Towards a Common Linked Data Model for Sentiment and Emotion Analysis

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Abstract

The different formats to encode information currently in use in sentiment analysis and opinion mining are heterogeneous and often custom tailored to each application. Besides a number of existing standards, there are additionally still plenty of open challenges, such as representing sentiment and emotion in web services, integration of different models of emotions or linking to other data sources. In this paper, we motivate the switch to a linked data approach in sentiment and emotion analysis that would overcome these and other current limitations. This paper includes a review of the existing approaches and their limitations, an introduction of the elements that would make this change possible, and a discussion of the challenges behind that change.

Keywords: sentiment, emotion, linked data

1. Introduction

As Internet access becomes ubiquitous, more and more websites and applications allow us to share our opinions with the rest of the world. This information has drawn the attention of researchers and industry alike. Researchers see this as an opportunity to collect information about society. For industry, it means quick and unobtrusive feedback from their customers. For private individuals, it can be of interest how the public "sentiment" towards them or their ideas, comments, and contributions reflect on the internet.

However, humans are not capable of processing the ever growing flow of information. As a consequence, sentiment and emotion analysis have received increased support and attention. Many tools that offer automated transformation of unstructured data into structured information have emerged. The provided content analysis functionalities may vary from brand impact based on its social media presence, trend analytics possibly accompanied with predictions for future trends, sentiment identification over a brand or a product.

Unfortunately, the different formats to encode information currently in use are heterogeneous and often custom tailored to each application. The biggest contender is Emotion Markup Language (EmotionML) (see Sec. 4.1.). EmotionML provides a common representation in many scenarios and has been widely adopted by the community.

However, there are still plenty of open challenges not fully covered by EmotionML, as it was solely developed to represent emotional states on the basis of suggested and user-defined vocabularies. Sentiment analysis has not been one of the 39 use cases that motivated EmotionML[1]. Also, a bridge to the semantic web and linked data has been discussed, but been postponed due to the neccessity to reduce complexity for the first version.

In this paper, we motivate the switch to a linked data approach in sentiment analysis that would overcome these and other current limitations. We introduce the elements that would make this change possible and discuss the challenges behind that change.

The rest of this paper is structured as follows. Section 2. contains a brief overview of the terminology in the field; Section 3. introduces the main applications of Sentiment and Emotion Analysis; Section 4. briefly discusses the state of the art in data representation and formats in sentiment analysis; Section 5. presents recent public projects related to sentiment and emotion analysis in any modality; Section 6. explains how a linked data approach would allow more complex applications of sentiment analysis; Section 7. reviews current models and formats that a common linked data representation could be based on; Section 8. exemplifies how current applications would highly benefit from a linked data approach; finally, we draw conclusions from the above.

2. Terminology

The literature of natural language processing differs from the one of affective computing in the terminology used for defining opinion/sentiment/emotion phenomena(Clavel and Callejas, 2015). Indeed, the natural language processing community more frequently uses opinion, sentiment and affect while the affective computing community tends to prefer the word emotion and provides in-depth studies of the term emotion and its specificity according to other linked phenomena such as moods, attitudes, affective dispositions and interpersonal stances (Scherer, 2005). The

[1] https://www.w3.org/2005/Incubator/emotion/XGR-emotion/#AppendixUseCases

distinction between opinion, sentiment and affect is not always clear in the Natural Language Processing (NLP) community (Ishizuka, 2012). Some studies consider sentiment analysis in a broader sense including the analysis of sentiments, emotions and opinions (Chan and Liszka, 2013; Ortigosa et al., 2014a) and consider positive vs. negative distinction as the study of sentiment polarity. Other studies consider sentiment as the affective part of opinions (Kim and Hovy, 2004). Another point of view is also given in Krcadinac et al. (Krcadinac et al., 2013) which states that sentiment analysis concerns positive vs. negative distinction while affect analysis or emotion recognition focus on more fine-grained emotion categories. However, we can refer to Munezero (Munezero et al., 2014) for in-depth reflections of the differences between affect, emotion, sentiment and opinion from a NLP point of view. To sum up, they claim that affects have no expression in language, that emotions are briefer than sentiment and that opinions are personal interpretations of information and are not necessarily emotionally charged unlike sentiments. Other approaches (Martin and White, 2005) prefer to use the general term attitudes to gather three distinct phenomena: affect (personal reaction referring to an emotional state), judgment (assigning quality to individuals according to normative principles) and appreciations (evaluation of an object, e.g. a product or a process).
In the scope of this paper, we use the term 'Sentiment and Emotion Analysis' to cover the range of tecniques to detect subjectivity and emotional state.

3. Applications of Emotion and Sentiment Analysis

Sentiment analysis is now an established field of research and a growing industry (Liu, 2012). There are many applications for sentiment analysis as well as for emotion analysis. It is often used in social media monitoring, tracking customer attitudes towards brands, towards politicians etc Moreover, it is also practical for use in business analytics. Sentiment analysis is in demand because of its efficiency and it can provide an quick overview based on the analysis of humanly impossible to analyse data sources. Thousands of text documents can be processed for sentiment in terms of seconds as opposed to large amounts of time humans would need to make sense out of hotel reviews for example.
Below we categorize the sentiment analysis application in different areas of service. At the public service level we look at sentiment analysis approaches for e-learning systems, tracking opinions about politicians and identification of violent social movements in social media. For businesses and organizations sentiment analysis is used in products benchamrcking, brand reputation and ad placement. From the individual's perspective we are looking at decision making based on opinions about products and services as well as identifying communities and individuals with similar interests and opinions.

1. Public service
   (a) E-learning environments (Ortigosa et al., 2014b): Sentiment and emotion analysis information can be used by adaptive e-learning systems to support personalized learning, by considering the user's emotional state when recommending him/her the most suitable tasks to be tackled at each time. Also, the students' sentiments towards a course serve as useful feedback for teachers.
   (b) Tracking public opinions about political candidates: Recently, with every political campaign, it has become a standard practice to see the public opinion from social media or other sources about each candidate.
   (c) Radicalization and recruitment detection (Zimbra and Chen, 2012): Sentiment analysis is used for detection of violent social movement groups.
2. Businesses and organizations
   (a) Market analysis and benchmark products and services: Businesses spend a huge amount of money to find consumer opinions using consultants, surveys and focus groups, etc
   (b) Affective user interfaces (Nasoz and Lisetti, 2007): An example is in the automotive domain where human-computer interaction is enhanced through Adaptive Intelligent User Interfacesthat are able to recognize users' affective states (i.e., emotions experienced by the users) and responding to those emotions by adapting to the current situation via an affective user model.
   (c) Ads placements: A popular way of monetize online is add placement. Sentiment and emotion analysis is exploited in various ways to a) place ads in key social media content, b) place ads if one praises a product or c) place ads from a competitor if one criticizes a product.
3. Individuals
   (a) Make decisions to buy products or to use services.
   (b) Find collectives and individuals with similar interests and opinions.

4. State of the Art

This section introduces works that are relevant either because they aim to provide a common language and framework to represent emotional information (as is the case of EmotionML), or because they they provide a specific representation of affects and emotions.

4.1. EmotionML

EmotionML (Burkhardt et al., 2016) is W3C recommendation to represent emotion related states in data processing systems. It was developed as a XML schema by a subgroup of the W3C MMI (Multimodal Interaction) Working Group chaired by Deborah Dahl in a first version from approximately 2005 until 2013, most of this time the development was lead by Marc Schröder. It is possible to use EmotionML both as a standalone markup and as a plug-in annotation in different contexts. Emotions can be represented in terms of four types of descriptions taken from the scientific literature: categories, dimensions, appraisals, and action tendencies, with a single <emotion> element containing one or more of such descriptors. The following snippet exemplifies the principles of the EmotionML syntax.

```
<graysentencered redidred=blue"
    bluesent1blue"black>
blackDoblack blackIblack blackhave
    black blacktoblack blackgoblack
    blacktoblack blacktheblack
    blackdentistblack?
black</graysentenceblack>
black<grayemotionred redxmlnsred=blue"
    bluehttpblue://bluewwwblue.bluew3
    blue.blueorgblue/2009/10/
    blueemotionmlblue"red redcategory
    red-redsetred=blue"bluehttp
    blue://.../bluexmlblue#blueeveryday
    blue-bluecategoriesblue"black>
black<graycategoryred rednamered=blue"
    blueafraidblue"red redvaluered=
    blue"blue0.4blue"/black>
black<grayreferencered redrolered=blue"
    blueexpressedByblue"red redurired=
    blue"blue#bluesent1blue"/black>
black</grayemotionblack>
```

Since there is no single agreed-upon vocabulary for each of the four types of emotion descriptions, EmotionML provides a mandatory mechanism for identifying the vocabulary used in a given <emotion>. Some vocabularies are suggested by the W3C (Ashimura, Kazuyuki et al., 2014) and to make EmotionML documents interoperable users are encouraged to use them.

4.2. WordNet Affect

WordNet Affect (Strapparava et al., 2004) is an effort to provide lexical representation of affective knowledge. It builds upon WordNet, adding a new set of tags to a selection of synsets to annotate them with affective information. The affective labels in WordNet Affect were generated through a mix of manual curation and automatic processing. Labels are related to one another in the form of a taxonomy. Then, a subset of all WordNet synsets were annotated with such labels, leveraging the structure and information of WordNet. Hence, the contribution of WordNet Affect is twofold: a rich categorical model of emotions based on WordNet, and the linking of WordNet synsets to such affects.

4.3. Chinese Emotion Ontology

The Chinese Emotion Ontology (Yan et al., 2008) was developed to help understand, classify and recognize emotions in Chinese. The ontology is based on HowNet, the Chinese equivalent of WordNet. The ontology provides 113 categories of emotions, which resemble the WordNet taxonomy and the authors also relate the resulting ontology with other emotion categories. All the categories together contains over 5000 Chinese verbs.

4.4. Emotive Ontology

Sykora et al. (Sykora et al., 2013) propose an ontology-based mechanism to extract fine-grained emotions from informal messages, such as those found on Social Media.

5. Relevant Projects

This section presents some recent note-worthy projects linked to emotion or sentiment analysis in any of its different modalities.

5.1. ArsEmotica

ArsEmotica (Bertola and Patti, 2016) is an application framework where semantic technologies, linked data and natural language processing techniques are exploited for investigating the emotional aspects of cultural heritage artifacts, based on user generated contents collected in art social platforms. Tha aim of ArsEmotica is to detect emotion evoked by artworks from online collections, by analyzing social tags intended as textual traces that visitors leave for commenting artworks on social platforms. The approach is ontology-driven: given a tagged resource, the relation with the evoked emotions is computed by referring to an ontology of emotional categories, developed within the project and inspired by the well-known Plutchik's model of human emotions (Plutchik and Conte, 1997). Detected emotions are meant to be the ones which better capture the affective meaning that visitors, collectively, give to the artworks. The ArsEmotica Ontology (AEO) is encoded in OWL and incorporates, in a unifying model, multiple ontologies which describe different aspects of the connections between media objects (e.g. artworks), persons and emotions. The ontology allows to link art reviews, or excerpts thereof, to specific emotions. Moreover, due to the need of modeling the link among words in a language and the emotions they refer to, AEO integrates with LExical Model for Ontologies (lemon) to provide the lexical model (Patti et al., 2015). Where possible and relevant, linkage to external repositories of the LOD (e.g. DBpedia) is provided.

5.2. EuroSentiment

The aim of the EuroSentiment project [2] was to provide a shared language resource pool, a marketplace dedicated to services and resources useful in multilingual Sentiment Analysis. The project focused on adapting existing lexicons and corpora to a common linked data format. The format for lexicons is based on a combination of lemon (for lexical concepts), Marl (opinion/sentiment) and Onyx (emotions). Each entry in the lexicon is described with part of speech information, morphosyntactic information, links to DBpedia and WordNet and sentiment information of the entry was identified as a sentiment word. The format for corpora uses NIF instead of lemon, while keeping the combination of Onyx and Marl for subjectivity. The results of the project include: a semantic enriching pipeline for lexical resources, a set of lexicons and corpora for sentiment and emotion analysis; conversion tools from legacy non-semantic formats; an extension of the NIF format and API for web services; and, lastly, the implementation of said

[2] `http://eurosentiment.eu`

API in different programming languages, which helps developers develop and deploy semantic sentiment and emotion analysis services in minutes.

5.3. MixedEmotions

The MixedEmotions project [3] plans to continue the work started in the EuroSentiment project, investigating other media (image and sound) in many languages in the sentiment analysis context. Its aim is to develop novel multilingual multi-modal Big Data analytics applications to analyse a more complete emotional profile of user behavior using data from mixed input channels: multilingual text data sources, A/V signal input (multilingual speech, audio, video), social media (social network, comments), and structured data. Commercial applications (implemented as pilot projects) are in Social TV, Brand Reputation Management and Call Centre Operations. Making sense of accumulated user interaction from different data sources, modalities and languages is challenging and yet to be explored in fullness in an industrial context. Commercial solutions exist but do not address the multilingual aspect in a robust and large-scale setting and do not scale up to huge data volumes that need to be processed, or the integration of emotion analysis observations across data sources and/or modalities on a meaningful level. MixedEmotions thus implements an integrated Big Linked Data platform for emotion analysis across heterogeneous data sources, different languages and modalities, building on existing state of the art tools, services and approaches to enable the tracking of emotional aspects of user interaction and feedback on an entity level.

5.4. SEWA

The European Sentiment Analysis in the Wild (SEWA) project [4] deploys and capitalises on existing state-of-the-art methodologies, models and algorithms for machine analysis of facial, vocal and verbal behaviour to realise naturalistic human sentiment analysis "in the wild". The project thus develops computer vision, speech processing, and machine learning tools for automated understanding of human interactive behaviour in naturalistic contexts for audio and visual spatiotemporal continuous and discrete analysis of sentiment, liking and empathy.

5.5. OPENER

OpeNER (Open Polarity Enhanced Name Entity Recognition) is a aims to to provide a set of free Natural Language Processing tools free that are easy to use, adapt and integrate in the workflow of Academia, Research and Small and Medium Enterprise. OpeNER uses the KAF (Bosma et al., 2009) annotation format, with ad-hoc elements to represent sentiment and emotion features. The results of the project include a corpus of annotated reviews and a Linked Data node that exposes this information.

[3]`http://mixedemotions-project.eu`

[4]`http://www.sewaproject.eu/`

6. Motivation for a Linked Data Approach

Currently, there are many commercial social media text analysis tools, such as Lexalytics [5], Sentimetrix [6] and Engagor [7] that offer sentiment analysis functionalities from text. There are also a lot of social media monitoring tools that generate statistics about presence, influence power, customer/followers engagement, which are presented in intuitive charts on the user's dashboard. Such tools indicatively are Hootsuite, Klout and Tweetreach which are specialized on Twitter analytics. However, such solutions are quite generic, are not integrated in the process of product development or in product cycles and definitely are not trained under domain-specific terminology, idioms and characteristics. Industry-specific approaches are also available (Aldahawi and Allen, 2013; Abrahams et al., 2012), but still they are not easily configured under integrated, customizable solutions. Opinion mining and trend prediction over social media platforms are emerging research directions with great potential, with companies offering such services tending not to disclose the methodologies and algorithms they use to process data. The academic community has also shown interest into these domains (Pang and Lee, 2008). Some of the most popular domains are User Generated Reviews as well as Twitter mining, particularly due to the availability of information without restriction access (Aiello et al., 2013). An enormous amount of tweets is created daily, Twitter is easily accessible which means that there are available twitter data from people with different background (ethnical, cultural, social), there are tweets in many different languages and finally there is a large variety of discussed topics.

Encoding this extra information is beyond the capabilities of any of the existing formats for sentiment analysis. This is hindering the appearance of applications that make deep sense of data. A Linked Data approach would enable researchers to use this information, as well as other rich information in the Linked Data cloud. Furthermore, it would make it possible to infer new knowledge based on existing reusable vocabularies.

An interesting aspect of analysing social media is that there are many features in the source beyond pure text that can be exploited. Using these features we could gain deeper knowledge and understanding of the user generated content, and ultimately train a system to look for more targeted characteristics. Such a system would be more accurate in processing and categorizing such content. Among the extra features in social media, we find the name of the users who created the content, together with more information about their demographics and other social activities. Moreover users can interact, start conversations over a posted comment, and express their agreement or disagreement either by providing textual responses or explicitly through "thumbs-up" functionalities. Apart from the actual content, it is also the context in which it was created that can serve as a rich source of information and be used to generate more powerful data analytics and lead to smarter company deci-

[5]`https://www.lexalytics.com/`

[6]`http://www.sentimetrix.com/`

[7]`http://www.engagor.com/`

sions. [8]

7. Semantic Models and Vocabularies

This section describes models and vocabularies that can be used to model sentiment and emotion in different scenarios, including annotation of lexical resources (lemon) and NLP services (NIF).

7.1. Marl

Marl is a vocabulary to annotate and describe subjective opinions expressed on the web or in particular Information Systems. This opinions may be provided by the user (as in online rating and review systems), or extracted from natural text (sentiment analysis). Marl models opinions on the aspect and feature level, which is useful for fine grained opinions and analysis.
Marl follows the Linked Data principles as it is aligned with the Provenance Ontology. It also takes a linguistic Linked Data approach: it is aligned with the Provenance Ontology, it represents lexical resources as linked data, and has been integrated with lemon (Section 7.4.).

7.2. Onyx

Onyx (Sánchez-Rada and Iglesias, 2016) is a vocabulary for emotions in resources, services and tools. It has been designed with services and lexical resources for Emotion Analysis in mind. What differentiates Onyx from other vocabularies in Section 4. is that instead of adhering to a specific model of emotions, it provides the concepts to formalize different emotion models. These models are known as vocabularies in Onyx's terminology, following the example of EmotionML. A number of commonly used models have already been integrated and published as linked data [9]. The list includes all EmotionML vocabularies (Ashimura, Kazuyuki et al., 2014), WordNet-Affect labels and the hourglass of emotions (Cambria et al., 2012).
A tool for limited two-way conversion between Onyx representation and EmotionML markup is available, using a specific mapping.
Just like Marl, Onyx is aligned with the Provenance Ontology, and can be used together with lemon in lexical resources.

7.3. NLP Interchange Format (NIF)

NLP Interchange Format (NIF) 2.0 (Hellmann, 2013) defines a semantic format and an API for improving interoperability among natural language processing services.
NIF can be extended via vocabularies modules. It uses Marl for sentiment annotations and Onyx have been proposed as a NIF vocabulary for emotions.

7.4. lemon

lemon is a proposed model for modelling lexicon and machine-readable dictionaries and linked to the Semantic Web and the Linked Data cloud. It was designed to meet the following challenges RDF-native form to enable leverage of existing Semantic Web technologies (SPARQL, OWL, RIF etc.). Linguistically sound structure based on LMF to enable conversion to existing offline formats. Separation of the lexicon and ontology layers, to ensure compatibility with existing OWL models. Linking to data categories, in order to allow for arbitrarily complex linguistic description. In particular, the LexInfo vocabulary is aligned to lemon and ISOcat. A small model using the principle of least power - the less expressive the language, the more reusable the data. Lemon was developed by the Monnet project as a collaboration between: CITEC at Bielefeld University, DERI at the National University of Ireland, Galway, Universidad Politécnica de Madrid and the Deutsche Forschungszentrum für Künstliche Intelligenz.

8. Application

This section contains a noncomprehensive list of popular tools that would potentially benefit from the integration of a unified Linked Data model.

8.1. GATE

GATE (General architecture for Text Engineering) (Cunningham et al., 2009) is an open source framework written entirely in JAVA that can be used for research and commercial applications under the GNU license. It is based on an extensible plugin-architecture and processing resources for several languages are already provided. It can be very useful to manually and automatically annotate text and do subsequential sentiment analysis based on gazetteer lookup and grammar rules as well as machine learning, a support vector machine classifier is already integrated as well as interfaces to linked open data, e.g. DBPedia.

8.2. Speechalyzer

Speechalizer (Burkhardt, 2012) is a java library for the daily work of a 'speech worker', specialized in very fast labeling and annotation of large audio datasets. Includes EmotionML import and export functionality.

8.3. openSMILE

The openSMILE tool enables you to extract large audio feature spaces in realtime for emotion and sentiment analysis from audio and video. It is written in C++ and is available as both a standalone commandline executable as well as a dynamic library (A GUI version is to come soon). The main features of openSMILE are its capability of on-line incremental processing and its modularity. Feature extractor components can be freely interconnected to create new and custom features, all via a simple configuration file. New components can be added to openSMILE via an easy plugin interface and a comprehensive API. openSMILE is free software licensed under the GPL license and is currently available via Subversion in a pre-release state [10].

9. W3C Community Group

The growing interest in the application of Linked Data in the field of Emotion and Sentiment Analysis has motivated

[8] `http://www.alchemyapi.com/api/sentiment-analysis`

[9] `http://www.gsi.dit.upm.es/ontologies/onyx/vocabularies/`

[10] `http://sourceforge.net/projects/opensmile/`

the creation of the W3C Sentiment Analysis Community Group (CG)[11]. The community group is a public forum for experts and practicians from different fields related to Emotion and Sentiment Analysis, as well as semantic technologies. In particular, the community group intends to gather the best practices in the field. Existing vocabularies for emotion and sentiment analysis are thoroughly investigated and taken as a starting point for discussion in the CG. However, its aim is not to publish specifications but rather to identify the needs and pave the way.
It further deals with the requirements beyond text-based analysis, i.e. emotion/sentiment analysis from images, video, social network analysis, etc.

10. Conclusions

Sentiment and Emotion Analysis is a trending field, with a myriad of potential applications and projects exploiting it in the wild. In recent years several European projects have dealt with sentiments and emotions in any of its modalities, such as SEWA and OpeNER. However, as we have explained in this paper, there are several open challenges that need to be addressed. A Linked Data approach would address several of those challenges, as well as foster research in the field and adoption of its technologies. The fact that projects such as ArsEmotica or EuroSentiment have already introduced semantic technologies to deal with similar problems supports this view. Nevertheless, to guarantee the success and adoption of the new approach, we need common vocabularies and best practices for their use. This work is a first step in this direction, which will be continued by the community in the upcoming years with initiatives such as the Linked Data Models for Emotion and Sentiment Analysis W3C Community Group.

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Abrahams, A. S., Jiao, J., Wang, G. A., and Fan, W. (2012). Vehicle defect discovery from social media. *Decision Support Systems*, 54(1):87–97.

Aiello, L. M., Petkos, G., Martin, C., Corney, D., Papadopoulos, S., Skraba, R., Goker, A., Kompatsiaris, I., and Jaimes, A. (2013). Sensing trending topics in twitter. *Multimedia, IEEE Transactions on*, 15(6):1268–1282.

Aldahawi, H. A. and Allen, S. M. (2013). Twitter mining in the oil business: A sentiment analysis approach. In *Cloud and Green Computing (CGC), 2013 Third International Conference on*, pages 581–586. IEEE.

Ashimura, Kazuyuki, Baggia, Paolo, Oltramari, Alessandro, Peter, Christian, and Ashimura, Kazuyuki. (2014). Vocabularies for EmotionML. 00004.

Bertola, F. and Patti, V. (2016). Ontology-based affective models to organize artworks in the social semantic web. *Information Processing & Management, Special issue on Emotion and Sentiment in Social and Expressive Media*, 52(1):139–162.

Bosma, W., Vossen, P., Soroa, A., Rigau, G., Tesconi, M., Marchetti, A., Monachini, M., and Aliprandi, C. (2009). KAF: a generic semantic annotation format. In *Proceedings of the GL2009 workshop on semantic annotation*. 00054.

Burkhardt, F., Schröder, M., Baggia, P., Pelachaud, C., Peter, C., and Zovato, E. (2016). Emotion markup language (emotionml) 1.0.

Burkhardt, F. (2012). Fast labeling and transcription with the speechalyzer toolkit. *Proc. LREC (Language Resources Evaluation Conference), Istanbul*.

Cambria, E., Livingstone, A., and Hussain, A. (2012). The hourglass of emotions. In *Cognitive behavioural systems*, pages 144–157. Springer. 00072 bibtex: Cambria2012.

Chan, C.-C. and Liszka, K. J. (2013). Application of Rough Set Theory to Sentiment Analysis of Microblog Data. In *Rough Sets and Intelligent Systems-Professor Zdzis\law Pawlak in Memoriam*, pages 185–202. Springer. 00000.

Clavel, C. and Callejas, Z. (2015). Sentiment analysis: from opinion mining to human-agent interaction. *Affective Computing, IEEE Transactions on*, PP(99):1–1, to appear.

Cunningham, H., Maynard, D., Bontcheva, K., Tablan, V., Ursu, C., Dimitrov, M., Dowman, M., Aswani, N., Roberts, I., Li, Y., and others. (2009). *Developing Language Processing Components with GATE Version 5:(a User Guide)*. University of Sheffield. 00111.

Hellmann, S. (2013). *Integrating Natural Language Processing (NLP) and Language Resources using Linked Data*. Ph.D. thesis, Universität Leipzig. 00002.

Ishizuka, M. (2012). Textual affect sensing and affective communication. In *Cognitive Informatics & Cognitive Computing (ICCI* CC), 2012 IEEE 11th International Conference on*, pages 2–3. IEEE. 00004.

Kim, S.-M. and Hovy, E. (2004). Determining the sentiment of opinions. In *Proceedings of the 20th international conference on Computational Linguistics*, page 1367. Association for Computational Linguistics. 01159.

Krcadinac, U., Pasquier, P., Jovanovic, J., and Devedzic, V. (2013). Synesketch: An open source library for sentence-based emotion recognition. *Affective Computing, IEEE Transactions on*, 4(3):312–325. 00011.

Liu, B. (2012). *Sentiment Analysis and Opinion Mining*. Synthesis Lectures on Human Language Technologies. Morgan & Claypool Publishers.

Martin, J. R. and White, P. R. (2005). *The Language of Evaluation. Appraisal in English*. Palgrave Macmillan Basingstoke and New York.

[11] `https://www.w3.org/community/sentiment/`

Munezero, M., Montero, C. S., Sutinen, E., and Pajunen, J. (2014). Are they different? affect, feeling, emotion, sentiment, and opinion detection in text. *Affective Computing, IEEE Transactions on*, 5(2):101–111. 00012.

Nasoz, F. and Lisetti, C. L. (2007). Affective user modeling for adaptive intelligent user interfaces. In *Human-Computer Interaction. HCI Intelligent Multimodal Interaction Environments, 12th International Conference, HCI International 2007, Beijing, China, July 22-27, 2007, Proceedings, Part III*, pages 421–430.

Ortigosa, A., Martín, J. M., and Carro, R. M. (2014a). Sentiment analysis in Facebook and its application to e-learning. *Computers in Human Behavior*, 31:527–541. 00051.

Ortigosa, A., Martín, J. M., and Carro, R. M. (2014b). Sentiment analysis in facebook and its application to e-learning. *Computers in Human Behavior*, 31:527 – 541.

Pang, B. and Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and trends in information retrieval*, 2(1-2):1–135.

Patti, V., Bertola, F., and Lieto, A. (2015). Arsemotica for arsmeteo.org: Emotion-driven exploration of online art collections. In *Proceedings of the Twenty-Eighth International Florida Artificial Intelligence Research Society Conference, FLAIRS 2015, Hollywood, Florida. May 18-20, 2015*, pages 288–293.

Plutchik, R. E. and Conte, H. R. (1997). *Circumplex models of personality and emotions.* American Psychological Association. 00258.

Scherer, K. R. (2005). What are emotions? And how can they be measured? *Social science information*, 44(4):695–729. 01546.

Strapparava, C., Valitutti, A., and others. (2004). WordNet Affect: an Affective Extension of WordNet. In *LREC*, volume 4, pages 1083–1086. 00859.

Sykora, M. D., Jackson, T. W., O'Brien, A., and Elayan, S. (2013). Emotive ontology: Extracting fine-grained emotions from terse, informal messages. *Computer Science and Information Systems Journal*. 00011.

Sánchez-Rada, J. F. and Iglesias, C. A. (2016). Onyx: A Linked Data approach to emotion representation. *Information Processing & Management*, 52(1):99–114, January. 00003.

Yan, J., Bracewell, D. B., Ren, F., and Kuroiwa, S. (2008). The Creation of a Chinese Emotion Ontology Based on HowNet. *Engineering Letters*, 16(1):166–171. 00022.

Zimbra, D. and Chen, H. (2012). Scalable sentiment classification across multiple dark web forums. In *2012 IEEE International Conference on Intelligence and Security Informatics, ISI 2012, Washington, DC, USA, June 11-14, 2012*, pages 78–83.