposed an extension to this method for multiclass problems called ReliefF. Haddi et al. [9] have demonstrated the crucial importance of the text pre-processing steps and feature selection in order to achieve better performance of sentiment classification techniques described in the next subsection.

2.3. Sentiment classification techniques

Saif et al. [10] divide the approaches to Twitter sentiment analysis into roughly supervised (machine) learning approach and lexicon-based. Supervised learning approaches require training data for sentiment classifier learning. In Twitter, training data are typically obtained by either assuming that tweets’ polarities can be inferred using emoticons or by taking consensus from the results returned by the sentiment detection websites. They point out, that supervised approaches are domain-dependent and require re-training with the arrival of new data. On the other hand, lexicon-based approaches do not require training data. Instead, they use lexicons of words weighted with their sentiment orientations when dealing with polarity classification. Medhat et al. [5] describe (besides machine learning and lexical approaches) also hybrid and other sentiment classification approaches. The overview of sentiment classification techniques is presented in Figure 2:

Figure 2: Sentiment classification techniques
Adopted from [5]
2.3.1. Machine Learning Approach

Machine learning approach relies on machine learning algorithms to solve sentiment analysis problem as a regular text classification problem that makes use of syntactic and/or linguistic features. Medhat et al. [5] further divide machine learning approaches into supervised learning and unsupervised learning methods. Among supervised learning methods probabilistic classifiers use mixture models for classification. The mixture model assumes that each class is a component of the mixture. Each mixture component is a generative model that provides the probability of sampling a particular term for that component. These kinds of classifiers are also called generative classifiers.

The Naïve Bayes classifier is the simplest and most commonly used classifier. Naïve Bayes classification model computes the posterior probability of class, based on the distribution of the words in the document. The model works with the BOWs feature extraction which ignores the position of the word in the document. It uses Bayes Theorem to predict the probability that a given feature set belongs to a particular problem. Williams et al. [11] were successful in employing the Naïve Bayes classifier in using idioms to perform sentiment analysis and document polarity. They also propose similar approach to tackle the more complex problem of emotion classification.

Bayesian Network is considered a complete model for the variables and their relationships. Therefore, a complete joint probability distribution over all the variables is specified for a model. In text mining the computational complexity of Bayesian Network is very expensive, which is why it is not frequently used. Bayesian Network was used by Hernandez et al. [12] where the attitude of the author is characterized by three different (but related) target variables and proposed the use of multi-dimensional Bayesian network classifiers. It joined the different target variables in the same classification task in order to exploit the potential relationships between them. They extended the multi-dimensional classification framework to the semi-supervised domain in order to take advantage of the huge amount of unlabeled information available in this context.

Maximum Entropy classifier converts labeled feature sets to vectors using encoding. This encoded vector is then used to calculate weights for each feature that can then be combined to determine the most likely label for feature set. Maximum Entropy classifier was successfully used by Duric and Song [8] to perform sentiment analysis as binary task, but propose to extend its usage as unsupervised aspect extraction scheme and scaled polarity analysis.

Linear classifiers include Neural Network and Support Vector Machines. Neural Network consist of many neurons where the neuron is the basic unit. The inputs to the neurons are denoted by the vector $\overline{X}_i$ which is the word frequencies in the $i$th document. There are a set of weights $A$ which are associated with each neuron used in order to compute a function of its inputs. The linear function of the neural network is: $p_i = A^T \overline{X}_i$. In a binary classification problem, it is assumed that the class label of $\overline{X}_i$ is denoted by $y_i$ and the sign of the predicted function $p_i$ yields the class label. Vinodhini and Chandrasekaran [2] have compared performance of several Neural Network algorithms for sentiment classification of online reviews and proved their superior performance. They propose usage of ensemble methods for greater precision accuracy.
Support Vector Machines (SVM) learns a hyperplane in higher dimensional space that separates the training data and gives the highest margin between positive and negative class. It maps the original feature space into higher dimensional space using kernel functions (e.g., linear, polynomial ...). SVM was successfully employed by Kranjc et al. [13] for active learning scenario for sentiment analysis on Twitter data. Preethi et al. [14] proposed the extension of the usage of SVM to temporal sentiment analysis and causal rules extraction from Tweets for event prediction. Xia et al. [15] evaluated SVM in various scenarios for successful polarity shift detection in their proposed PSDEE cascade model (Polarity Shift Detection, Elimination and Ensemble).

2.3.2. Lexicon-based Approach

Lexicon-based approach relies on opinion words to solve sentiment classification tasks. There are also opinion phrases and idioms which together are called opinion lexicon. A dictionary is prepared to store the polarity values of lexicons [16]. There are three main approaches in order to compile or collect the opinion word list. Manual approach is very time consuming and it is usually combined with the other two automated approaches as a final check to avoid mistakes that resulted from automated methods [5]. Dictionary-based approach uses small set of opinion words collected manually with known orientations. This set is grown by searching in the well known corpora WordNet [16] or thesaurus for their synonyms and antonyms. The newly found words are added to the seed list and the next iteration starts. Rong et al. [17] were successful with such approach and they also proposed upgraded approach with auto-encoder based bagging architecture to tackle the known challenge of the curse of dimensionality. The dictionary based approach has a major disadvantage which is the inability to find opinion words with domain and context specific orientation.

The Corpus-based approach helps to solve the problem of finding opinion words with context specific orientations. Its methods depend on syntactic patterns or patterns that occur together along with a seed list of opinion words to find other opinion words in a large corpus. Maks and Vossen [18] proposed a lexicon model for the description of verbs, nouns and adjectives for usage in deep sentiment analysis and opinion mining applications. The model aims to describe detailed subjectivity relations that exist between the actors in a sentence expressing separate attitudes for each actor. The model includes a categorization into semantic categories relevant to opinion mining and sentiment analysis and provides means for the identification of the attitude holder and the polarity of the attitude and for the description of the emotions and sentiments of the different actors involved in the text. The model seeks to combine the insights from a complex model like Framenet with operational models like SentiWordNet. Saif et al. [10] proposed an upgraded approach to SentiStrength algorithm called SentiCircles, which builds a dynamic representation of words that captures their contextual semantics in order to tune their pre-assigned sentiment strength and polarity in a given sentiment lexicon. They assessed the performance of their proposed method in entity level sentiment detection, which detects sentiment towards a particular entity or topic and tweet level sentiment detection, which identifies the overall sentiment of individual tweets.
2.3.3. Hybrid and other approaches

**Hybrid techniques** cannot be roughly categorized as Machine Learning approach or Lexicon-based approach. Montejo-Raez et al. [19] proposed one such method that combines SenticNet, construction of feelings vector, Latent Semantic Analysis (LSA) for dimensionality reduction and SVM for final sentiment classification. They used the resources from WeFeelFine project that harvests emotions from social media since 2005 and 20 most frequent feelings are displayed in Figure 3:

![Figure 3: 20 most frequent feelings in WeFeelFine](Source:[19])

Ghiassi et al. [20] introduced and approach to supervised feature reduction using n-grams and statistical analysis to develop a Twitter-specific lexicon for sentiment analysis. They augmented this lexicon with brand-specific terms for brand-related tweets. They developed DAN2 neural network and successfully compared its performance to SVM on their Twitter-specific lexicon.

**Ontology-based approach** was proposed by Kontopoulos et al. [21] for sentiment analysis of twitter posts. As an initial step they developed domain specific ontology using OntoGen for the concept of “smartphone” from the set of retrieved tweets. They broke down each tweet into a set of aspects relevant to the subject. The final result was assignment of sentiment score to each distinct aspect (each technical property of smartphone). Thakor and Sasi [22] focused only on negatively labeled twitter posts associated with customers’ dissatisfaction in the Postal service. Ontology model was used to identify the services for which customers had published negative tweets.

Liu and Chen [23] propose **Multi-label classification based** approach for sentiment classification because some of the microblogs have multiple emotional states. They compared 11 state of the art multi-label classification methods to determine the
best performance. They successfully compared the performance of methods on two datasets, one having 5 and the other 10 different group of sentiments labeled.

2.4. Temporal sentiment dynamics and causality analysis

Preethi et al. [14] define temporal sentiment analysis as detection of sentiment change over time and causal relation analysis to identify cause and effects of events over time. They combine both approaches and in first step they extract aspect keywords from different time periods. Second step is sentiment analysis using SVM and third causal rule detection between aspect keywords using support and confidence. The final step is prediction based on causal rule identified and time based analysis of tweets. Zavattaro et al. [24] used machine learning approach to track sentiment change over time and discovered that positive tone in twitter discussions tends to activate users and increases their involvement. Siganos et al. [25] followed the sentiment of Facebook users using Facebook Gross National Happiness Index (FGNHI) on country level and showed significant correlation between moods expressed on social network on Sunday and stock market price volatility and trading volume on Monday. The causal analysis between sentiment and contemporaneous stock market returns was done using regression analysis.

Sluban et al. [26] propose an approach for identifying sentiment leaning by combining structural and content-based analysis of Twitter data. From structural properties of the retweet network, they identify influential users and communities. From the contents of their tweets, they characterize discussion topics and their sentiments. Sentiment of different communities showed perceivable differences in their leanings towards different topics.

Jang et al. [4] propose a deep sentiment analysis method by mining the causality between personality-value-attitude (PVA) for analyzing business ads in social media platform YouTube. They propose a method for estimating causality between user profiles, value structures, and attitudes based on the replies and published content on social network. Proposed PVA model is displayed in Figure 4:

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Figure 4: Personality-value-attitude (PVA) model
Source:[4]
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Attitude polarity shows the number of opinions about the source materials. Value structure polarity captures the value placed by writers of such opinions on the source materials. Value theory describes three categories of human values: utilitarian values, which emphasize usefulness, hedonistic values, which emphasize enjoyment, and normative values, which focus on the public good or social order. Text analytics is applied to assess the strength of these individual values. User profile value are acquired using commenters’ networks on social media platforms, information about interest areas is extracted trough analysis of the characteristics of the posted videos, and aspects of personality are captured trough analysis of the characteristics of the comments.

2.5. Application of appraisal theory

Whitelaw et al. [6] propose an application of appraisal theory for sentiment analysis. Main attributes of appraisal and their highest level options are displayed in Figure 5:

![Appraisal Attributes Diagram](image)

**Figure 5: Main attributes of appraisal and their highest-level options**
Adopted from [6]

When building appraisal taxonomy, values were assigned for four main types of attributes (attitude, graduation, orientation and polarity) using semi-automated techniques for relevant terms. Lexicon was then expanded using WordNet and two online thesauri. Multidimensional vectors for expressing feature sets were constructed from previously built lexicon. Sentiment classification for each feature set was then successfully performed using Weka’s implementation of Sequential minimal optimization (SMO).
3. CRITICAL EVALUATION OF THE EXISTING RESEARCH

Among the feature selection methods, extended Point-wise Mutual Information (PMI) with contextual entropy model proposed by Yu et al. [7] looks promising and applicable to the task of fine-grained sentiment analysis as it considers both co-occurrence strength of emotion words and their contextual distribution. As their model was developed for financial domain, it might need further adaptations to be applicable in other domains.

Duric and Song [8] approached sentiment analysis as binary classification problem. Although their method might not be suited for fine-grained sentiment analysis task, their approach to feature selection task using content and syntax model HMM-LDA, which models entities and modifiers as long-range and short-range dependencies, might be applied to identify and extract aspects from documents and be later used for fine-grained sentiment analysis task or detection of sentiment change.

Williams et al. [11] were successful in employing Naïve Bayes classifier and idioms to perform sentiment analysis and document polarity. The main limitation of their proposed method was significant overhead involved in handcrafting lexico-semantic rules for recognition of idioms and their polarity. This crucial step would need to be automated for the proposed solution to be applicable to larger scale solutions. As the initial annotation of both idioms and sentences with wide range of emotions rather than merely sentiment polarity, larger scale lexicon of this type might be suitable for the fine-grained sentiment analysis task.

Multidimensional Bayesian Network classifier was employed by Hernandez et al. [12] to identify the attitude of the author expressed by three related target variables, Will to influence, Polarity and Subjectivity. Their semi-supervised approach looks promising to tackle the problem of the huge amount of unlabeled data, although computationally intensive nature of Bayesian Network classifier would need to be addressed accordingly.

Support Vector Machines (SVM) have been used extensively for sentiment analysis tasks. Preethi et al. [14] proposed the extension of the usage of SVM to temporal sentiment analysis and causal rules extraction from Tweets for event prediction but their proposal lacks practical implementation and evaluation of performance. On the other hand, Xia et al. [15] evaluated SVM in various scenarios for polarity shift detection in on-line review documents. Their proposed method would have to be evaluated in social media environment like Twitter due to its specific short document nature.

A lexicon model for deep sentiment analysis and opinion mining applications has been proposed by Maks and Vossen [18] that describes detailed and subtle subjectivity relations that exist between the different participants of a verb, noun or adjective. The relations can be labeled with subjectivity information concerning the identity of the attitude holder, the polarity of the attitude and its target. Their model needs to be enlarged, as it only holds 600 items for each part-of-speech and tested for the automatic detection of subjectivity and polarity properties of word senses in a larger scale application. Saif et al. [10] proposed an upgraded approach to SentiStrength called SentiCirlces for sentiment classification at the entity and tweet levels. They lack however a gold-standard dataset for evaluating their approach to entity-level sentiment analysis. Their approach would also need to be evaluated against machine learning approaches like SVM and Maximum Entropy classifiers.
Hybrid approach proposed by Montejo-Raez et al. [19] that combines SenticNet, construction of feelings vector, Latent Semantic Analysis (LSA) for dimensionality reduction and SVM for final sentiment classification, successfully breached the gap between different languages and domains. Their approach with feelings vector could potentially be also used for fine-grained sentiment analysis task.

Ontology-based approach for sentiment analysis of Twitter posts was used by Kontopoulos et al. [21]. They assigned sentiment score to each distinct aspect. In view of tracking sentiment dynamics, their approach doesn’t cover the sentiment of the author and the sentiment change over time. Thakor and Sasi [22] constructed ontology model to identify the services for which customers had published negatively labeled tweets. Their model was built from relatively small sample of only around 250 tweets, which raises the need to further refine the relations between objects in ontology model and extend the model itself.

Multi-label classification based approach for sentiment classification of Twitter posts was proposed by Liu and Chen [23]. As several multi-label methods were evaluated, the need for better feature selection method became evident. Another problem that needs to be addressed is domain independency, as authors also pointed out, that classifiers evaluated might not perform as well when applied to other domains.

Preethi et al. [14] defined the model for tracking the sentiment change of authors in Tweeter posts and causality relations. Their proposed model would need to be implemented and evaluated against existing systems. Siganos et al. [25] demonstrated significant correlation between sentiment of Facebook users and stock market returns. Their research was done only on country level and would need to be evaluated also on more fine-grained level of particular company on stock market and its sentiment dynamics on social networks.

Deep sentiment analysis method proposed by Jang et al. [4] mining the causality between user profiles, value structure and attitudes (PVA) needs an application on a larger scale, to demonstrate its robustness. As the method was developed for YouTube, its application on other social media platforms might require modifications to model definition, namely user profile.
4. PROPOSITIONS FOR IMPROVEMENT

Feature selection method Extended Point-wise Mutual Information (PMI) proposed by Yu et al. [7] could be used for the task of fine-grained sentiment analysis as it considers both co-occurrence strength of emotion words and their contextual distribution. Features could be defined based on appraisal theory described by Whitelaw et al. [6]. Another approach to be considered is modeling the emotion features using ontology-based approach as proposed by Kontopoulos et al. [19]. Fine-grained sentiment analysis could then be performed using multi-label approach proposed by Liu et al. [23]. If selected feature selection method would reduce the dimensionality problem, Bayesian Network method proposed by Hernandez et al. [12] could potentially also be applicable.

For the task of sentiment detection change and causality analysis, features could be defined using Personality-Value-Attitude (PVA) model proposed by Jang et al. [4]. Alternative approach for feature selection could be HMM-LDA model proposed by Duric and Song [8], as it models entities and modifiers as long-range and short-range dependencies. Further steps for polarity shift detection could follow the methodology proposed by Preethi et al. [14] and, as it lacks practical implementation, SVM classification could be applied as described by Xia et al. [15], although extended for polarity shift detection of individual authors across time series of Tweeter documents. Such extension could also be applied to the approach for sentiment leaning detection of influential communities from Sluban et al. [26], where personality of influential communities (or individuals) could additionally be labeled using PVA model.
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