Sentiment Analysis meets Linguistic Linked Data: An overview of the State of the Art

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Abstract

Sentiment Analysis has received plenty of attention from both industry and academia because its application can reveal new insights from social interactions. The wide range of final users of these services includes public services, businesses, and individuals. Linked data technologies provide an effective and seamless way for integrating services and interlinking language resources. This paper provides an introduction to the main approaches, applications, and datasets.

Keywords

sentiment analysis, linked data, linguistic linked open data, emotion analysis

1. Introduction

Sentiment Analysis has garnered attention from both industry and academia due the insights it can reveal from social interactions. The final users of these services range from public services (e.g., tracking opinions about political candidates and radicalization detection), through businesses, to individuals [1].

Nevertheless, Sentiment Analysis presents many challenges [2, 3]. One of them is the description and interoperability of language resources and services [4]. The Linguistic Linked Open Data (LLOD) has been proposed as a solution with several benefits in addition to providing interoperability, such as allowing multimodal analysis aggregation, and the use of bilingual LLOD resources for transfer learning in Sentiment Analysis [5].

This work aims to provide an overview of the current efforts in integrating sentiment technology in the LLOD. For a general view of ontologies related to affective states, we refer to [6]. For an introduction to LLOD's main approaches, we refer to [7, 8].

The remainder of this paper is structured as follows First, we introduce the motivation for using a linked data approach to model sentiment and emotions in Sect. 2. Next, we present the main approaches (Sect. 3). Then we provide an overview of the main applications of linked data technology in Sentiment and Emotion Analysis (Sect.4) and the available datasets (Sect. 5). Finally, Sect. 6 provides insights and conclusions.

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2. Why a Linked Data Approach to Affect Resources: Use cases

According to Emotion Markup Language (EmotionML) [9], the main advantages of using a language for representing emotions are enabling software components to represent and process data and enabling interoperability among different components. They distinguish three prominent use cases: manual annotation of emotion-related material, automatic recognition of emotions, and generation of emotion-related responses.

In the case of linguistic resources, we can elaborate further on these use cases. The primary resources that are annotated with sentiment and emotion are lexicons and corpora. Regarding lexicons, there are different needs, such as annotating the prior polarity [10] or emotion [11] of a word or the contextual one. In addition, both sentiment and emotion (affects) can be associated at a word or compound phrase-level [12].

Regarding the automatic recognition of sentiment and emotions, even though the linguistic community is mainly focused on text analysis, there is an increasing interest in multimodal sentiment and emotion analysis [13], i.e., the inclusion of other modalities such as video and audio. Different modalities often use different sentiment or emotion models, so combining them requires integrating different models. Moreover, it also requires the integration of sentiment services from different providers. Finally, three main applications have been identified for emotion and sentiment generation: emotionally-aware social chatbots [14], sentimental [15] and emotional [16] text generation, and affect-aware ambient intelligence [17]. Table 1 collects these use cases.

Using linked data technologies to formalize sentiment and emotion representations brings additional benefits, such as interoperability between different representation formalisms used in Natural Language Processing (NLP) tools and linguistic resources [18, 7]. Moreover, standardized data models specifically designed to enable interoperability and interlinking of datasets can improve reusability [8] and visibility. Interlinked datasets may also include annotations beyond sentiment and emotion labels, such as additional information about content authors or general facts. In the field of Sentiment Analysis this information is referred to as social context and it can be exploited in classification tasks [19].

3. How: main approaches

In this section, we review the main strategies for the representation of sentiment and emotions in linguistic resources and then we focus on those that follow the linked data principles. A detailed review of sentiment lexicons and datasets can be found in [20].

Several linguistic resources have been extended to include sentiment and affect. The most common type of annotation for sentiment [21] is polarity, which is represented using a predefined category (e.g., positive, negative, and neutral) or a continuous value in a predefined range (e.g., a value between -1 and 1). The most popular resource is SentiWordNet [22], which extends WordNet [23]. SentiWordNet assigns automatically to each WordNet synset two sentiment scores: positivity and negativity.

Regarding emotion representation, there are several competing representation models, ranging from categorical ones (e.g,. Ekman's Big Six [24] and Plutchik's wheel of emotions [25]) to

Scenario	Use cases
UC-AL - Annotate Lexicon	ALS1 Annotate prior sentiment of lexical entry ALS2 Annotate contextual affect of lexical entry ALS3 Annotate affect of compound lexical entries ALE1 Annotate prior emotion of lexical entry ALE2 Annotate contextual emotion of lexical entry ALE3 Annotate emotion of compound lexical entries
UC-AC - Annotate Corpus	ACS1 Annotate sentiment of corpus ACE1 Annotate emotion of corpus
UC-S - Interoperable affect services	SS1 Sentiment service annotation SS11 Polarity conversion SS12 Multimodal sentiment analysis SS2 Evaluation sentiment service providers SE1 Emotion service annotation SE11 Emotion Model conversion SE12 Multimodal emotion analysis SE2 Evaluation emotion service providers
UC-G - Generation affect responses	GS1 Sentimental social chatbots GS2 Sentimental Ambient Intelligence GS3 Sentimental text generation GE1 Emotional social chatbots GE2 Emotional Ambient Intelligence GE3 Emotional text generation

Table 1
Use cases

dimensional ones (e.g., Russel's circumplex model [26], Pleasure-Arousal-Dominance (PAD) [27], and Cambria's Hourglass of Emotions [28]) through other approaches, such as appraisal and action-tendency models. The existence of such varied models, and the fact that each sub-field within Emotion Analysis seems to favor a different one, makes emotion representation very challenging. The need for a common representation model of emotions motivated the creation of W3C specification, EmotionML. EmotionML [9] is a W3C specification for representing emotion-related states in data processing systems. It provides a meta-model for representing different emotion models. The specification includes twelve vocabularies for representing categories, appraisals, dimensions, and action tendencies. EmotionML brings the expertise of the Emotion Annotation and Representation Language (EARL) (EARL) [29] language developed by the European network of excellence Human-Machine Interaction Network on Emotion (HUMAINE) from 2004 to 2007. EmotionML collected 39 use-cases in emotion recognition, annotation, and generation. The most popular linguistic resources for emotion analysis are WN-Affect [30], Linguistic Inquiry and Word Count (LIWC) [31], and Affective Norms for English Words (ANEW) [32]. WN-Affect [30] adds an affective label to WordNet synsets for annotating emotions, moods, personality traits, cognitive and physical states, attitudes, sensations, behaviours, emotional responses, emotion-eliciting situations, and hedonic signals. LIWC is a dictionary of grammatical, psychological, and content word categories. In particular, LIWC includes categories for affective processes, positive emotions, negative emotions, anger, anxiety, and sadness. Finally, ANEW annotates 2,477 English words following the PAD model.

The definition of linked data models for sentiment and emotion in the LLOD has received an increasing interest in the field. As a consequence, the Linked Data Models for Emotion and Sentiment Analysis W3C Community Group was created in 2014 with the aim of identifying requirements and defining a common linked data model [33]. This group serves as a forum for experts in different areas related to Emotion and Sentiment Analysis to exchange ideas and discuss better and more versatile ways to represent emotion and sentiment. Some of their conclusions are summarized in a document on guidelines for developing Linked Data Emotion and Sentiment Analysis services [1]. They propose the use of the Marl and Onyx vocabularies for the annotation of sentiment and emotions, respectively. Marl [34, 35] is a vocabulary to annotate and describe expressed opinions. The vocabulary follows a linked data approach and is aligned with the Provenance Ontology (PROV-O) [36]. It has been proposed as an alternative to represent sentiment features in language resources [37, 35] in combination with Lemon [38] and NLP Interchange Format (NIF) [39]. On the other hand, Onyx [40] proposes a generic ontology for emotion representation based on the EmotionML model. Onyx is also aligned with PROV-Os, as well as with WordNet-Affect [30]. Onyx has been used for representing emotion features of language resources in combination with Lemon and NIF [35]. Regarding sentiment and emotion services, they propose an extension of NIF that includes specific parameters for specifying domain, polarity range, emotion model, and conversion needs. A reference implementation [41] is made available for fostering the adoption of the guidelines. The community has also developed several tools that provide limited two-way conversion between semantic (e.g., Onyx and Marl) and non-semantic formats (e.g., EmotionML), such as Senpy [41].

Other proposals within the linked data community are Human Emotion Ontology (HEO), OntoEmotions, Ars Emotica, SenticNet, and the Smiley ontology. HEO [42] is based on EmotionML and it is focused on multimedia annotation. The OntoEmotions ontology [43, 44, 45] is an ontology of emotional categories adapted to five basic categories (Sadness, Happiness, Surprise, Fear, and Anger) and used for categorizing emotion words, which are instances of both the Emotion and Word superclasses. OntoEmotions has been used for developing an emotional list of words used for annotating texts using non-semantic formats [44] in the fairy tales domain. Ars Emotica Ontology (AEO) [46] aims at providing an emotion-driven exploration of online arts collections. For this purpose, the ontology provides support for primary and complex emotions following the Plutchik's wheel model [25]. SenticNet [47, 48] is another popular language resource. It is a commonsense knowledge base for Sentiment Analysis that extends Concept Net 5 [49] with semantic and affect information. Finally, the Smiley ontology [50] proposes an ontology for representing explicitly emoticons' emotions.

In addition, there are linked data versions of the WN-Affect [51, 37] and LIWC [52] taxonomies based on Simple Knowledge Organization System (SKOS). Another resource, SentiWordSKOS [53], integrates SentiWordNet and a SKOS version of the categories of the Hourglass model of SenticNet.

Other works propose culturally tailored approaches to emotion ontology development, such as the Chinese Emotion Ontology [54] which exploits the affective events included in the HowNet lexical resource for Chinese [55], and the Japanese Emotion Objects' ontology [56] based on EmotionML and aligned with Nakamura's emotive expressions dictionary [57].

Application	Usage	Use case	Field	Schema	Ref.
Emotion-driven art collections exploration	Art work annotation	ALE1, SE1	Cultural heritage	AEO, Lemon, WN-Affect	[46]
Cultural objects recommendation	Cultural item annotation	SS1	Cultural heritage	Marl	[58]
Combining German Sentiment Lexicons	Lexical entry annotation	ALS1	Digital humanities	Lemon, Marl	[59, 60]
Polarity of German compound words	Lexical entry annotation	ALS3	Digital humanities	Ontolex Lemon, Marl	[61]
Annotation Dictionary of Bavarian Dialects in Austria	Lexical entry annotation	ALS1, ALS3	Digital humanities	OntoLex, Lemon, Marl	[62]
Annotating polarity of a Latin lexicon	Lexical entry annotation	ALS1	Digital humanities	Ontolex, Lemon, Marl	[63]
Emotion aware e-learning platform	Multimodal emotion annotation	SE1, GE2	E-Learning	Onyx	[64]
KG for Movies recommendation based on the emotional state using a chatbot	Annotation of movie reviews and the user chat log.	GE1, SE1	Entertainment	WN-Affect, Onyx	[65]
Hybrid books in smart environments	Book annotation	ACE1, GE2	Entertainment	Onyx	[66]
Clinical Decision support system.	Patients' opinion annotation	SS1	Health	Marl, CSO	[67]
Assisting financial investment decisions and tracking EU political trends	Real-time annotation of social networks	SS1	Finance & Politics	Marl	[68]
Decision support of Financial analysts	Tweet annotation	SS1, SE1	Finance	Marl, Onyx	[69]
Assess feedback of marketing campaigns. Sentiment toward brands.	Sentiment and Emotion annotation of tweets.	ACS1, ACE1	Marketing	Marl, Onyx	[70]
Sentiment in the purchase funnel and the marketing mix	Tweet annotation	ACS1, ACE1	Marketing	Onyx, Marl	[71]
Multimedia news description	Video news annotation	SS1, SS12,ACS1, SE1,SE12, ACE1	Media	Marl, Onyx, NIF	[72, 73]
Multimodal emotion analysis	Aggregation of annotations	SS1, SS11, SS12, SS2, SE1, SE11, SE12, SE2	Media, Customer Support, Entertainment	Marl, Onyx	[74]
Discovery of tourism places in social media	Place annotation	SS1	Tourism	Marl	[75]
Generation of domain specific sentiment lexicons	Lexical entry annotation	ALS2, SS1	Tourism & e-Commerce	Marl, NIF, Lemon	[76, 77]

Table 2
Applications of Linked Data Annotations for Sentiments

4. Applications

This section presents affect applications that follow a linked data approach. We have included only applications that explicitly mention the usage of linked data. As shown in Table 2, these applications have been classified according to their field of application field and the schemas used.

In the *cultural heritage* field, two works propose the annotation of emotion for artworks based on social tagging. Patti et al. [46] propose the enrichment of users' experience through an emotion-driven visualization. For this purpose, they introduce the AEO ontology, which connects artworks, creators, and emotions, extending the OntoEmotions ontology [43, 44, 45]. The emotion-related classes are organized into primary and complex emotions following Plutchik's model. AEO is integrated with Lemon and WordNet-Affect for linking words to emotions. Díaz-Agudo et al. [58] also propose an innovative emotion-driven experience in museums, where visitors can share their artworks' interpretation which can be used for recommending other artworks based on community detection algorithms. For this purpose, they use a Semantic annotator that uses Marl for sentiment representation.

Several works have proposed the annotation of lexical entries in the *digital humanities* field in different languages, such as German [59, 60, 61], Bavarian dialects in Austria [62], and Latin [63]. SentiMerge [59] shows how four current sentiment lexicons for German can be combined by using OntoLex, Lemon and Marl. This approach can also be used to represent the polarity of compound words [61]. The same approach was followed for representing the polarity of a database of Bavarian Dialects in Austria [62]. Sprugnoli et al. [63] develop the language resource *LatinAffectus*, which provides prior sentiment annotated lexical entries uses Ontolex Lemon and Marl.

Muñoz et al. [64] develop an emotion-aware *e-learning system* that analyzes students' emotions and adapts the learning experience to keep its attention through emotion regulation strategies. Onyx is used for integrating emotions detected based on facial expression and self-reports. Emotion regulation rules are expressed using the Evented WEb (EWE) ontology [78].

Regarding the *entertainment field*, Breitfuss et al. [65] develop a chatbot for recommending movies based on the user emotion expressed in the chat and similar emotions expressed in movie reviews. For this purpose, they develop a Knowledge Graph (KG) of movie reviews annotated with emotions using Onyx and WN-Affect. Sigarchaian et al. [66] propose a new entertainment experience, so-called hybrid books. These books are annotated with emotions (in this case, HTML annotated with RDFa and Onyx) that broadcast these emotions to its smart environment where smart devices can adapt to the environment (e.g., change lights, temperature or reproduce sounds).

Yang et al. [67] propose a clinical decision support system in the *health field* that integrates opinions of patients in the decision process so that preferred decisions can be made according to each patient's preferences, based on the opinions of similar patients. They develop the Clinical Sentiment Ontology (CSO) ontology, which models the relations between clinical diagnosis, clinical conditions, and opinions expressed. Those opinions are collected from the social network *Patients Like Me* and annotated with Marl.

Krieger et al. [68] develop the TrendMiner Ontology for annotating real-time information from dynamic data streams, such as blogs, Twitter, newswires, and wikis. They address two case studies, one in the *financial domain*, for providing decision support in investment decisions, and another one in the *political domain*, where political popularity and trends are tracked over time. They use Marl for annotating opinions. Finally, Sánchez-Rada et al. [69] develop a system that tracks the expressed sentiments and emotions about financial entities for assisting financial investors. For this purpose, they use Marl and Onyx in combination with Financial Industry Business Ontology (FIBO) [79].

Marketing is another field of application for these technologies. Navas-Loro et al. develop two corpora in this field: the Sentiment Analysis towards Brands (SAB) corpus [70] and the Marketing Analysis in Spanish (MAS) corpus [71]. The SAB corpus provides tweets in Spanish annotated with both sentiment and the towards a brand, using Marl and Onyx. The SAB corpus extends the previous corpus by adding two dimensions: the purchase funnel (when the opinion has been expressed in the purchase process: awareness, evaluation, purchase, post-purchase, or ambiguous) and the marketing mix (what is evaluated in the opinion: product, price, promotion, or place).

In the *media domain*, Sánchez-Rada et al. [72] develop an annotation system of YouTube videos that integrates sentiment and emotion analysis of different modalities (e.g., audio tone and audio transcription) using Marl and Onyx. The authors model emotion conversion as a PROV-O activity [73]. Paul Buitelaar et al. [74] present the MixedEmotions toolbox that provides a linked data platform for multimodal emotion analysis. The platform is applied in three main use cases: brand reputation analysis from social media, call center monitoring, and emotion-driven smart TV. In addition, this platform includes Senpy [41], a linked data framework for NLP services that uses Marl and Onyx for sentiment and emotion annotation and conversion.

In the tourism domain, Gazzè et al. [75] develop the Tourpedia knowledge graph, which combines data extracted from social media (e.g., Facebook, Foursquare, Google Places, and Booking.com). The purpose of this dataset is to provide the sentiment associated with different touristic venues (e.g., accommodations, restaurants, points of interest, and attractions). They use Marl for annotating sentiments.

Finally, Vulcu et al. [76, 77] present a system for generating domain-specific sentiment lexicons, evaluated with reviews from the hotel and electronics domains. The system uses Marl for annotating the sentiments.

5. Datasets

This section collects available linguistic linked data resources annotated with sentiment or emotions resulting from some of the works presented in the previous section. Table 3 provides an overview of their characteristics.

6. Conclusions and Future work

From the review of the linked data approaches for sentiment and emotion analysis presented in this paper, we can conclude that these technologies are reaching a certain level of maturity. As expected, most works have been focused on annotating lexicons and using sentiment services.

Dataset	Description	Size	Schema	URL	Ref.
KGMovies	Knowledge Graph of Emotions in Movies Reviews	37,798,497 triples	Onyx, WnAffect	[80]	[65]
TweetsKB	Knowledge graph of annotated tweets	2 billion tweets, 48 billion triples	Marl	[81]	[82]
SABCorpus	Sentiment toward Brands	4548 tweets	Marl, Onyx	[83]	[70]
MASCorpus	Sentiment in the purchase funnel	3763 tweets	Marl, Onyx	[84]	[71]
LiLa Dataset	Semantic annotated Latin lemmas	134,228 lemma objects and 58,278 hypolemma objects	Marl	[63]	[85]
SentiMerge	Combination of four German Sentiment Lexicons	96918 lexical entries	Marl	[59]	[86]
Tourpedia	Sentiment of reviews associated to different tourist venues (accommodations, restaurants, points of interest and attractions) in eight cities	6M RDF triples, 500.000 places	Marl	[75]	[87]
SenticNet	SenticNet knowledge base	200.000 common sense concepts (v6)	SenticNet	[47]	[88]

Table 3
Datasets

Nevertheless, except for text generation, we have found reports of experiences in all identified use cases.

The evolution of the LLOD and the consolidation of specifications such as Ontolex-Lemon [89] can also contribute to adopting linked data technologies for representing language resources and integrating NLP services. Nevertheless, the LLOD approach still needs to provide more tools and resources for fostering its adoption by the NLP community.

When considering the future of these technologies, multimodal sentiment and emotion analysis provides an excellent use case, since there is the need to integrate different approaches, and linked data technologies provide a seamless solution, as shown in existing works.

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