Polarity Classification of Subjective Words Using Common-Sense Knowledge-Base

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Abstract. Semantic orientation of a word indicates whether the word denotes a positive or a negative evaluation. We present an approach to compute semantic orientation of words using machine-interpretable commonsense knowledge. We employ ConceptNet (a large semantic network of commonsense knowledge) for determining the polarity or semantic orientation of a sentiment expressing word. We apply heuristics on certain predefined predicates expressing semantic relationship between two concepts for classifying words that have a positive or negative polarity and finding words that have similar polarity. The advantages of the proposed approach are that it does not require any pre-annotated training dataset or manually created seed list. The proposed solution relies on a lexical resource which is created by volunteers on the Internet and not by trained or specialized knowledge engineers. We test our approach on publicly available pre-classified sentiment lexicon and present the results of our experiments and also examine the tradeoffs and limitations of the proposed solution. We conclude that it is possible to determine polarity of words with high accuracy by exploiting a machine-understandable layman's knowledge and basic facts that ordinary people know about the world.

Keywords: Word-Level Polarity Classification, Common-Sense Knowledge Base, Sentiment Analysis, Opinion Mining.

1 Introduction

Semantic orientation of a word indicates whether the word denotes a positive evaluation (such as praise or positive opinion) or a negative evaluation (such as criticism or negative opinion) [8][7]. Semantic orientation of a word is also referred as the valence or polarity of a word and systems to automatically determine semantic orientation of a word has applications in the area of sentiment analysis, opinion mining, multi-perspective question and answering and filtering abusive messages. Opinion mining and sentiment analysis of a product review or any subjective statement is an area which has received significant interest in recent times and polarity determination of a word is fundamental to the problem of sentiment analysis (refer to a detailed survey on opinion mining and sentiment analysis by Bo Pang and Lillian Lee [5]). Polarity determination at world level

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(fine-grained analysis) forms a component of a larger system wherein polarity determination at sentence, paragraph or document level needs to be performed. There are two sub-problems within the problem of determining semantic orientation of a word. One sub-problem consists of computing the direction (positive or negative) and the other sub-problem consists of computing the intensity or strength (weak or strong) within the computed direction. For example, the word good is a weak positive word whereas excellent or fabulous or astonishing is a strong positive word. Similarly, the word bad is a weak negative word whereas horrible or terrible is a strong negative word. Automatically determining the semantic orientation of word is required for developing sentiment lexicon as it is tedious and time consuming to manually label all the words in a language with its polarity and intensity.

The earliest work to solve the problem of automatically determining the semantic orientation of a word was done by Hatzivassiloglou et al [8]. The basis of the approach by Hatzivassiloglou et al is that adjectives conjoined by words such as *and* or *or* share the same polarity whereas adjectives conjoined by words such as *but* will have opposite polarity or orientation. The methods consists of extracting pairs of adjectives using conjunctions like *and*, *or*, *but*, *either-or*, or *neither-nor* from 1987 Wall Street Journal Corpus (a document set consisting of 21 million words) and assigning similar or different polarities to adjectives based on the type of conjuctions. Turney et al. proposed a general strategy for inferring semantic orientation of a word based on their hypothesis that the semantic orientation of a word tends to correspond to the semantic orientation of its neighbors [7]. Neighborhood between words is determined using statistical association or statistical dependence between words (word co-occurrence). Kamps et al. use WordNet to measure semantic orientation of adjectives by exploiting the graph-theoretic model of WordNet's synonym relations [3]. Esuli et al. present a technique for determining the semantic orientation of terms through gloss classification (performs quantitative analysis of the glosses or definitions of terms given in on-line dictionaries) [1]. Wilson et al. presents an approach to recognizing contextual polarity of phrases (a two-step process that employs machine learning that begins with a large stable of clues marked with prior polarity and then identifies the contextual polarity of the phrases that contain instances of those clues in a corpus) [9].Takamura et al. present a technique that consists of construcing a lexical network by connecting similar or related words and adopting the Potts model for the probability model of the lexical network [6].

1.1 Paper Contributions

We propose a novel technique for determining the polarity of a word by making use of a semantic network of common-sense knowledge. Previous approaches compute semantic orientation of words in a corpus-driven manner by performing statistical analysis on a corpus or rely on lexical resources created by experts and trained knowledge engineers. Previous approaches also rely on a pre-annotaed training dataset or a seed list of pre-classified sentiment words for performing its task. In this paper, we present a new approach that differs from the previous approaches and has the following advantages. The main advantages of our solution is that it relies on a lexical resource (called as ConceptNet) that represents common-sense knowledge created by volunteers on the Internet (14,000 contributors from around the world as mentioned in the paper by Liu et al. [4]) and not by trained or specialized knowledge engineers. Also, the proposed approach does not require any pre-annotated training dataset or manually created seed list to perform its tasks. Creating training dataset of pre-classified words and manually building specialized lexical resources for sentiment analysis application requires trained and specialized people and can be a time-consuming as well as tedious process. The proposed solution overcomes the dependency on experts by automatically creating sentiment lexicon and computing semantic orientation of words based on common-sense knowledge created by ordinary people as volunteers and not specialized knowledge engineers. The proposed approach performs polarity classification of sentiment word belonging to any lexical category (adjective, adverb noun and verb) unlike some approaches that are able to perform polarity classification of words belonging to just adjectives. We present empirical results (based on experiments performed on publicly available test dataset and a standard benchmark for this task) which prove that it is possible to predict with good accuracy the polarity of a word by using laymans common-sense knowledge. The limitation of our approach is that the accuracy and coverage of the words is a function of the number of concepts, assertions, relations and quality of data in the common-sense knowledge-base. The work presented in this paper is a step in the direction of our research on investigating the usefulness of machine understandable commonsense knowledge in the application domain of sentiment analysis and opinion mining.

2 Solution Approach

We leverage ConceptNet (which is machine-interpretable semantic network representing common-sense knowledge) for polarity classification of words. The common-sense knowledge present in ConceptNet is collected from volunteers on the Internet since the year 2000 and represents facts that ordinary people knows about the world [2]. The data present in ConceptNet is contributed by ordinary people unlike lexical resources such as WordNet and FrameNet which are mainly created by trained and specialized knowledge engineers. As ConceptNet is a semantic network, it consists of nodes connected by edges. The nodes represent the concepts and the edges represent predicates. Predicates express semantic relationships between two concepts. Some relationships between concepts in the ConceptNet semantic network are: IsA, MadeOf, UsedFor, CapableOf, DesireOf, CreatedBy, InstanceOf, PartOf, PropertyOf and EffectOf [2]. In ConceptNet, an assertion is uniquely defined by five properties: language, relation, concept1, concept2 and frequency. The Language property defines the language an assertion is expressed in (such as English). The Relation property defines the relation or the name of the predicate that connects the two concepts in the assertion (such as IsA, PartOf). Concept 1 and Concept 2 define the first and the second argument

Table 1. Pre-defined pattern over assertions belonging to the Desires relation

Assertion Property	**Value of the Assertion Property**
Language	English
Relation	Desires
Concept 1	a person or human or everyone
Concept 2	Word whose polarity needs to be determined
Assertion Type	+1 or -1

of the relation (words and phrases). The Frequency property expresses how often the given concepts would be related by the given relation, ranging from never to always. Also for each assertion, there is a field which defines the assertion type. The value of the assertion type is +1 if the assertion makes a positive statement (such as Diamonds are pretty) and -1 if it makes a negative statement (such as a person doesn't want anxiety).

(Step 1). The first step of the proposed solution consist of checking if the word matches the pattern or structure defined in Table 1. The pattern is based on our hypothesis that if a *person* or *human* or *everyone* (as Concept 1) desires (Relation type as Desires) something (represented as Concept 2), then Concept 2 (in our case a sentiment expressing word whose polarity needs to be determined) will have positive connotation if the assertion type is positive (i.e. has a value of +1) and will have negative connotation if the assertion type is negative (i.e. has a value of -1). This step does not require any seed list or pre-classified sentiment word and has an advantage over approaches that depend on having a training dataset or manually created seed list. We validated our hypothesis by entering few terms on the web-based interface provided at the ConceptNet website. For example, some of the words which are expressed as Concept 2 and where the Concept 1 is person, Relation is Desires, Assertion Type is +1 are: accomplish (verb), admiration (noun), affection (adjective), beautiful (adjective), bliss (noun), clever (adjective), comfort (verb) etc. Similarly, some of the words which are expressed as Concept 2 and where the Concept 1 is person, Relation is Desires, Assertion Type is -1 are: agonize (verb), annoyance (noun), anxiety (noun), bad (adjective), boredom (noun), cancer (noun), confuse (verb), criminal (noun), criticism (adjective), damaging (adjective) etc. We noticed that some words fall into a category where Concept 1 is person (or human or everyone), Relation is Desires and Assertion Type is both +1 and -1. Since, there is a conflict in assertion type, we do not predict the polarity of such words and leave it blank to be computed in the next steps of the overall process.

(Step 2). The second step of the solution consists of checking a pattern based on *DefinedAs* relationship. The pattern is based on the hypothesis that two concepts connected to each other using a *DefinedAs* relation in the same assertion will have the same polarity (synonym or semantically similar relationship). Hence, if the polarity of one of the concept is known in such a relation then the polarity of the connected work can also be computed. This step uses the classifications from the previous step to perform classifications of unclassified words. The seed for this step comes from previous step and hence this step as well as the subsequent steps does not require any pre-created seed list or training dataset. Unlike Step 1 (which is applied once), Step 2 is executed repeatedly until there is no additional coverage between two consecutive steps. This is done because the first run of Step 2 may result in polarity determination of certain words that can help in predicting polarities of words which could not be determined during the first run of Step 2. For example, let us say that there are two assertions "A DefinedAs B" & "B DefinedAs C" where A,B & C are three concepts in the ConceptNet semantic network. If the polarity of A is known and B is unknown after Step 1, then at the end of the first run of Step 2, polarity of B can be determined. The polarity of concept C can be determined after the second run of Step 2. Thus, Step 2 is repeated as long as the coverage is increasing. We validated our hypothesis by entering few terms on the web-based interface provided at the ConceptNet website. Some illustrative examples of two concepts connected to each other using DefinedAs relation: (blossom, flower), (devil, Satan), (eliminate, exclude), (grotesque, bizarre), (indelicate, indecent), (savage, vicious), (advance, progress), and (whip, beat). The concepts in ConceptNet are natural language fragments and we noticed that often the relationship is of the type A DefinedAs Same B" and "A DefinedAs Opposite B" where A and B are concepts. For example, one of the assertions in ConceptNet is: "Advance DefinedAs same Progress" (can be interpreted as synonyms). Some illustrative examples on concepts having the same polarity that we have provided belong to the assertion type A DefinedAs Same B". This can be handled by locating the word *same* in the concept and removing it from the concept string for extracting the word whose polarity needs to be determined. We noticed several assertions of type A DefinedAs Opposite B (can be interpreted as antonyms). Such assertions can be handled by extracting the term *opposite* from the concept string and flipping the polarity of B i.e. applying the inference that concept Bs polarity is opposite to the polarity of concept A. Some illustrative examples of two concepts connected to each other using *DefinedAs* relation and where the assertion is of type "A DefinedAs Opposite B" are: (dawn, dusk) (selfishness, selflessness), (slow, fast), (abnormal, normal), (bad, good), (clean, dirty), (cruel, kind), (evil, good), (evil, nice), (happiness, sadness), (hard, soft), and (yes, no).

(Step 3 and Step 4). Similar to Step 2, the third and fourth step consists of classifying a word using the polarity of words computed from previous steps (viewed as pre-annotated dataset or seed list for this step) and exploiting the *IsA* and *HasProperty* predicate of ConceptNet. This is based on the hypothesis that Concepts (in our case sentiment expressing nouns, verbs, adverbs or adjectives) connected to each other using *IsA* relationship are semantically *related* (may not be *similar* as in the case of *DefinedAs* predicate) and share the same polarity. Similar to the previous Step, we check the value of assertion type (+1 or -1) and the presence of terms like *same* and *opposite* in the concept for computing the semantic orientation of an unclassified word connected to a word (whose polarity is known) through the *IsA* and *HasProperty* predicate. Step 2,3 and 4 are executed repeatedly (*DefinedAs* analysis followed by *IsA* analysis followed by *HasProperty* analysis) to traverse the semantic network and assign polarities of connected words by exploiting properties of pre-defined predicates. Some illustrative examples of words connected to each other in the ConceptNet semantic netowrk through *IsA* predicate and having posistive polarity are: (cleanliness, good), (faith, trust), (happiness, bliss), (heart, love), (urge, desire), (virtue, good) and (honor, virtue). Some illustrative examples of words having negative polarity and connected through *IsA* predicate are: (assault, crime), (die, tragedy), (fraud, deception), (fraud, cheat), (injury, damage), (kill, crime), (slay, kill) and (war, conflict).

3 Empirical Evaluation

The test data for validating our approach consists of the publicly available subjectivity lexicon which can be freely downloaded from the "MPQA Releases - Corpus and Opinion Recognition System" website of the University of Pittsburgh [1]. The subjectivity lexicon has been used in [9] as well several other work. The subjectivity lexicon consists of 2007 words that have an entry in the ConceptNet. The 2007 words belonging to our test dataset have been pre-classified as positive or negative in the subjectivity lexicon (a benchmark for the task of polarity classification of subjective words). Thus, the actual polarity of all the 2007 words is known in advance which can be compared to the predicted polarity from our approach to determine the accuracy of the proposed solution. Amongst a total of 2007 distinct words in the test dataset, 830 words have positive polarity and 1177 words have negative polarity.

After executing Step 1, we obtained the results presented in Table 2. As mentioned in Step 1, we assign polarities to words where there is no conflict of polarities i.e. words that have been assigned a single polarity only. For example, after executing Step 1, we noticed that there were 22 words which had both positive and negative assertion types. The words are: busy, dance, death, drunk, dying, enlightenment, fairness, faith, free, happiness, hunger, laugh, less, little, live, rich, ridicule, scared, screw, shelter, truth and war. Table presents total and category-wise coverage after executing Step 1. We noticed that our system was able to classify 550 words out of 2007 (coverage of 27.4%) after removing 22 words that had a conflict of polarity. Table 3 presents the confusion matrix. As shown in Table 3, the classification accuracy that we obtained was 95.45%. Step 1 resulted in good coverage (able to classify 27.40% of the words) and high classification accuracy (correctly predicted the polarity of 95.45% of the words that it was able to classify). The results obtained after Step 1 validates our hypothesis that the assertion in ConceptNet in which the relation type is *Desires* and the first concept is *person*, *human* and *everyone* can be used to infer the polarity of the second concept (the second argument of the *Desires* predicate).

After executing Step 2 once (i.e. applying *DefinedAs* predicate), we were able to correctly classify (with 100% accuracy) nine more words. The pair of words

[1] URL: http://www.cs.pitt.edu/mpqa/

Table 2. Total coverage and category-wise coverage after executing Step 1

	Positive & Negative	Positive	Negative
Test Data	2007	830	1177
Coverage Absolute	550	245	305
Coverage Percentage	27.40%	29.51%	25.91%

Table 3. Confusion matrix and classification accuracy after executing Step 1

	Predicted	
	Positive	**Negative**
Actual Positive	227	7
Actual Negative	18	298
Correct Classification	(227+298)/550 = 95.45%	
Incorrect Classification	(7+18)/550 = 4.54%	

Table 4. Confusion matrix and accuracy after executing Step 2,3 and 4

	Predicted	
	Positive	**Negative**
Actual Positive	288	23
Actual Negative	51	398
Correct Classification	(288+398)/760 = 90.26%	
Incorrect Classification	(23+51)/760 = 9.74%	

connected to each other using *DefinedAs* predicate and having *same* polarity were: (fancy, like), (gratitude, thank), (liberal, generous), (murky, dark), (paranoia, fear). The polarity of *like*, *thank*, *generous*, *dark* and *fear* were computed from previous step which resulted in correctly classifing the polarity of words fancy, gratitude, liberal, murky and paranoia in Step 2. In this step, the system was also able to correctly classify (with 100% accuracy) words connected using *DefinedAs* relationship but having opposite polarity (as implied by the presence of the word *opposite* in the concept): (cold, warm), (cruel, kind), (hard, easy) and (rich, poor). We noticed that in this step, the accuracy was 100% but the coverage was low. Table 4 presents the final results obtained after executing Steps 2,3 and 4 repeatedly (Step 2 followed by Step 3 followed by Step 4) until no further classifications were observed. As shown in Table 4, the approach correctly predicted 686 words from a total of 760 words that it could classify (an accuracy of 90.26%). The system was able to create a sentiment lexicon of 760 words from a common-sense knowledge base without using any training dataset or a seed list with an accuracy of around 90%.

4 Conclusions

This paper investigates the usefulness of commonsense knowledge for classifying polarity of sentiment expressing words as positive or negative. Evaluation on test data consisting of publicly available pre-annotated subjectivity lexicon shows that leveraging common-sense knowledge that is shared by the vast majority of people for determining semantic orientation determination of words is feasible. The main advantage of the system is that it does not require any training data, hand-crafted seed list or any external resource that is created by trained and specialized knowledge engineers. The accuracy and coverage of the words is a function of the number of concepts, assertions, relations and quality of data in the common-sense knowledge-base.

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