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Knowledge-Based Sentiment Analysis and Visualization on Social Networks

Julio Vizcarra[1] · **Kouji Kozaki**[1,2] · **Miguel Torres Ruiz**[3] · **Rolando Quintero**[3]

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Abstract
A knowledge-based methodology is proposed for sentiment analysis on social networks. The work was focused on semantic processing taking into account the content handling the public user's opinions as excerpts of knowledge. Our approach implements knowledge graphs, similarity measures, graph theory algorithms, and a disambiguation process. The results obtained were compared with data retrieved from Twitter and users' reviews in Amazon. We measured the efficiency of our contribution with precision, recall, and the F-measure, comparing it with the traditional method of looking up concepts in dictionaries which usually assign averages. Moreover, an analysis was carried out to find the best performance for the classification by using polarity, sentiment, and a polarity–sentiment hybrid. A study is presented for arguing the advantage of using a disambiguation process in knowledge processing. A visualization system presents the social graphs to display the sentiment information of each comment as well as the social structure and communications in the network.

Keywords Sentiment analysis · Knowledge engineering · Conceptual similarity · Knowledge graph · Disambiguation

✉ Julio Vizcarra
kaivzro@gmail.com

1 The Institute of Scientific and Industrial Research (ISIR) Osaka University, Mihogaoka 8-1, Ibaraki, Osaka 567-0047, Japan

2 Department of Engineering Informatics, Faculty of Information and Communication Engineering, Osaka Electro-Communication University, 12-16 Hayakocho, Neyagawa-shi, Osaka 572-0837, Japan

3 Centro de Investigación en Computación CIC, Instituto Politécnico Nacional, UPALM-Zacatenco, CIC. Building, 07738 Mexico City, Mexico

Introduction

Nowadays, the huge content transmitted on social networks has become a rich source of information for human understanding as well as a way of expression where the users share their sentiment status and personal opinions through comments. The sentiment identification can classify comments as positive or negative (polarity) and reveal implicit emotions such as anger, trust, sadness, etc., on certain topics or users. In addition, the sentiments presented in the opinions can be relevant in the design of custom services and social plans for public health, marketing, e-commerce, etc. Moreover, sentiment analysis has become one of the fastest growing research areas in computer science due to the explosion in computer-based sentiment studies with the availability of subjective texts on the Web [21]. Furthermore, sentiment analysis has gained attention over the years among the general public as it is currently shown in Google trends [12], hence the importance of developing a methodology for sentiment analysis on social media considering shared opinions in daily life.

Based on the previous motivation, the present work aims to identify sentiment information presented in opinions on social networks. Our approach analyzes the content and implements semantic processing on the implicit knowledge in the comments. For each opinion, a formal representation is created and associated with estimated values of sentiment and polarity.

This paper is an extended version of the work presented at PAOS/PASSCR 2018 [31]. This article describes in detail the knowledge graph construction, semantic calculation, the disambiguation process, and sentiment analysis. In the implementation section, more experiments were carried out and analytic graphs included. Finally, a visualization system was introduced for sentiment analysis in social networks.

Background

This section lists some relevant works related to the proposed methodology presenting their key features. As a summary, we present a discussion where we remark on the main contributions of our work. Describing briefly, some similar works related to sentiment analysis are as follows: Anja Rudat [27] explored the criteria influencing selection for retweeting in Twitter. Additionally, the work of Victor Campos [5] provided concrete visual confirmation. It was explained that the multicultural visual sentiment is a deeply geographic-dependent entity as much as it is a semantically dependent one; trying to discover relations on social networks. Yuan Wang [33] proposed a methodology that inferred social relationships in microblogs based on physical interactions using users' location records. The work of Garcia-Pablos [9] proposed an unsupervised system for aspect-based sentiment analysis. One limitation of this work was the necessity of defining seed concepts and domains manually as input of the methodology. The work of Divya

Sehgal [28] proposed a real-time sentiment analysis using dictionaries, but mostly focused on big data techniques that prioritize the velocity over accuracy and deeper analysis. Implementing data mining, Ana Catarina Calheiros [4] proposed a sentiment classification of eco-hotels through a text mining approach. The work used different sources of customer reviews to gather relevant topics that characterize sentiment in a given hospitality environment. Theodore Georgiou [10] proposed a community detection algorithm utilizing social characteristics and geographic locations. The contribution of Kan Hong [14] provided emotional stress recognition and classification by signal amplification of emotional and physical stress. The work explored the medical domain considering physical and thermal signals for the classification.

The semantic processing the work of Shivam Srivastava [29] developed an algorithm to cluster places not only based on their locations but also their semantics in social networks. The contribution of this work was the geosocial clustering from check-in data. The work of Shuai Wang et al. [32] applied a semantics-based learning technique for a set of concepts previously labeled. The algorithm grouped target-related words to extract the semantics from words.

Moreover, in the field of social network analysis, the work of Shuiguang Deng [6] proposed a recommendation service based on a trust enhancement method. Considering social influence, Meng Jiang [17] studied interpersonal influence and explains the importance of this factor for behavior prediction. Additionally, Huang Liwei [15] explored the user's preference, and social and geographical influence to recommend proper points of interest. The machine learning implementation of Souvick Ghosh [11] processed the media text to determine the polarity and sentiment using manually labeled Facebook posts. The study of Tian [30] demonstrated that Facebook reactions and comments are a good source of data for investigating indicators of users' emotional attitudes. The work suggested that emojis can also be used to detect users' sentiment.

Reviewing the state of the art, most of the research studies worked with key social attributes that in general dismissed the semantics [27, 33] focusing mainly on the lexical processing. Other approaches implemented recommender systems [4, 17] using explicit users' information. Related works considered averages and dictionaries [28], keywords [4], or reactions in the social media [15, 30]. Methodologies that implemented machine learning techniques [9, 32] were based on a large, high-quality training dataset on a specific domain. Our approach handles the comments as excerpts of knowledge, taking into account the implicit information in the comments. In this gap, we prioritize the semantic level, sense, and meaning of the whole comment. The proposal computed semantic similarity measures, conceptual expansion, graph theory algorithms and disambiguation using a multi-domain knowledge base. The methodology is flexible, which implies that the domains and its application can be adjusted by modifying the knowledge base.

The advantage of our sentiment analysis is the context and the words' sense handling in the calculation, in order to discover the purpose of a comment. As the methodology is based on a well-structured knowledge base the definition of concepts and domains is more accurate. Our contribution creates a bridge between lexical and semantic levels for processing the implicit sentiment information and for better content understanding. Regarding adaptability, comparing our system to the related work, it is not necessary to recompute and train for each specific case of study.

Methodology

This section describes the methodology in three main stages. The first stage "social networks discovery" retrieves opinions from events or public profiles by reading their comments in a social graph. The stage of "knowledge processing" constructs the formal representation for each comment. This module carries out processes of automatic knowledge graph construction enhanced by disambiguation. Finally, the stage of "sentiment analysis," estimates the total polarity and main sentiment presented in the comments.

Social Network Discovery Stage

In this module for a public event or user's profile, a target-based process retrieves users' comments and maps the structure of the social graph. Considering popularity, Twitter and Facebook were selected for the discovery and data extraction. In the case of Facebook, the scanning process retrieves comments and their replies exploring public posts, photos, and videos. Similarly for Twitter, the posts and their replies are retrieved for a maximum lapse of 7 days due to the policies (Fig. 1).

Knowledge Processing Stage

In the knowledge processing stage, the content of each comment is defined by a formal representation (knowledge graph). In this stage, the concepts in a comment are processed using a lexical and semantic processing by using a knowledge base (KB) which is composed of large knowledge graphs and this stage creates subgraphs that represent each comment. The knowledge graphs considered are Wordnet [25], Japanese Wordnet (Japanese language) [2, 16] and Open Multilingual Wordnet (several languages) [2, 3] for the understanding of content on a wide number of domains for each language. The KB is enriched with sentiment descriptions by mapping graphs

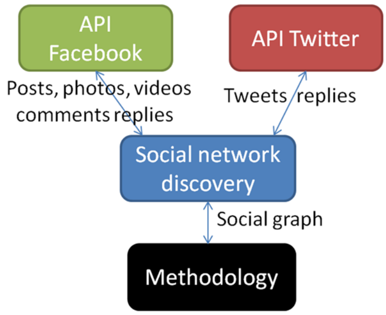

Fig. 1 Social network discovery and retrieval

with dictionaries such as SentiWornet [1] and NRC Emotion Lexicon [23, 24] into them.

In the first step, a lexical pre-processing is computed to transform a concept in a way that it can be mapped in the KB. The second step is to construct the representation of each comment by knowledge graph expansion; in this process, each concept is expanded by semantic relations until finding a common root where all the senses of all the concepts are connected. The third step is to assign a similarity measure for all the concepts connected in expansion. Finally, a process of disambiguation is computed to find only one sense for each concept and reduce the size of the final graph.

Lexical Pre-processing

In this step, for each concept in the comment, a lexical pre-processing is computed to provide to the next stage of the methodology an adequate term that matches the KB. The processes related are listed as follows:

- Tokenizer. In this process, a sequence of strings is divided into pieces (words) called tokens.
- Removal of stop words. If a concept belongs to a stop word list (lexical words or with little meaning), it is removed.
- Stemming. The purpose of this processing is to reduce words (inflected or derived) to their word stem (base or root form). Each concept is reduced to its stem using the Krovetz algorithm [18].
- Removal of unknown concepts in the KB. This process is executed to reduce and discard concepts that cannot be mapped to the KB and it also reduces extraprocessing.

Regarding the negation [7, 19] for English language, the methodology considered the cases of Not-negator (couldn't, didn't, etc.) and N-negator (no, not, etc.) as stop words. That is, the meanings of negation are not considered, since our approach focuses on the semantic level. We suppose that the negation can be explored as future work with a deeper lexical–syntactic analysis and natural language processing.

Knowledge Graph Expansion

In this step, the concepts obtained from the lexical processing are expanded on the knowledge graph in the KB until finding a common root that connects all their senses.

Let us define $G(C, R)$ as a knowledge graph with the set of concepts C and the set of relationships R; the knowledge base expansion (Ge) (Eqs. 1, 2) for a concept c $\in$ C is the iterative process (α iteration) of discovering new concepts in knowledge graph (G) using semantic relations (ρ) (Eq. 4) that connect a origin concept c to the other destination concepts $C\alpha$ (Eq. 3):

$$Ge_0^{\rho}(c,G) = G_0(C_0,R_0) = G_0(\{c\},\emptyset) \tag{1}$$

$$Ge_{\alpha}^{\rho}(c,G(C,R)) = G_{\alpha}(C_{\alpha}^{\rho},R_{\alpha}^{\rho}) \tag{2}$$

$$C_{\alpha}^{\rho} = \begin{cases} \alpha = 0 \ \{c\} \\ \alpha > 0 \ C_{\alpha-1} \cup \left\{ y \in C : x \in C_{\alpha-1}, \rho(x,y) \in R \right\} \end{cases} \tag{3}$$

$$R_{\alpha}^{\rho} = \begin{cases} \alpha = 0 \ \emptyset \\ \alpha > 0 \ \left\{ \rho(x,y) \in R : x,y \in C, x \in C_{\alpha-1} \right\}. \end{cases} \tag{4}$$

Figure 2 presents an example of expansion for the concepts C_z, C_y represented by an ellipse and a rectangle. Initially, the senses for the input concepts are identified as a knowledge graph in the KB. Based on the example, the correspondences are for $C_z \in S_a, S_b$ and $C_y \in S_1, S_2, S_3$. After the sense identification is performed, the process of expansion iteratively continues discovering concepts C_x, until finding a concept root C_R that connects all the senses.

Similarity Measure

Once the concepts were expanded in the previous stage (see "Knowledge processing stage"), the next process is to establish similarity measures among all concepts and obtain a weighted graph $WG_D(C,R)$. To accomplish this task, two different approaches were implemented, based on the calculation of each semantic relationship in the graph. The algorithms are listed as follows:

1) Automatically. The similarity measure of conceptual distance DIS-C [26] was implemented, that automatically establishes the similarity values between concepts following the idea of visibility in the knowledge graph.
2) Manually. For each semantic relationship in the knowledge graph, the methodology establishes a static weight. This fixed value is a rational number located in the range between [0,1].

Either of the previous approaches can be implemented, depending on the number of concepts produced in the knowledge graph expansion (the automatic approach consumes considerably more memory and time compared to manual processing).

Figure 3 presents an example taken from the previous expansion and estimates the similarity measure. For a set of relations: $\left\{R_x, R_y, ., R_n\right\}$ (left side) the similarity measure process calculates the weight of each relation (W^+) and their inverse (W^-) producing the set of weights: $\left\{W_x^{+-}, W_y^{+-}, ., W_n^{+-}\right\}$. In the end of the calculation, a strongly connected graph is obtained. For instance, considering a pair of concepts C_x, C_y, they will be connected through weighted direct and inverse relations $R^+(x,y), R^-(y,x)$, respectively.

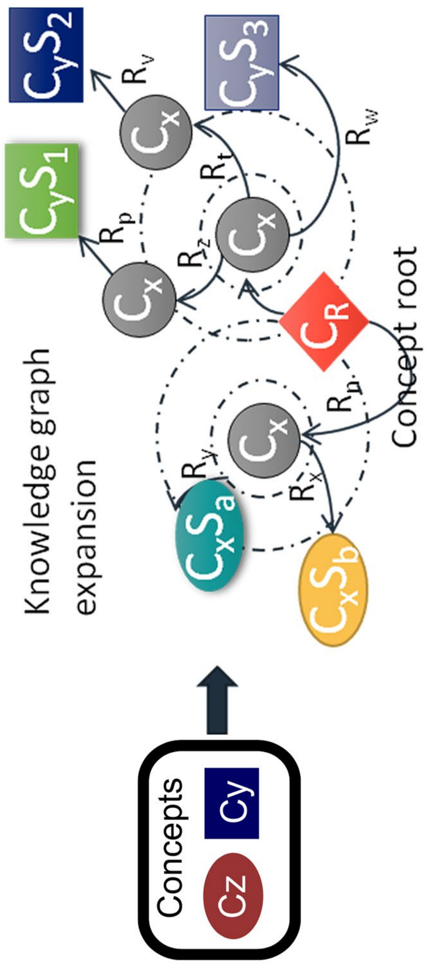

Fig. 2 Graph expansion

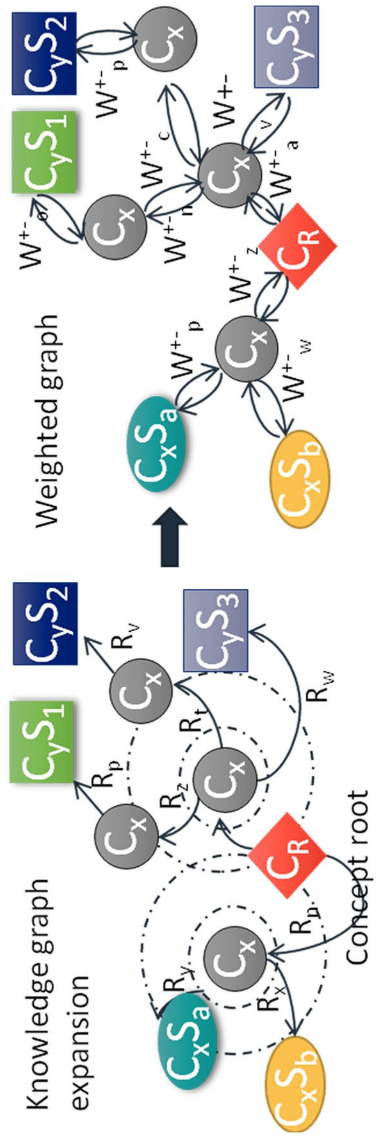

Fig. 3 Similarity measure

Disambiguation

In this stage, a weighted graph $WG_D(C, R)$ is processed to disambiguate its concepts and reduce its dimension (number of nodes and relationships) by implementing a Steiner tree algorithm. In our methodology, we implemented the SketchLs algorithm [13] because of its capability for handling large graphs. The disambiguation process starts by taking a set of concepts previously processed by the Natural Language Processing (NPL) step and located in the weighted graph $WG_D(C, R)$ (Fig. 4). If the concept is located in the KB, the disambiguation process starts counting the number of occurrences (senses). In this scenario, we have the following cases:

(1) If a concept has only one sense, it does not need to be disambiguated, but it has to participate in the disambiguation of the rest of the concepts.
(2) (2) If a concept has more than one occurrence, this implies that it has to be disambiguated.

Based on the number of concepts in the text (set), the disambiguation process has the following cases:

(3) If the text(set) has only one concept and it has several senses, then a dictionary of polysemy has to be consulted to find the most probable sense.
(4) If the text(set) has more than one concept, with at least one with several senses, then the disambiguation is computed normally.

The disambiguation process is depicted in Fig. 5. The method takes the weighted graph $WG_D(C, R)$ created previously (a) (see "Knowledge processing stage"). To compute the Steiner tree algorithm (SketchLs), the concepts that have several senses are grouped as single nodes (b). After applying the SketchLs algorithm (c), the single nodes are divided and their original relations are replaced obtaining the final Steiner tree (d).

Sentiment Analysis Stage

Polarity Calculation

In this step, the polarity for a comment Polarity(Comment$_x$) is calculated taking into account the individual polarity of each concept $Po\left(C_x\right)$. The process starts dividing the concepts in subsets X_g considering if a concept C_x has positive or negative polarity Po(C_x) (see Eqs. 5, 6). To calculate the polarity Pot(X_g) for a set of concepts X_g, the arithmetic mean is computed (Eq. 7). The total polarity of a comment Polarity(Comment$_x$) is calculated by the sum of positive plus negative polarities (X_P and X_N, respectively) (see Eq. 8):

$$X_P = \left\{ C_x \mid Po\left(C_x\right) > 0; C_x \epsilon X_P \right\} \tag{5}$$

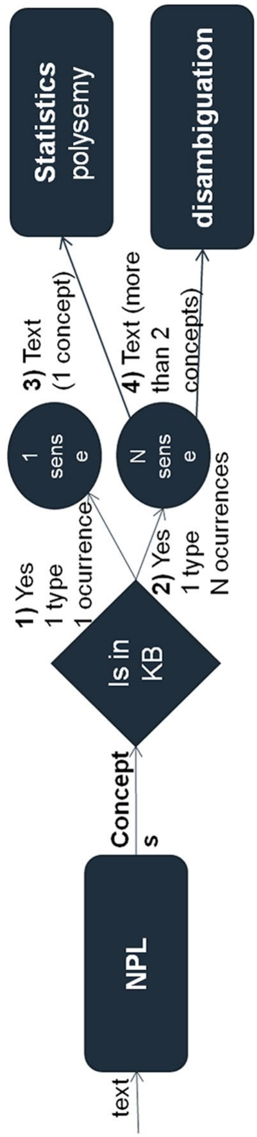

Fig. 4 Disambiguation cases

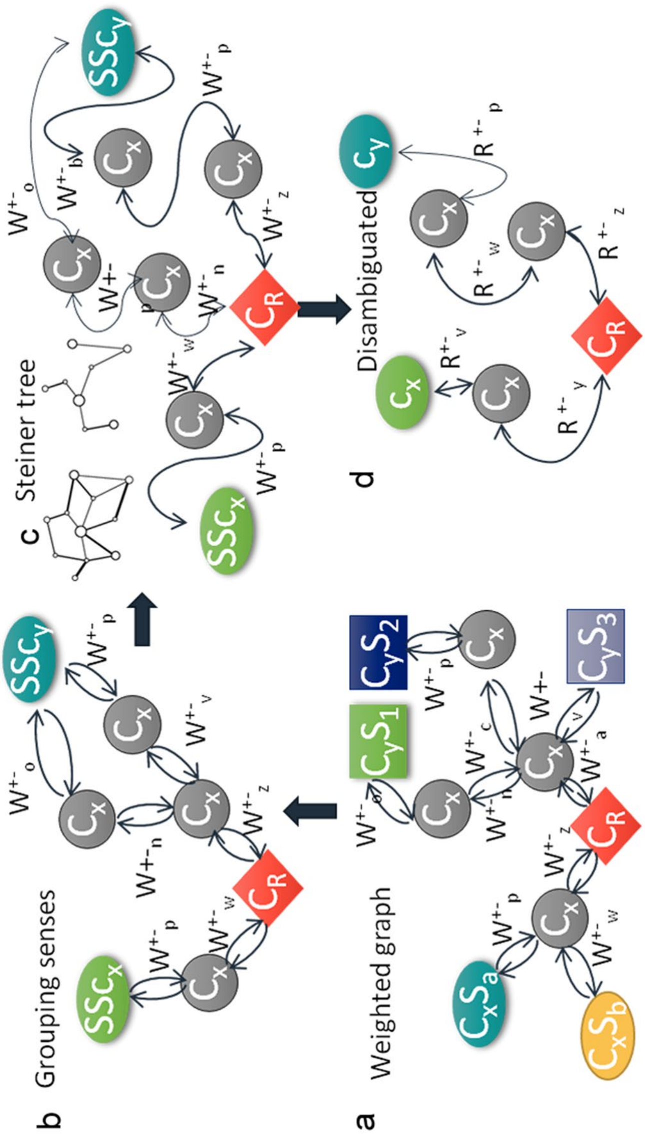

Fig. 5 Disambiguation by graph theory

$$X_N = \{C_x \mid Po(C_x) < 0; C_x \epsilon X_N\} \tag{6}$$

$$\overline{\mathrm{Pot}(X_g)} = \frac{\sum_{i=0}^{n} Po(C_x)}{n}; C_x \epsilon X_g \tag{7}$$

$$\text{Polarity}(\text{Comment}_x) = \overline{Pot(X_P)} + \overline{Pot(X_N)};\ X_P, X_N \subseteq Comment_x. \tag{8}$$

Sentiment Identification

In this step, the sentiment status is identified in a comment Sentiment(Comment$_x$). For each concept $C_i \in$ Comment$_x$, C_i is expanded in the knowledge graph until finding one or more concepts associated with a sentiment S_x ($C_x \rightarrow S_x$). The next step is to find the closest sentiment S_x to C_i by computing semantic similarities and the shortest path algorithm. Consecutively, a pre-defined numerical weight $Ws(C_x)$ is assigned for the sentiment S_x which is in the range between [-1,-1] (Eq. 9). Once the weight of the sentiment is established, the next step is to calculate the sentiment value $Sen(Cx)$ for the concept C_x by multiplying the sentiment weight $Ws(C_x)$ by its polarity $Po(C_x)$ (Eq. 10). Finally, the sentiment status with the highest sentiment value $Sen(C_x)$ is assigned to the comment Comment$_x$ (Eq. 11):

$$Ws(C_x) = w(S_x); C_x \rightarrow S_x, w(S_x) \in [-1, 1] \tag{9}$$

$$\mathrm{Sen}(C_x) = Po(C_x) Ws(C_x) \tag{10}$$

$$\text{Sentiment(Comment\_}\{x\}) = \max(\{\mathrm{Sen}(C_i) | C_i \in \text{Coment}_x | \}). \tag{11}$$

Figure 6 presents the iterative process of expansion for finding the sentiment associated with a concept C_x in the knowledge base. During the expansion, if the iteration discovers at least one concept linked to a sentiment, then the expansion stops. Consequently, the algorithm Dijkstra with Fibonacci heap [8] is executed to select only one concept/sentiment for the concept C_x. Some differences in this expansion compared to the knowledge processing stage (see "Knowledge processing stage") are as follows:

- The expansion in the sentiment identification works on an individual concept C_x instead of a set.
- The iterative process in the sentiment identification stops when at least one concept is linked to a sentiment instead of a common root for a set.
- Regarding the graph theory algorithm applied, the sentiment identification implements Dijkstra instead of Steiner tree.
- Both expansions work on the same KB using different methods.

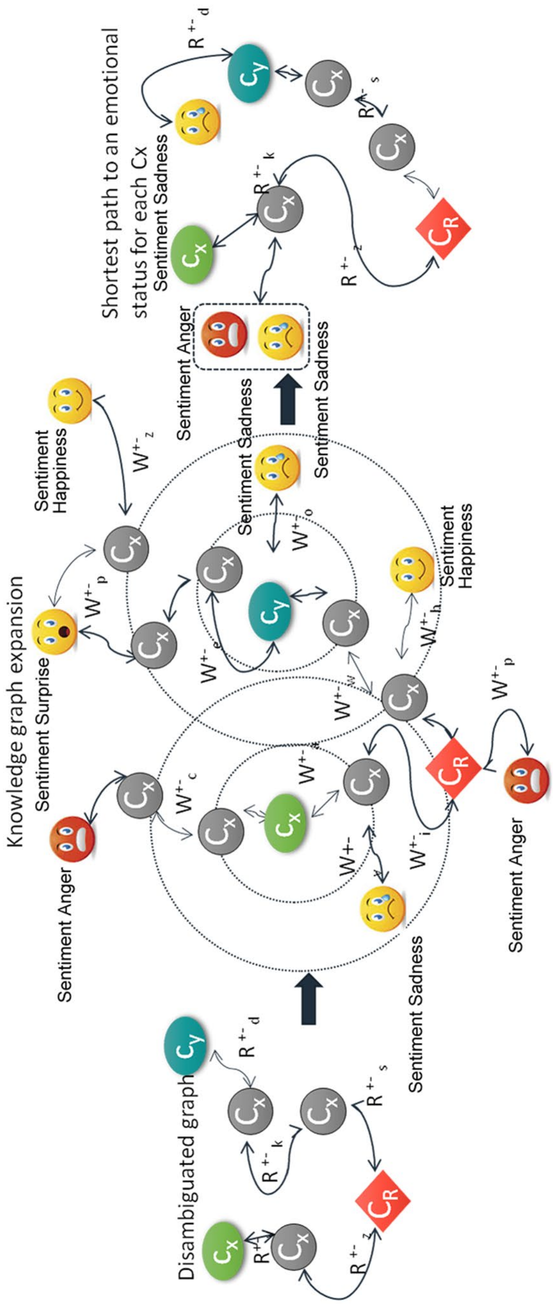

Fig. 6 Sentiment identification

Implementation

This section presents the experiments on an example taken from the social network (Twitter) and processed by our methodology. It is divided into three subsections: "knowledge base," "knowledge processing" ", and sentiment analysis."

KB

In this section, we describe the KB's structure which is composed of general knowledge graphs for common language understanding on several domains and dictionaries of sentiments/polarity aligned to the knowledge graphs.

General Knowledge Graphs

- WordNet [25] (version 3.1). WordNet is a large lexical database of English nouns, verbs, adjectives, and adverbs which are grouped into sets of cognitive synonyms (synsets) expressing a distinct concept. Synsets are interlinked by means of conceptual–semantic and lexical relations.
- The Japanese WordNet [2, 16]. It was originally developed at the National Institute of Information and Communications Technology to support Natural Language Processing research in Japan.
- Open Multilingual WordNet [2, 3]. It provides access to 34 Open WordNets merged and linked to the Princeton English WordNet.

Sentiment Dictionaries

- SentiWordNet [1]. A lexical resource explicitly devised for supporting sentiment classification and opinion mining applications.
- NRC_emotion_lexicon [23, 24]. It is a list of English words[14,182 unigrams (words)] and their associations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and polarities (negative and positive). The annotations were manually done by crowd sourcing.

Knowledge Processing

To explain the results obtained by the knowledge processing and sentiment analysis stages, an example was processed from Twitter on the CNN news account. The comment considered is "a number of people feared dead after a dam bursts in Kenya with hundreds left homeless officials say."

Lexical Processing

The lexical processing starts by identifying the language. In the case of English or Spanish, the words are evaluated if most of them are mapped in these specific

Table 1 Lexical processing for the comment taken from Twitter

Input	A number of people dead after a dam bursts in Kenya with hundreds left homeless officials say
Output	People-dead-after-dam-burst-kenya-hundred-left-homeless-official-say

language in the KB. On the other hand, for the Japanese language, it is necessary to identify if some characters, Kanji or Kana, are located in the text. Once the language, it is identified specific grammatical rules using Apache Lucene [22] are computed: tokenizer, stemming, and KB mapping. Having taken the Twitter comment from CNN news. Table 1 presents the text to be analyzed (input) in the lexical processing and concepts obtained (set of 12 tokens) that are also located in the KB (output).

KB Expansion

Following the processing on the comment taken from Twitter, Fig. 7 presents graphically the expansion on the KB. The set of concepts marked in a circle represent the distant senses where the conceptual distance is further once the expansion was completed, i.e., when a common root was found. These further concepts are not considered in the next processes.

Table 2 presents some statistics of the expansion process. During the first iteration, the common root “attribute”was found, that connects the 12 concepts and, in total, the expanded graph contains 761 concepts.

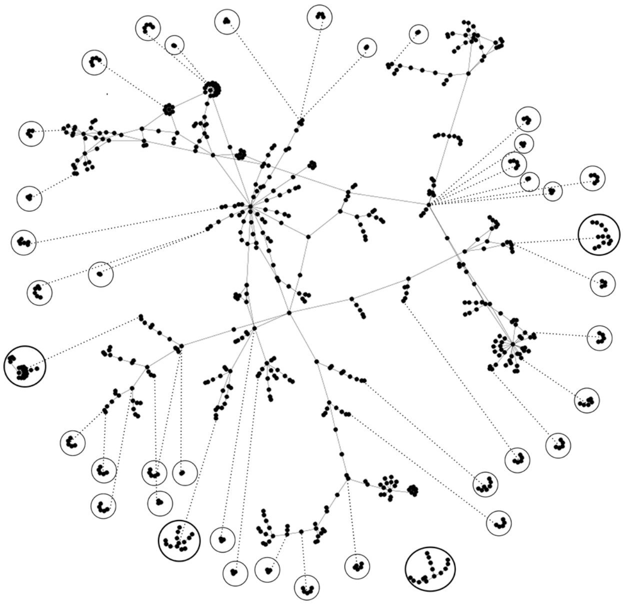

Fig. 7 Expansion of the comment taken from Twitter

Table 2 Results of the knowledge expansion

Iteration	1
Root	label: attribute
Concepts	761

Table 3 Weights for each relation manually assigned

Relation	Weight
Hyponym, hypernym	0.50
Member_holonym, member_meronym	0.25
Part_holonym, part_meronym	0.25
Instance_hypernym, instance_hyponym	0.75

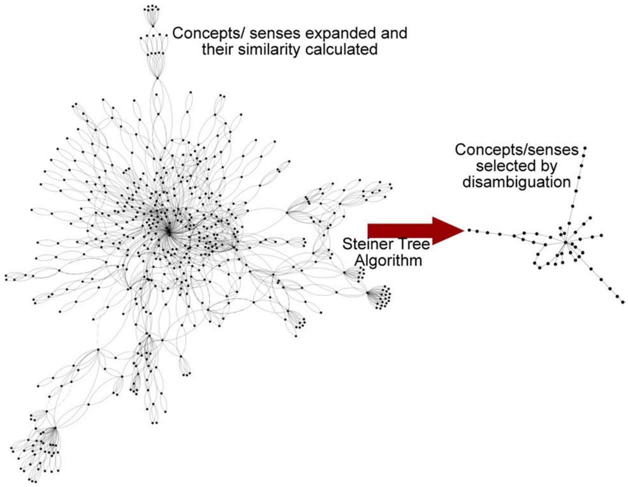

Fig. 8 Weighted graph strongly connected and Steiner tree produced

Semantic Similarity Measure

Based on the graph previously created by expansion, the next step is to produce a weighted graph by the calculation of semantic similarities among concepts with both automatic and manual approaches. In the case of automatic calculation, the algorithm DIS-C was applied. On the other hand, in the manual calculation, we established weights of each sentiment as shown in Table 3. It is important to mention that both approaches maintain the weighted graph's topology with differences only in the edges' values (weights).

Disambiguation

This section presents the results produced by the disambiguation process on the weighted graph previously created. For the comment taken from Twitter, Fig. 8

Table 4 Part of speech for each concept from the comment in Twitter

Concept	Part of speech	Description (Gloss)
Number	Noun	A concept of quantity involving zero and units
Leave	Noun	Permission to do something
Official	Noun	A worker who holds or is invested with an office
Homeless	Noun	Poor people who unfortunately do not have a home to live in
Say	Verb	Communicate or express nonverbally
Burst	Verb	Be in a state of movement or action
People	Noun	(Plural) any group of human beings...
Dam	Noun	Female parent of an animal especially domestic livestock
Century	Noun	100 years
Kenya	Noun	A republic in eastern Africa; achieved independence from the United Kingdom in 1963...
Dead	Noun	People who are no longer living

presents graphically on the left side the graph constructed by similarity measure (weighted graph) and on the right side the Steiner tree produced.

As a result of the disambiguation process, the methodology also identifies the part of speech based on WordNet. Following the example taken from Twitter, Table 4 describes each sense assigned to a concept: name, part of speech, and description (gloss).

During the disambiguation processes, the Steiner tree algorithm was applied (SketchLs). The statistics are shown in Table 5 as to the number of iterations, nodes processed, M number of seed sampling, etc. (see [13] for more detail).

Sentiment Analysis

In this section, an example (comment) is presented in Fig. 9 where the graph expansion tries to find concepts related with sentiments. For each concept C_x, a sentiment is assigned.

Regarding the methodology, Table 6 presents the weights which we assigned to each sentiment for the calculation of $Ws(C_x)$. These weights for each sentiment are multiplied by the polarity to obtain a sentiment $\mathrm{Sen}(C_x)$ for each concept in the comment.

Table 5 Results Steiner tree for comment in Twitter

Seed Sampling (M)	6
Nodes	560
Iterations	15

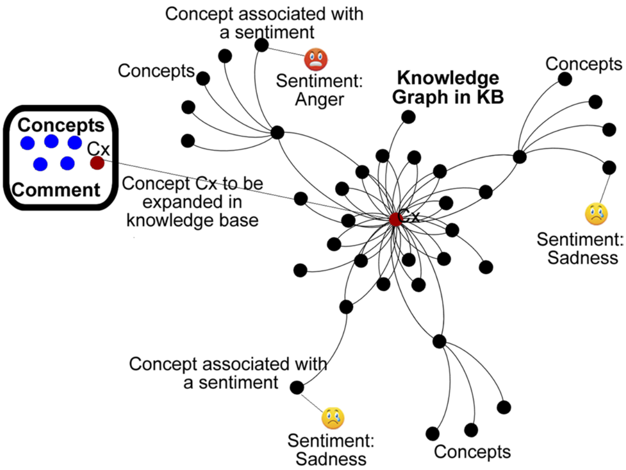

Fig. 9 Sentiment expansion for a comment

Table 6 Weights for each sentiment assigned manually

Sentiment	Weight
Joy	1
Trust	0.75
Anticipation	0.5
Surprise	0.25
Anger	– 1
Disgust	– 0.75
Sadness	– 0.5
Fear	– 0.25

Table 7 Sentiment–polarity assigned to each concept

Concept	Sentiment	Polarity
(Flare,burst)	Fear,anger	– 0.25
(Homeless)	Anticipation,disgust,anger	– 0.125
(Fear)	Fear,sadness,anger,surprise	– 0.875
(Say)	Surprise,anticipation	0.5

Following the processing on the comment taken from Twitter, Table 7 presents the sentiment estimation. Our methodology calculates the closest sentiment and the polarity value for each concept.

Finally, the methodology estimates the total polarity and main sentiment presented in the comment taken from Twitter (Table 8). It is important to mention if some concepts have equal values of $\mathrm{Sen}\left(C_x\right)$, then more than one sentiment can be assigned to a comment.

Table 8 Sentiment–polarity assigned to comment

Sentiment	Polarity	Comment
Anger	– 0.1875	a number of people feared dead after a dam bursts in Kenya with hundreds left homeless officials say

Other relevant examples from the CNN news account were processed by our methodology and are presented in Table 9. We noticed a better classification using the basic sentiments instead of polarity. The correct estimations considering sentiment are **underlined** in the columns labeled and estimated.

Evaluation

This section measures the performance of our methodology comparing it with labeled data with sentiment information. We considered as manual processing Twitter posts that we manually labeled and as automatic processing comments ranked by the users in Amazon reviews. As traditional method (baseline), we proposed the process of only looking up concepts of polarity in dictionaries.

The labeling in the charts follows a specific structure depending on the approach applied in the calculation of similarity measures, the sentiment information considered (sentiment/polarity), and the baseline. The cases are described in the following list:

- In the knowledge processing, the automatic and manual similarity calculation are defined as “ SemRelAuto ” and “ SemRelManual, ” respectively.
- In the case of sentiment method implemented, the label is defined as “Polarity” and Sentiment “SS.”
- In the baseline using the process of looking up words for polarity in dictionaries, this method was only processed by lexical processing and named as “Polarity Lex.”

As an example of this labeling, the tag “SSSemRelAuto” considers the sentiment(SS) and semantic processing using an automatic similarity calculation (SemRelAuto).

Sentiment Evaluation on Amazon Reviews

We evaluated the performance of our contribution with precision, recall, and the F-measure on 11702 comments using the dataset Amazon reviews provided by the Stanford Network Analysis Project (SNAP) [20] and shared by Xiang Zhang [34]. In this dataset, the users give scores for products in the range of 1–5 starts. We related the scores with 1–2 starts with negative sentiments (anger, disgust, sadness, and fear) and negative polarity. Similarly, we associated scores with 4–5 starts with positive sentiments (joy, trust, anticipation, and surprise) and positive polarity. Neutral comments with three starts were not considered.

Figure 10 presents the evaluation of our methodology with several experiments, such as using different sentiment information and similarity measure calculation.

Table 10 presents the confusion matrix considering the processing “SSRelAuto.”

Table 9 Other examples processed in twitter

Labeled (Manual)	Estimated (Methodology)	Polarity	Comment
Trust	Trust	0.2916	This couple found a buried safe containing $52,000 worth of money, gold and jewelry in their backyard, but didn't keep it
Trust	Trust	– 0.15	In an effort to keep conversations and search results on topic, Twitter announced it will use new "behavioral signals"to push down more tweets that "distort and detract"
Anger	Anger	0.0416	A massive poaching ring in Oregon and Washington is accused of killing more than 200 animals including deer, bears, cougars, bobcats and a squirrel
Anger	Anger	0.0416	An estimated 239,000 girls under the age of five die in India each year due to neglect linked to gender discrimination, a new study finds
Sadness	Sadness	0.25	@CNN Her father had a heart surgery and cant walk so
Sadness	Sadness	– 0.25	Teen develops 'wet lung' after vaping for just 3 weeks
Joy	Joy	0.125	I am proud to be a woman and a feminist. The politics of Meghan Markle
Disgust	Joy	– 0.125	@CNN He'd done some great work before Black Panther. I hope he's not doing that gesture for the rest of his life
Anger	Joy	0.125	@CNN And they wander why people say fake news. Facts mean nothing to CNN. Anything to drive their narrative
Disgust (sarcasm)	Trust	– 0.125	@CNN Is it filled with candy? Can I hit it with a bat
Trust	Anger	0.3125	This gel is as flexible as jello, but five times stronger than steel
Anger	Sadness	0.2708	By most accounts, Rosemarie Melanson should be dead. The Las Vegas shooting victim was among the first to be shot and lost consciousness

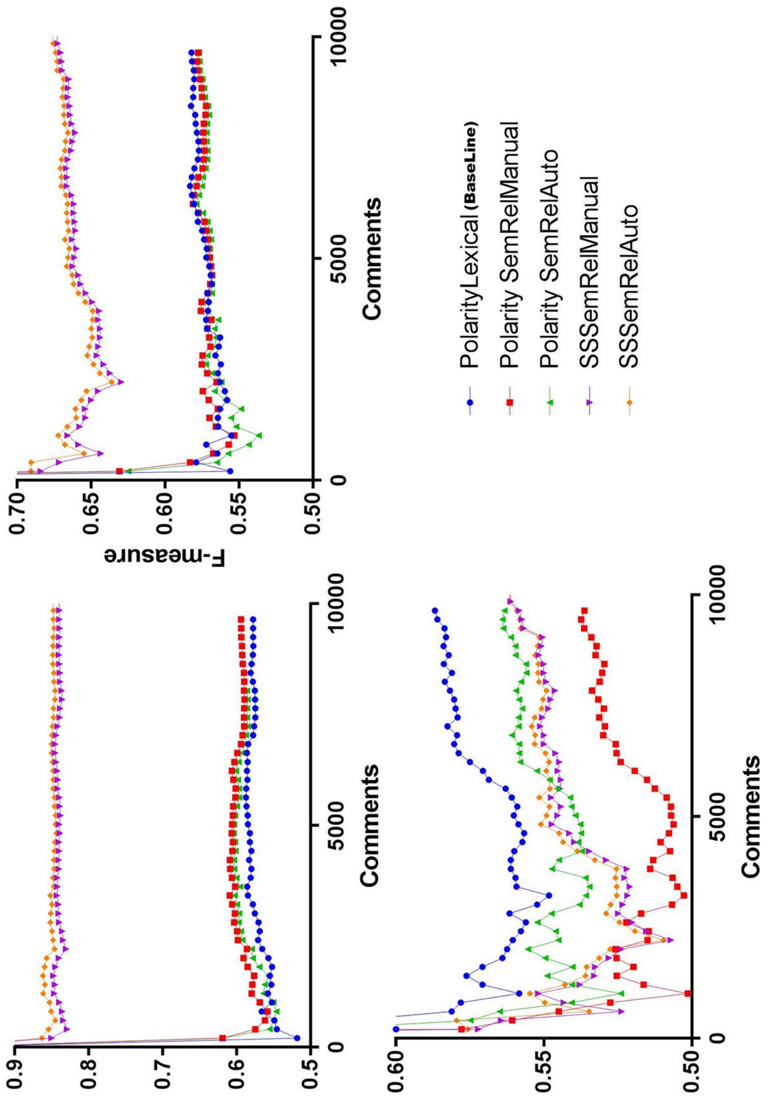

Fig. 10 Evaluation on Amazon reviews

Table 10 Confusion matrix for Amazon reviews

Predicted values	Actual values	
	Positive	Negative
Positive	5087 (TP)	904 (FP)
Negative	1518 (FN)	3917 (TN)

Additionally, Fig. 11 presents experiments of the disambiguation process working on the same sentiment information (polarity). We compared our methodology with semantic processing (polarity Auto and polarity Manual) against ten random sense selections (PolarityLexicalR1-R10) and the baseline (polarity lexical).

Regarding the influence of the negation, an analysis using Amazon reviews was carried out. Currently the system is not able to automatically identify negation. Consequently, we manually identified the case N-negator (no, not) and the concept modified. As the results, 350 comments contain N-negators and 80 of them have opposite meaning by them.

Based on the experiments during the total estimation of sentiment and polarity for a comment, each concept, modified by negation, affects in certain grade the calculation. The scenarios where estimation varies are: (1) the concept modified by negation has a high polarity value (negative or positive), (2) the comment contains a low number of concepts (short comment), (3) a comment can be associated with two or more sentiments, and (4) the total estimation of polarity is near to 0. In the previous cases, the sentiment can commonly be incorrectly estimated from anger or disgust to trust or joy and from negative to positive polarity.

In addition, we noticed a slight variance in the sentiment calculation, because the negation is highly related to comments with negative sentiment (anger or disgust) and negative polarity. Usually, comments with negative sentiments are more explicit than positive (joy or trust) and include more relevant concepts on the negative domain. Consequently, the total sentiment estimation is not highly affected because of the presence of a high number of negative concepts.

An extended analysis of negation is proposed as future work to evaluate the overall performance by handling comments with negation.

Sentiment Evaluation on Twitter

For this evaluation, 500 comments were retrieved from Twitter on the account CNN news, and we manually associated them with an estimated sentiment and polarity. Figure 12 presents the results only considering precision. The methods compared were the "PolarityLex" (baseline) and "SSSemRelAuto." In this experiment, the precision using sentiment presented better results and corresponds with the performance obtained in the previous evaluation using Amazon reviews.

During the experiments, we noticed that the methodology provides different results depending on specific sentiments (Fig. 13). The methods compared were the "PolarityLex" (baseline) and "SSSemRelAuto." We noticed that for the sentiment anger or disgust, our methodology obtained better precision, because, usually, the comments are

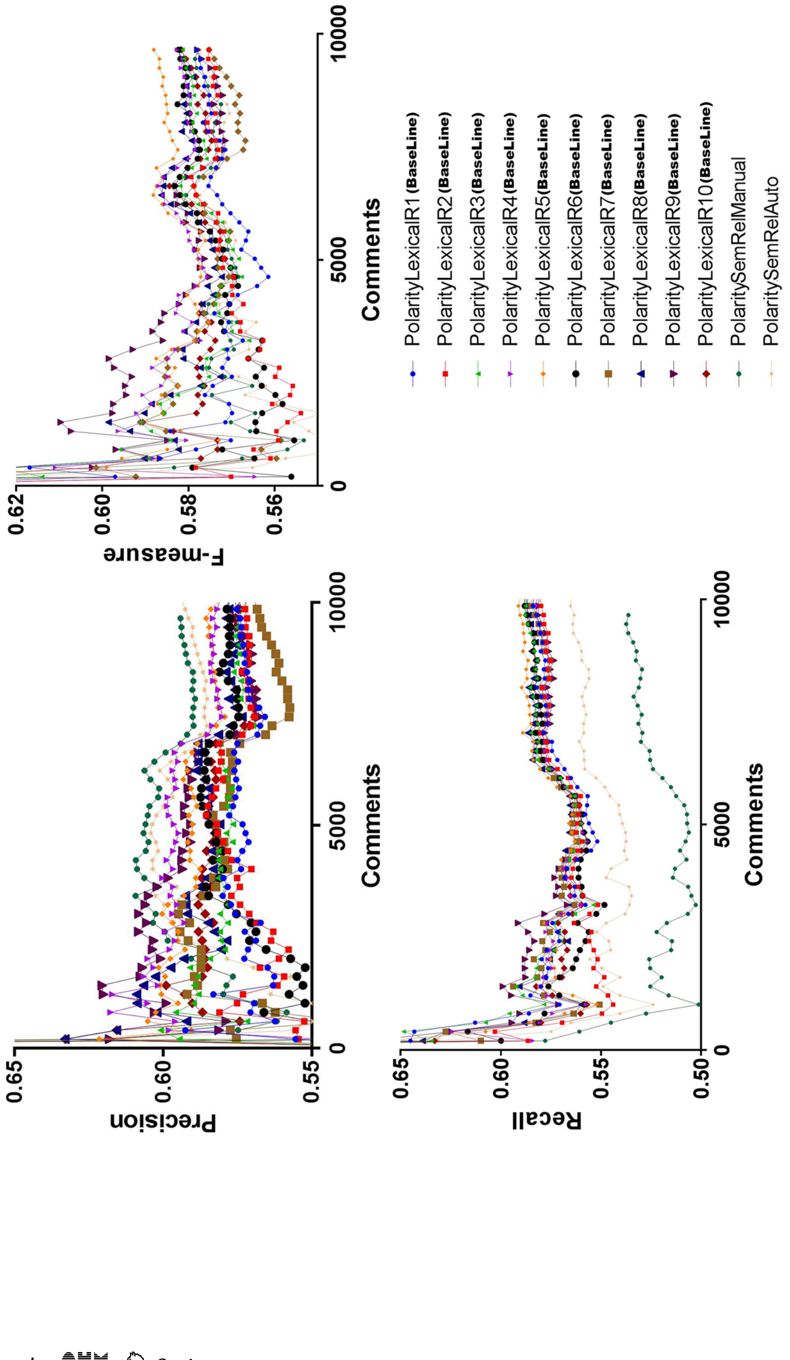

Fig. 11 Evaluation of the disambiguation process

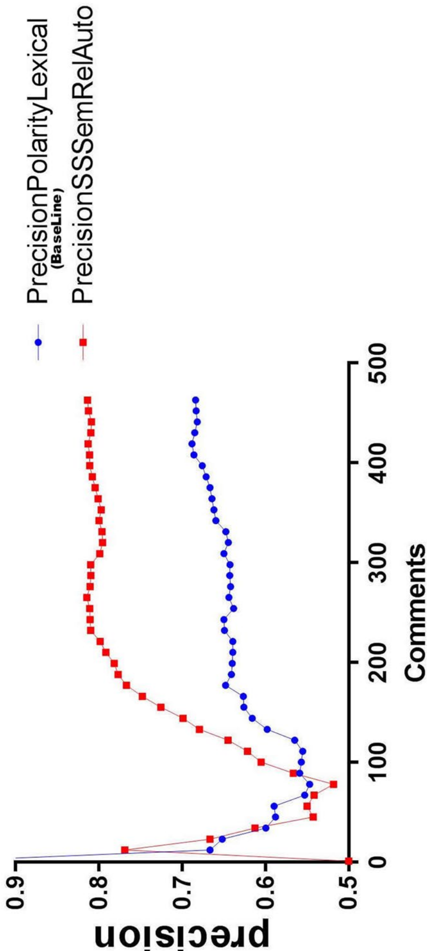

Fig. 12 Evaluation of the account CNN news on Twitter

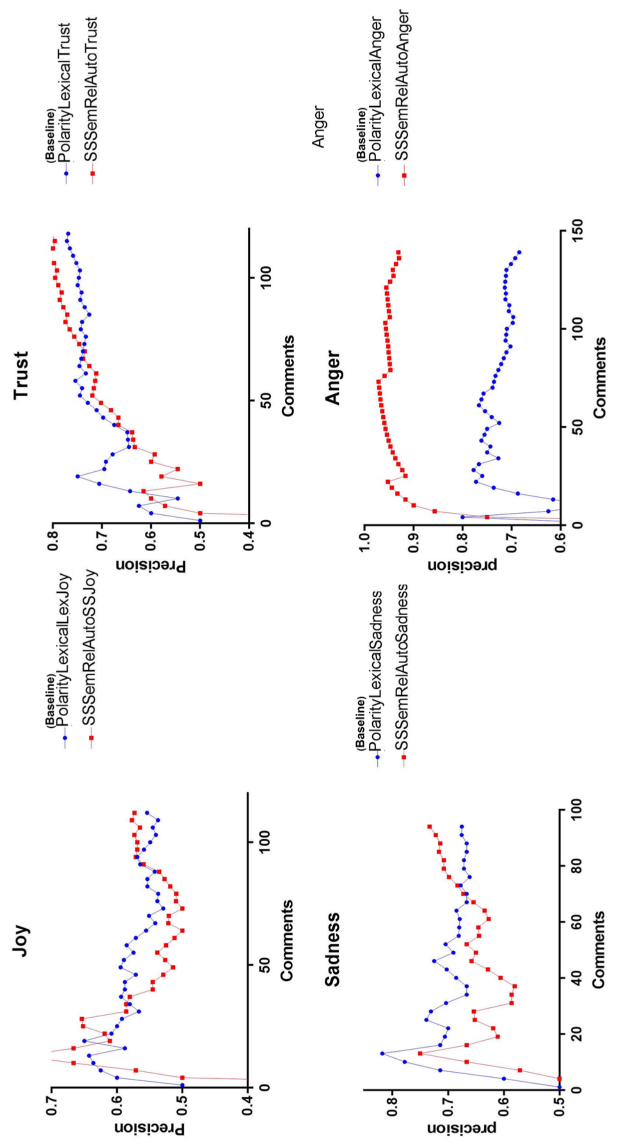

Fig. 13 Evaluation of specific sentiments

more explicit. On the other hand, joy was more complicated to identify because of the usage of sarcasm or more implicit sentiments in the comments.

Discussion of the Evaluation

In this section, a discussion is presented based on the previous experiments. We compared our methodology against labeled data from Amazon reviews and Twitter. We noticed similar behavior regarding precision on both evaluations. In the charts of precision, recall, and the F-measure, we proposed the x-axis as the number of comments to evaluate the error-tolerability. We noticed better stability (fewer variations in the estimation) in the curves for methods using semantic processing and disambiguation (our methodology) compared to only lexical processing and averages using the dictionary of polarity (baseline).

In the classification, we noticed a better precision using the basic sentiments instead of polarity. Regarding the best relation precision/computing consumption, the combination of sentiment, manual weights in semantic processing, and disambiguation (SSRelManual) presented better performance. On the other hand, the highest precision was obtained by automatic weight calculation (SSRelAuto). However, the automatic approach incurred a significant increment in the usage of computing resources. Despite the disambiguation presenting a slightly better precision, it provided the best combination of senses/concepts and the smallest graph that represents the knowledge in a comment. This implies less processing and we obtained the best estimation in the sentiment identification.

Visualization

To provide a tool of analysis and visualize the results of our methodology, a web system was developed. The implementation can be useful for those whose interests include sentiment or other aspects of human understanding. In addition, researchers and specialists from other disciplines can study the user's behavior. During the visualization, the social graph's information as well as the sentiment estimations can be consulted. The system is able to present relevant information that aims to identify emotional status of a target user and their interactions in the network.

The results of the web system are displayed by means of graphs. The social graph describes the network's structure and its sentiment information related to the comments by colors. For instance, Fig. 14 presents the polarity (left side) and the sentiment graph (right side) obtained from CNN news account.

Table 11 represents the meaning of the nodes' color.

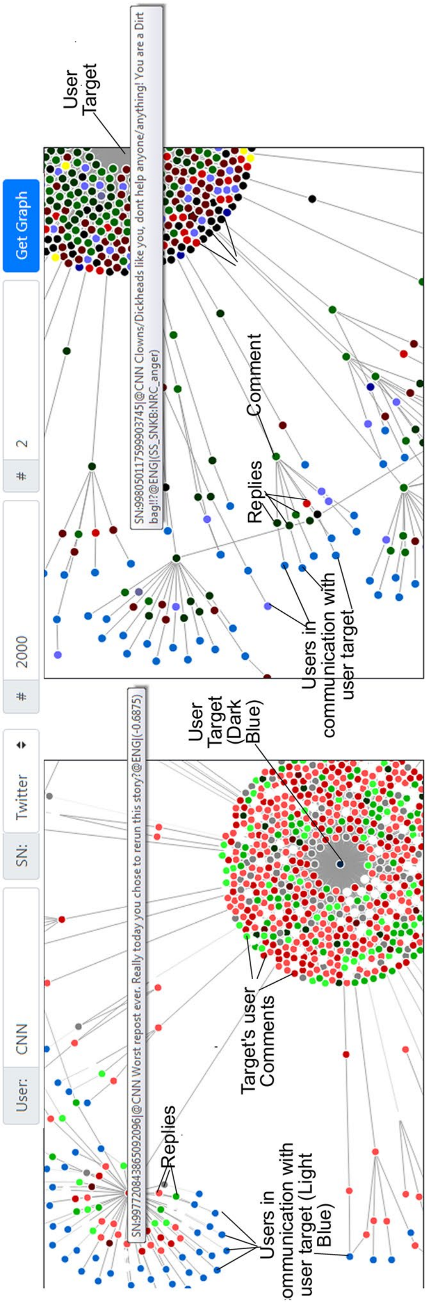

Fig. 14 Polarity and sentiment graphs for CNN news account

Table 11 Nodes' colors in the social graphs

Color	Meaning
(a) Both graphs (users)	
Dark blue	User target
Light blue	Secondary users
(b) Polarity (comments)	
Gray	Neutral
Red scale	Negative
Green scale	Positive
(c) Sentiment (comments)	
Green	Joy
Light green	Trust
Gray	Anticipation
Yellow	Surprise
Dark red	Anger
Light red 2	Disgust
Light blue	Sadness
Dark blue	Fear

Conclusions

In this paper, a content-based methodology was proposed for the polarity calculation and sentiment status identification. The novelty of the presented work is the capability of handling the comments as excerpts of knowledge. We provided a mechanism of semantic processing using knowledge graphs, graph theory algorithms, semantic similarities, and disambiguation. For the sentiment identification, our work explored three different approaches (polarity, sentiment, and sentiment–polarity hybrid) where the sentiment–polarity processing presented the best results.

We performed several experiments to compare our contribution with the traditional method of looking up concepts in dictionaries (baseline). This baseline usually counts the polarity associated with the concepts and assigns averages.

The methodology implemented was focused on the semantic processing, taking into account the content in the public users' opinions. A content-based visualization system was also developed as a tool for specialists and researchers interested in the sentiment analysis on social networks. The social graphs displayed present estimations of polarity and sentiment status where the behavior of a target user can be analyzed.

Regarding the influence of negation, a study was carried out. We noticed that the negation is frequently used in negative comments and implies a slight variance in the sentiment calculation. As future work, an extensive lexical–syntactic analysis and natural language processing are proposed to handle the negation automatically.

The results obtained in the present work and the visualization tool (html and javascript source code) can be consulted at the github site: https://github.com/samscarlet/SBA.

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