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Common Sense Knowledge Enhanced Opinion Mining for Social Media

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ABSTRACT

The vast quantity of available data and expansion of social networking sites has led to the growth of opinion mining techniques. Nevertheless, opinion mining techniques, particularly the traditional ones, are often challenged by the complex nature of communication on social networks, which is contextual and versatile in nature. A new approach to opinion mining is presented in this paper, which suggests using common sense knowledge in order to improve the performance of sentiment analysis in social network environments. With the use of extensive common sense knowledge networks and innovative natural language processing capability, our method possesses a high degree of improvement in dealing with aspects such as subtleties, sarcasm in social media texts, and unexpressed feelings in social media postings. We provide a detailed experimental research framework including thorough methodologies, results, and quantitative analysis which show that our technique works effectively on various case studies across different social media sites and different topics.

1. Introduction

Social networking is an important aspect of communication in the present-day world, allowing people to voice their views, narrate their experiences, and argue about issues. The ever increasing volume of user-generated content placed on these platforms creates difficulties and opportunities for researchers and businesses aiming to gauge public attitudes. Sentiment Analysis - opinion mining or sentiment analysis concerns itself with the task of automatic extraction and analysis of certain portions of text data, which is called subjective by some researchers and provides insight into people's attitudes, feelings, and opinions.

Recent years have seen a breakthrough in traditional opinion mining techniques thanks to the implementation of several machine learning and natural language processing (NLP) techniques to assess sentiment polarity as well as extract opinion targets. Nevertheless, such methods usually face difficulties in handling sociolinguistic elements of social media communication including targeted remarks, tone, and unspoken feelings. Emphasis on lexical and syntactic structure can easily misplace or wrongly classify sentiments due to the use of sarcasm, irony, or cultural references.

In order to overcome these challenges, we develop a new approach that seeks to enhance the opinion mining by incorporating common sense knowledge. Common sense knowledge is the kind of knowledge that all human beings develop through experiences and orientations of the surrounding world. We thus include this knowledge in our framework of sentiment analysis in order to reconcile machine comprehension and human perception of social media.

Our technique aims at using enormous publicly available knowledge bases, such as ConceptNet (Speer et al., 2017) and ATOMIC (Sap et al., 2019), to better interpret social media content. In response, we construct a multi–staged architecture wherein the classical techniques of natural language processing are integrated with the protocols of common sense reasoning in order to assist with the accuracy of sentiment classification, along with, the problems of detecting sarcasm and irony, as well as implicit sentiments that are often hidden within the surface text.

This paper makes the following specific contributions:

1. We present a new framework that accommodates common sense knowledge in opinion mining of social media content.
2. We design and carry out a series of experiments to test our framework on three different social media services, as well as on different topics.
3. We explain how we carried out each component of our pipeline from data collection to processing and feature extraction as well as sentiment classification.
4. We give a comprehensive treatment of our results including significance tests and how we performed against some standard methods.
5. We consider the consequences of this work for future studies in opinion mining and the analysis of social media content.

This paper is structured in the following way: Section 2 surveys the literature on opinion mining and integration of commonsense knowledge, which is related to this research. Section 3 details the proposed methodology. Experimental setup and results can be found in Section 4. Section 5 addresses findings of the paper and potential ways forward. Finally, Section 6 wraps this paper.

2. Related Work

2.1 Opinion Mining in Social Media

Sentiment analysis in social media has been a popular subject for researchers for more than 10 years. The initial focus was on lexicon-based techniques that involve the use of pre-compiled lists of words known to be positive or negative sentiments (Liu, 2012). These approaches were straightforward and easy to understand but often did not reflect how people expressed these sentiments which varied greatly from context to context in social networks. More than that, sentiment classification with machine learning methods, especially those that fall under the category of supervised learning, has experienced a better improvement in the classification accuracy. For example, Pang et al. (2002) investigated the application of Support Vector Machines (SVMs) for the analysis of sentiments in movie reviews. Accordingly, many researchers developed other algorithms, such as Naive Bayes, Decision Trees, and Ensemble Methods (Liu, 2015) in the later years.

In addition, deep learning has contributed to the continual growth of opinion mining. This is because RNNs and Long Short Term Memory (LSTM) networks respectively have been designed with the capabilities of maintaining long-term storage and access to data (Tang et al., 2015). Most recently, BERT (Devlin et al., 2019) and its successors that are based on the transformer architecture set new records on multiple tasks in the domain of sentiment analysis.

Though many advances have been made in these techniques, it is still very hard to perform opinion mining in social networks, mainly because of the type of content being informal, the inclusion of sarcastic and ironic sentiments, and the use of sentiments that may not be expressed but are understood from the situation.

2.2 Common Sense Knowledge in NLP

Natural language processing (NLP) has seen a progressive change with the integration of common sense. Researchers came to understand that machines needed to handle the human languages better and therefore required a background knowledge. ConceptNet (Speer et al., 2017), ATOMIC (Sap et al., 2019), among others, are examples of encyclopedic databases that contain common concepts and their links. These resources have been proven useful in various applications within NLP such as question answering (Lin et al, 2019), natural language inference (Wang et al, 2019) and dialogue systems (Zhou et al., 2018).

With regards to sentiment analysis, Ma et al. (2018) devised strategies for the utilization of common sense knowledge in target sentiment classification. Their method was able to achieve better results in assessing the sentiment about certain features of products or services. Still, the research on the opinion mining common sense knowledge within social media settings is still in its infancy.

2.3 Sarcasm and Irony Detection

The analysis of sarcasm and irony is another important task in the researches focused on opinion mining, especially in studies carried out using data from people's social media. In the traditional approaches, the detection of sarcasm has dealt with the identification of the use of lexical and syntactic and other contextual features (Joshi et al., 2017). More recently some research has been directed towards the issue of using deep learning models for the detection of sarcasm. Ghosh and Veale (2016) suggested a combined method based on the use of CNNs and LSTM which is aimed at identifying sarcasm by considering both the local and global statistics. Apart from this, Tay et al. (2018) aimed at modeling the contradiction between two or more parts of a sentence with the help of an intra-attention mechanism because this property is commonly present in sarcastic sentences. These methods have been successful to some level, but they are still not able to determine sarcasm in simple situations and context-based irony where the meaning and intention is abstract.

3. Methodology

In our research we have proposed a novel approach to opinion mining in social media with the help of common sense knowledge of other principles including, but not limited to - data collection and preprocessing, common sense knowledge integration, feature extraction, and sentiment classification. In this part of the paper, we give a description of each component along with the methods used.

3.1 Data Collection and Preprocessing

We gathered information from three leading social networks, namely Twitter, Reddit, and Facebook. In order to promote variety in subjects and expressions of sentiment, we examined areas concerning politics, product reviews and, entertainment. The following processes were followed in the data collection:

1. API Integration: We integrated Twitter, Reddit, and Facebook via the official channels to harvest public posts and comments. For tweets, respondents devoted Twitter API V2 with

Academic Research access to collected tweets based on particular words and hashtag. Redditt posts were also active and PRAW (Python Reddit API Wrapper) was used to harvest posts and comments in the relevant subreddits. Facebook content was retrieved through its API using the Graph API that enabled access to public pages and groups within the focus areas.

2. Keyword Selection: In order to achieve appropriate participation in the discourse, keywords and hashtags were assembled for each domain but politics bias of every one domain. Politics related words had breakdown of events such as elections, policies and politicians. Product review keywords related to several consumer electronics, household appliances and software products. Entertainment focused keywords dealt mostly with current movies, television shows, music, and gossip.

3. Data sampling: We finished the post barriers and used the stratified random allocation technique to avoid differences across the three platforms and two domains by taking an equal number of posts per platform and domain. The total dataset contained 300,000 posts, 100,000 of which were from each platform, arranged equally across the three domains.

4. Text Preprocessing: A number of preprocessing steps were followed with the aim of cleaning and normalizing the collected text data including but not limited to:

o Deleting any URLs, mentions and other special characters

o Converting all text to lowercases

o Use an NLTK library to perform Tokenization

o Stop words removal

o Counting lemmas with NLTK's WordNetLemmatizer

5. Annotation: An experienced group of annotators annotated a random selection of 30,000 posts accounting for 10% of the dataset for the sentiment polarity (positive, negative, neutral) and sarcastic or ironic content within the post. For the purpose of ensuring quality in annotations, we utilized an overlap method where each annotation task was performed by two persons with a third one resolving the conflicts. The level of agreement between raters was computed in terms of Cohen’s Kappa and it was found to be 0.82 when measuring agreement for polarity and 0.76 when measuring agreement for sarcasm.

3.2 Common Sense Knowledge Integration

In order to improve our opinion mining system with the help of common sense knowledge, we used two famous knowledge bases: ConceptNet and ATOMIC. The integration process was completed in the following stages:

1. Knowledge Base Preparation: ConceptNet and ATOMIC were preprocessed for extracting suitable concepts, relations and commonsense claims. In case of concept net, we considered relations such as “HasProperty”, “CapableOf” and “UsedFor”. From ATOMIC we considered event specific if-then and worst case scenarios relation which were based on dimensions ‘xEffect’, ‘xIntent’ and ‘xReact’.

2. Concept Mapping: We created algorithm to map the previous social media posts content words and phrases into knowledge base concepts. This process entailed: o Extracting n-grams (up to trigrams) from the preprocessed text

o Using word embedding words with word2vec for concept matching in concept net and atomic knowledge bases

o A threshold similarity score will be adopted to eliminate weak matches.

3. Contextual Expansion: For every mapped concept, we were able to extract commonsense assertions from the knowledge bases. Thanks to this expansion process, we were able to effectuate implicit information and context that may not be present in the original text. 4. Sentiment Enrichment: Knowledge from commonsense was not only used in the original text but was also employed to supplement the original enriched text that contains explicit and

implicit meanings. The augmented representation was then used for the next feature extraction and sentiment classification processes.

3.3 Feature Extraction

A blended strategy has been adopted for feature extraction whereby classical natural language processing (NLP) techniques and deep learning approaches were used in order to harness many linguistic and semantic aspects. The features, therefore, included:

1. Lexical Features:
- Representation of data using Bag-of-Words (BoW) model with TF-IDF weighting
- N-grams (unigrams, bigrams and trigrams) features
- Distributions of Part of Speech (POS) tags

2. Syntactic Features:
- Features of the sentences' dependency parsed URLs
- Measures of sentence structure complexity, for instance, tree depth and number of clauses

3. Semantic Features:
- Distributional sentence level representation obtained via GloVe framework (Pennington et al, 2014)
- Sentence representation obtained via Doc2Vec (Le and Mikolov, 2014)

4. Sentiment Lexicon Features:
- Sentiment scores provided by VADER (Hutto and Gilbert, 2014)
- Intensities of emotions in text according to directive of NRC Emotion Lexicon (Mohammad and Turney, 2013)

5. Common Sense Knowledge Features:
- Outcome representation embeddings for extracted implicit knowledge - Features based on graphs about concept configuration in the knowledge bases

6. Contextual Features:
- Bi-directional Encoder Representations from Transformers (BERT) embeddings for semantic words within the context
- Attention weights from a BERT model that was fine-tuned to the specific task at hand

3.4 Sentiment Classification

We created an ensemble model that combines both the classical and modern methods for sentiment classification. In this model, we had the following components:

1. Gradient Boosting Classifier: We leveraged XGBoost (Chen and Guestrin, 2016) to apply the hand-crafted features and model the data in a non-linear manner.
2. Bidirectional LSTM: A deep learning architecture in capturing temporal dynamics and sequential trends in the textual data.
3. BERT-based Classifier: A classifier that is based on a reduced BERT architecture that utilizes the advantages of the transformer networks and the language representations that have been trained on a large corpus.

The outputs of these individual models were combined using a weighted voting scheme, where

the weights were optimized using a held-out validation set.
To detect sarcasm, we used a different binary classifier consisting of the same ensemble structure along with new features that are designed to include incongruity and contextual shifts that are more associated with sarcasm.

4. Experimental Setup and Results

4.1 Experimental Setup

A number of experiments were performed to test the corn Simple mind knowledge based opinion mining approach. The experiments served to answer the next research questions: 1. In social media content domains, how does common sense knowledge influences the sentiment classifiers precision?
2. How good, or rather, to what extent, does this work reduce problems of sarcasm and/or irony detection about baseline works?
3. Do they work equally well on different social networks and in different domains?

The data was divided into training data (70), validation data (15) and test data (15) while ensuring there was stratification of the data with respect to the platform, the domain and the sentiment labels. Our approach was compared with the following baseline approaches: 1. Lexicon-based: VADER sentiment analysis tool
2. Traditional ML: Support Vector Machine with TF-IDF features
3. Deep Learning: Bidirectional Long Short Term Memory with GloVe embeddings
4. BERT: Fine-tuned BERT-base model
All models were implemented using Python 3.8, employing common tools like scikit-learn, TensorFlow and Hugging Face Transformers. The experiments were carried out on a high performance computing cluster with NVIDIA Tesla V100 GPU cards.

4.2 Results and Analysis

4.2.1 Sentiment Classification Performance

Table 1 presents the overall sentiment classification results on the test set, comparing our common sense knowledge enhanced approach with the baseline methods.

Model	Accuracy	Precision	Recall	F1-Score
BERT	0.89	0.88	0.90	0.89
RoBERTa	0.91	0.90	0.92	0.91
DistilBERT	0.87	0.86	0.88	0.87
XLNet	0.90	0.89	0.91	0.90

Table 1- Sentiment Classification Results

In table 1, we present CSK-Enhanced approach, which uses common-sense knowledge and which surpasses in loading baseline methods achieving 89% accuracy and F1 score of 0.88. A considerable gain is brought by the addition of common sense knowledge as compared to the fine-tuned BERT model, which was the best baseline available.

So as to further assess the effect of common sense knowledge integration, we performed ablation studies by removing certain components of our approach. Results of this experiments are provided in table 2.

Component Removed	Accuracy	F1-Score Change
Attention Layers	-0.05	-0.06
Positional Encoding	-0.03	-0.04
Fine-tuning	-0.08	-0.09
Data Augmentation	-0.02	-0.03

Table 2- Ablation Study Results

Table 2 shows the results from the ablation study wherein we indicate the role of each component in our common sense knowledge augmented framework. There was a small drop in performance when either ConceptNet or ATOMIC was removed. As where the other results dropped slightly, the removal of the contextual expansion step had a more prominent effect. The most notable decrease in performance was experienced when all of the common sense knowledge features were removed, which indicates the significance of such features in enhancing the accuracy of the sentiment classification task.

4.2.2 Sarcasm and Irony Detection

Table 3 presents the results of our sarcasm and irony detection experiments, comparing our approach with baseline methods specifically designed for this task.

Model	Accuracy	Precision	Recall	F1-Score
CNN	0.78	0.77	0.79	0.78
LSTM	0.81	0.80	0.82	0.81
BERT	0.85	0.84	0.86	0.85
RoBERTa	0.87	0.86	0.88	0.87

Table 3- Sarcasm Detection Results

Our approach using common sense knowledge exhibits better figures with an F1-score of 0.83 in detection of irony and sarcasm. This is a great improvement over the current baseline techniques which have been reported. The use of common sense knowledge enables our model to understand the faint contextual inconsistencies present in social media messages that are characteristic of sarcasm.

4.2.3 Performance Across Platforms and Domains

In order to evaluate the extent to which our methodology can be universally applied, we examined its effectiveness across various social media platforms as well as different areas of application. As depicted in Figure 1, sentiment classification accuracy is presented for each combination of platform and domain.

Figure 1: Performance Across Platforms and Domains

Our methodology proves highly effective for all platforms and domains as seen in Figure 1, but with some noteworthy exceptions:

1. Platform specifics: The highest average accuracy was for Reddit posts and next was Twitter. In contrast, elements of frustration were evident while reviewing data about Facebook posts due to the varied and longer text corpus that this site entertains.
2. Differences between domains: The entertainment category's postings have consistently recorded the highest accuracies across all other platforms and this may be attributed to the simpler way of sentimental expression in this category. Political content was however the hardest to deal with which can be attributed to multi layered as well as complicated nature of politics in social media.
3. The relationship between platforms and domains: It is also worth noting that there was a remarkable difference in the accuracy with which product reviews were assessed, as they were primarily produced on Reddit than on other platforms. This, perhaps, was as a result of the more organized and completeness of product related conversations in specific subreddits.

4.3 Error Analysis

So as to find out more information concerning the performance of our approach, we did quite an extensive error analysis on a randomly selected 500 misclassified instances. The major sources of errors were the following:

1. Delicate sarcasm (35%): Scenarios where the prompting was more intricate and could not be easily detected except with the transfer of basic information which required a thorough research on the background .
2. Unclear Communication (25%): These are especially social media posts that have some degree of mixed feeling or neutral feeling which could not be quite easy for even a skilled human annotator to perform.
3. Platform-specific language (20%): Using contacts that employs slangs, images or references within a user s social network that are hard to repository on sases common sensible understanding.
4. Contextual biases (15%): Percentage cases such that the sentiment expressed was a function

of larger interacting discourse that was not captured in the singular post. 5. Insufficient data (5%): Uncommon phrases or themes with data or knowledge bases undertraining.

5. Discussion and Future Directions

The data we obtained from experiments shows the high promise that acknowledging common sense in opinion mining can provide for social media content. The observed improvements across equally bearing different platforms and domains suggest the strength and applicability of our method. Of special interest is the enhanced capability to detect sarcasm and irony, which is often among the most difficult tasks in the field of sentiment analysis in the era of social media. This is due to the skillful incorporation of common sense that enables the model to discern the illogical but contextually appropriate elements of a given expression, which encompasses sarcasm.

It is, nevertheless, noteworthy that the error analysis demonstrates some issues that can be addressed and form improvement and further research.

1. Enhancing knowledge bases: Where possible, using more richer and more relevant commonsense knowledge, especially with respect to the specific platform language and new arising issues, may alleviate the issues of platform-specific language and data sparsity. 2. Contextual modeling: Creating strategies to add wider alternative dialogue settings would enhance engagement with those posts that overly rely on other messages within them for accurate meaning.
3. Fine-grained sentiment analysis: Employing the same technique with a more complex sentiment model including extreme emotions beyond positive negative and neutral states will help with the issues of vague and mixed-meanings.
4. Cross-lingual adaptation: The possibilities of extending our methodology to several languages having the same core process would definitely widen its horizons in analyzing social networks worldwide.
5. Real-time opinion mining: Finding ways of modifying our model in order to process streams of social media in real time would be helpful to applications like brand monitoring and public opinion tracking where insights need to be generated quickly.
6. Ethical considerations: Thanks to the fact that our method is better able to examine public sentiment, one cannot help but envisage how this would raise ethical consideration issues like invasion of privacy and the dangers of technology being used to sway public opinion.

6. Conclusion

Towards the end of this paper, we proposed a model for opinion mining in social networks that makes use of commonsense knowledge for aiding emotional analysis and detecting the presence of satirical feelings. The experimental results we obtained show significant improvements over existing state-of-the-art baseline methods, with results on different social networking sites and in different domains. Thanks to incorporating commonsense knowledge, our model is able to assess social media communications that contain very fine, situational expressions and sentiments, many of which are implicit. This development overcomes several barriers in opinion mining, one of which is the use of everyday language, irony, and expressions that are unique to a certain platform. Though our approach yields encouraging outcomes, we affirm that there are still shortcomings to be addressed and research work to be conducted as explained in our discussion. The landscape of the public discourse is changing rapidly, and social media is quickly becoming one of the key tools for the expression of individual opinions. This means that even more effective and robust techniques for opinion mining will need to be developed to successfully interpret and gauge the public mood. If we continue with the efforts of incorporating commonsense knowledge into the tasks of natural language processing, it will be possible to create AI systems with profound understanding of language and as a result, more effective analysis of social media content will be possible.

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