Sentiment Analysis Approaches based on Granularity Levels

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Abstract: The evolution of web 2.0 has enabled the emergence of social media where users can post, share and discuss their opinions about products, events, peoples and organizations. This increase of the user generated content (UGC) has allowed the publication of several works during the last decade in the scientific community working on sentiment analysis. Sentiment analysis, also known as opinion mining is the field of extraction and analysis of opinions, feelings and attitudes of users on the web. In this paper, we provide an overview of the field of sentiment analysis by discussing the workflow of mining opinions in different granularity levels and covering common and recent approaches and techniques used to solve tasks related to sentiment analysis process at every level.

1 INTRODUCTION

Knowing what people think has always been a very important information to make a decision. For this reason we often seek out the opinions of others. A few years ago, when a person needed opinions, he / she asked family and friends. Even organizations had to conduct surveys, opinion polls and focus groups to collect public or consumer opinions. Those days are gone. At the present time, people express their opinions on social media platforms like Twitter, Facebook, and others and e-commerce sites like Amazon. Collection and analysis of this huge volume of opinionated data are thus needed. Sentiment analysis (SA) is the field specialized in such tasks.

Sentiment analysis, also called opinion mining, is the field of study that analyzes peoples opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes as mentioned in (Liu, 2012).
This domain is also known in the literature as opinion mining, sentiment mining, opinion extraction, subjectivity analysis, etc. However, in this paper, we will limit ourselves to the use of sentiment analysis or opinion mining as they represent the most used keywords in journal publications and in conference proceedings based on (Ahlgren, 2016). In the last decade sentiment analysis has gained popularity. (Mantyla et al., 2018) mentioned that the number of papers published in the field of sentiment analysis is 6996 papers. This incredible increase makes opinion mining one of the active and growing search areas.

In this paper, we will cite recent researche techniques used in sentiment analysis based on granularity level (document, sentence and aspect). The rest of the paper is organized as follows: section 2 introduces some of the papers that defined sentiment analysis based on granularity level. In section 3 Coarse-grained-level (document and sentence) is highlighted. The aspect-level is covered in section 4. Other levels of SA are discussed in section 5. In Section 6 a comparison of the approaches of SA is being dealt with, and finally Section 7 concludes the paper.

2 GRANULARITY BASED SENTIMENT ANALYSIS

Sentiment Analysis is closely related to the field of Natural Language Processing (Sun et al., 2017), it is a big suitcase of NLP problems (Cambria et al., 2017). It is also studied in Information Retrieval and Data Mining.(Hemmatian and Karim Sohrabi, 2017) and (Bhatia et al., 2018) consider opinion mining as a subfield of the Web Content Mining process in the field of Web Mining.

Some papers that dealt with the tasks of opinion mining in a granularity level manner are presented above.

(Missen et al., 2012) reviewed the field of opinion mining from word to document level in a very detailed manner. They also highlighted the importance of so-

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cial networks for opinion mining tasks.

(Feldman, 2013) presented a general architecture for sentiment analysis systems. The input of the system is a corpus that will be converted to text and preprocessed using linguistic tools. The resulted text will be annotated by a Document Analysis Module. The annotation may be attributed to whole documents, to sentences or to fine grained entities (aspects).

(Liu, 2012) explored in his review/book the problems and the objectives of sentiment analysis. He used previous definition defining the opinion as a quintuple (ei, aij, sijkl, hk, tl), where ei is the name of an entity, aij is an aspect of ei, sijkl is the sentiment on aspect aij of entity ei, hk is the opinion holder, and tl is the time when the opinion is expressed by hk. Based on this definition, the objective of opinion mining is defined as determining all the quintuples of given texts.

As mentioned earlier, the next section will talk about sentiment analysis tasks based on granularity level. We first begin by coarse-grained level (Documents and sentences) and go deep in the hierarchy as the complexity increases to fine grained level (aspect).

3 COARSE-GRAINED LEVEL SENTIMENT ANALYSIS

3.1 Document-level Sentiment Analysis

In (Ravi and Ravi, 2015) 159 articles were distributed based on the granularity of sentiment analysis, 73 articles appeared in the document level which makes it the most studied topic in the field. Document-level sentiment classification, as known in the literature, is considered the simplest sentiment analysis task. The task of opinion mining at this level is to identify opinionated documents and classify them according to their polarities.

Authors in (Missen et al., 2012) mentioned that most of the researchers at this level follow a two-step approach: Topic Relevance Retrieval and Opinion Finding step.

The document is considered as a basic information unit which includes multiple sentences. Based on the quintuple introduced in the first section, the task of opinion mining is to determine the overall sentiment of the opinion holder about the entity described in the document. This approach helps the users in decision making by providing a summary of total number of positive and negative documents.

3.2 Sentence-level Sentiment Analysis

Just like document level opinion mining, sentence level opinion mining is also a classification problem. Sentences are regarded as short documents which makes the classification the same for both levels. Most of the researches at document level dont perform a three class classification (positive, negative, and neutral). However, at the sentence level, the neutral class cannot be ignored because sentences may express no opinion or sentiment. Thus, the purpose at this level is to classify each sentence in an opinion document as positive, negative or neutral opinion or sentiment.

Sentiment sentence classification is generally performed in two classes of classification problem. The first determines whether the sentence is expressing an opinion (sentiment) or not and the second classify the sentences as positive, negative or neutral. The first step in the process is known in the literature as Subjectivity Classification. It aims to distinguish opinions(subjective sentences) from facts (objective sentences) (Chaturvedi et al., 2018). Subjective sentences can express some personal feelings, views judgments or beliefs(Liu, 2015) that might vary from person to person, whereas, objective sentences express factual information which remains valid for all individuals. Because of that some researchers prefer to classify sentences as opinionated or non-opinionated.

The second step is called sentence sentiment classification. After classifying the sentences as being subjective (opinionated) or objective (non-opinionated), sentence sentiment classification aims to classify them as positive, negative or neutral. An assumption that generally researchers make at this level of analysis is that a sentence expresses a single sentiment. Thus, sentences that express more than one sentiment are treated differently. More complex sentences (interrogative, comparatives, conditionale and sarcastic sentences) also need advanced techniques.

3.3 Machine Learning Approaches

3.3.1 Supervised Learning

Supervised learning supposes that there are multiple classes to which a document can be classified. The process of learning is carried out using the data of training available for each class. The training set is used by a classifier to learn the different characteristics of documents. Learning task is done by using classification algorithms either probabilistic (naive Bayes, Bayesian Neutral Network, Maximum entropy) or non-probabilistic (Support Vector Machine, Artificial Neural Network, K-nearest Neighbor, Rule Based, Decision Tree) (Hemmatian and Karim Sohrabi, 2017).The performances of the classifier are validated using a test data. At the end of this process, every document should be tagged with its appropriate category (class).

Like most supervised learning approaches, feature engineering is the key to build a good sentiment analysis classifier. The most common used features are N-gram (Terms and their frequency), syntactic features (Part Of Speech, Syntactic Dependency) and semantic features (Sentiment words and phrases, sentiment shifters).

3.3.2 Unsupervised Learning

Unlike supervised learning, that considers the target value (label), unsupervised learning process does not provide any label data. Unsupervised classification belongs to semantic orientation approach. It aims to determine the semantic orientation of the phrases within the document. The algorithm described by (Turney, 2002) is totally unsupervised. He used syntactic pattern as a sequence of Part Of Speech tags. The algorithm consists of three steps. First, two consecutive words are extracted if their POS tags are conform to certain constraints. Then, it estimates the polarity of adjectives and adverbs present in opinion review by calculating their proximity using the pointwise mutual information (PMI) method. PMI (P,W) measures the statistical dependence between the phrase P and the word W based on their co-occurrence in a given corpus or over the Web (Feldman, 2013). Turney used two words for his approach excellent and poor. Finally, the overall polarity of the review is then deduced by aggregating the polarity of the adjectives and adverbs that compose it, and the review is classified as positive or negative.

In the last few years, deep learning has gained popularity in many fields and had shown valuable results. It is a powerful machine learning technique as mentionned in the recent survey (Zhang et al., 2018). Sentiment analysis is one of the fields that recently has been attracted to deep learning techniques. It has been shown that document and sentence representations can be very useful for SA tasks. For that purpose, deep learning techniques such as word embeddings, Long Short Term memory, reccurent, reccursive, convolutional neural networks were applied to sentiment analysis classification.

3.4 Lexicon based Approaches

Another approach to do sentiment analysis in document level, which can be seen as an unsupervised approach (Liu, 2012), is the lexicon-based approach. It consists of using a collection of known and precompiled sentiment terms tagged with their semantic orientation called sentiment lexicon (polarity or opinion lexicon). These terms are used to express the positive or negative feelings. The terms that make the lexicon are generally adjectives and adverbs, but names and verbs should also be considered.

The aim of using such a lexicon is to determine the overall sentiment of a given text based on the assumption that the collective polarity of a sentence or documents is the sum of polarities of the individual phrases or words. The document is classified as positive if the sum is positive, negative if the sum is negative and neutral if the sum is equal to zero.

Lexicon-based approach is divided into two main methods: corpus-based and dictionary-based. Dictionary based approach will use an existing dictionary, which is a collection of opinion words along with their positive or negative sentiment strength (Ravi and Ravi, 2015). Corpus based approach relies on the probability of occurrence of a sentiment word in conjunction with positive or negative set of words by performing a research on very huge amount of text (Ravi and Ravi, 2015).

The process may also include intensification and negation called sentiment shifters. Negations are used to reverse the semantic polarity of a particular term, while intensifiers are used to change the degree to which a term is positive or negative as mentioned in (Alistair and Diana,).

4 ASPECT-LEVEL SENTIMENT ANALYSIS

Polarity classification of opinion text at document and sentence level is helpful in many cases but it does not provide all the necessary details because they do not discover what exactly people liked and did not like. Generally, documents are made of several passages of opinions of different semantic categories. Thus, classification at coarse-level does not identify sentiments or opinion targets. For example, being positive/negative of the sentiments about an entity in a text document, do not mean that the author is being positive/negative about all the aspects of the expressed entity.

Due to the need of a finer grain analysis, aspect-level sentiment analysis represents a key step. Aspect-level sentiment analysis (previously called feature-based sentiment analysis) describes that an opinion consists of a sentiment and a target. The objective of the analysis at this level is to discover the specific tar-

gets and then specify their sentiment polarities. Using the quintuple definition (ei, aij, sijkl, hk, tl) (section 2), aspect-level sentiment analysis aims to locate the first three components. Therefore the analysis is divided into two tasks: Aspect extraction and Aspect sentiment classification.
The first task is also called opinion target extraction (Liu, 2015), because it concentrates on the extraction of both entities and their aspects. Entities appoint to products names, services, events, etc, and aspects,which can be expressed implicitly or explicitly, generally identify the attributes and components of entities.

The second step, similar to the identification of the polarity of opinions at coarse granularity, associates a polarity with the various extracted opinion targets.
The extraction of remaining components of the quintuple are studied as sub-tasks of aspect-level sentiment analysis called opinion holder extraction and time extraction. The extraction of all quintuples present in a document is helpful to produce a summary of opinions about entities and their aspects.
Such a summary is known as aspect-based summary (or feature-based summary) (Hu and Liu, 2004).

4.1 Machine Learning Approaches

4.1.1 Supervised Learning

Supervised learning approaches for aspect-level sentiment analysis uses the same machine learning algorithms for coarse-level analysis. The difference between the two levels (coarse and grained) resides in the features used for the learning. The features used for both document and sentence levels are not applicable for aspect-level because the key problem is that they are target independent, whereas, the core concept of the aspect-level sentiment analysis is the identification of opinion target. Researchers study this challenging problem either by generating a set of target dependent feature or by determining an application scope of sentiments that cover the target entity/aspect in a sentence.

And as supervised learning approaches, machine learning algorithms need a huge annotated data for training. In this case a collection of annotated aspects and non-aspects data is needed.

4.1.2 Unsupervised Learning

Although supervised approaches for aspect-level showed good results, it is hard to provide a huge aspects and non-aspects annotated data collection because manually labeling data is costly and time consuming.
For that reason, several researches have studied the task using unsupervised approaches.

Same as document and sentence levels, deep learning techniques were also applied to aspect-level by generating target and context representations, or by identification of important sentiment words for targets (Zhang et al., 2018).

4.2 Lexicon based Approaches

(Liu, 2015) stated that lexicon based approach for aspect-level sentiment analysis is based on three pillars: (1) a sentiment lexicon containing sentiment words, phrases, idioms and composition rules, (2) a set of rules to handle sentiment shifters,the "but" clauses and other types of sentences, (3) a sentiment aggregation function or a set of sentiment and target relationships acquired from parse trees.

4.3 Ontology based Approaches

An ontology is an explicit, machine-readable specification of a shared conceptualization (Studer et al., 1998). Ontologies provide a formal representation of knowledge since it models the terms in a specific domain and captures the semantic relation between these terms.

The usage of such relation is very important in aspect-level sentiment analysis especially in product reviews because in such reviews, products are generally qualified by their aspects. This hierarchical relation between products and their aspects can be captured using ontological approaches.

Table 1 below reviews some recent articles in sentiment analysis and opinion mining. The articles were collected from academic research sites and organized according to granularity level and the approaches presented previously.

5 OTHER LEVELS OF SA

Sentiment analysis is basically studied at the three levels mentioned previously (document, sentence and aspect), but these levels are not the only ones. A variety of researchers dealt with the problem using another levels such as word-level , clause-level, phrase-level and concept-level.

Table 1: Summary of articles in sentiment analysis and opinion mining.

Level	Approach	Technique	Studied issue	DataSet	Year	Reference
Document Level	Supervised learning	Naive Bayes, SVM, Maximum Entropy, Stochastic Gradient Descent	Movie review classification	IMDb movie review dataset	2016	(Tripathy et al., 2016)
	Unsupervised learning	K-means clustering	Mood swing analyzer	Facebook messages	2015	(Kalyani et al., 2015)
	Deep learning	Deep Memory Network, Long Short Term Memory	Document classification considering user and products	IMDb an Yelp	2017	(Dou, 2017)
	Deep learning	Convolutional NN, LSTM	Dual prediction of word and document sentiments	Movie review, IMDb, Twitter	2018	(Lee et al., 2018)
	Lexicon based	Dictionary based	sentiment classification system for social media genres (SmartSA)	Twitter, Digg and MySpace samples	2016	(Muhammad et al., 2016)
Sentence Level	Supervised learning	Conditional Random Fields	Context-aware approach for learning sentiment	Customer Review and Multi-domain Amazon datasets	2014	(Yang and Cardie, 2014)
	Supervised learning	Joint Framework	Segmentation and sentence polarity prediction	Tweet SemEval 2013 dataset and Rottentomatoes dataset	2015	(Tang et al., 2015)
	Deep learning	Recursive neural network, LSTM	Increasing phrase/sentence representation	Stanford Sentiment Treebank, Movie review dataset	2017	(Huang et al., 2017)
	Deep learning	Recursive neural network	Software libraries recommendation and negative results	Stackover Flow, Mobile app reviews, JIRA	2018	(Lin et al., 2018)
	Lexicon based	Dixtionary based	Sentiment classification of twitter messages	Stanford Twitter Sentiment, SemEval 2013	2014	(Musto et al., 2014)
Aspect Level	Supervised learning	Neural network, word embeddings and Compositional vector models	Aspect rating and weight detection	TripAdvisor Hotel reviews	2018	(Pham and Le, 2018)

Table 1: Continued.

Level	Approach	Technique	Studied issue	DataSet	Year	Reference
Aspect Level	Supervised learning	NB, SVM, KNN, Decision Tree, Bayes Network	Three ABSA subtasks	Arabic Hotels' reviews SemEval-2016: Task-5	2018	(Al-Smadi et al., 2018)
	Deep learning	LSTM	Chinese aspect term sentiment classification	SemEval2014 and four Chinese reviews datasets	2018	(Peng et al., 2018)
	Deep learning	(Sentic) LSTM	Targeted Aspect-Based SA	SentiHood, SemEval 2015	2018	(Ma et al., 2018)
	Unsupervised learning	Enriched LDA	Aspect extraction	English and Persian product reveiws	2017	(Shams and Baraani-Dastjerdi, 2017)
	Unsupervised learning	Topic modeling (combined with word embedding and ME classifier)	System for Aspect Based Sentiment Analysis (ABSA)	SemEval 2016 Task 5 dataset	2017	(Pablos et al., 2017)
	Lexicon based	Corpus based	A media monitoring system about the opinion mining in political field	Arabic journalistic text	2017	(Najar and Mesfar, 2017)
	Lexicon based	Dictionary based and syntactic dependency	Automating training data labeling	Twitter data-set (mobile phones)	2017	(Rathan et al., 2017)
	Lexicon based	Corpus based	Usage of Chinese radical parts for SA	IPEEN and TripAdvisor restaurent reviews	2018	(Chao and Yang, 2018)
	Ontology based		Retrieval and analysis of social media content	Twitter messages	2015	(Thakor and Sasi, 2015)
	Ontology based		Detection of adolescent depression signals	Twitter and social media channels	2017	(Jung et al., 2017)

6 COMPARISON OF APPROACHES

A comparison of Machine learning and lexicon base approaches is presented in Table 3 as they represent the two main approaches for sentiment classification at the document, sentence and aspect levels, whereas ontology based approaches are specially used at aspect level.

Lexicon based approaches are domain independent and do not need labelled data. It is a strong advantage over machine learning approaches that are dependent to the domain which means that a classifier trained in a certain domain will show weak results if it is used for a different domain. Another big inconvenient for ML methods is the need of labelled data, which requires human participation and annotation that could be expensive and time consuming.

7 CONCLUSION

Sentiment Analysis is gaining more and more popularity nowadays and that is because we all need each others opinions and point of views. Opinion mining has been studied in different domains and languages

Table 2: Comparison of machine learning and lexicon based approaches.

Approaches	Advantages	Inconvenient
Machine Learning	• Unnecessity of dictionaries • High accuracy of classification • High precision and adaptability	• Dependent to the domain • Slow time • Needs human participation and labelled data
Lexicon based	• Does not need labelled data • Domain independent • Fast time	• Needs strong linguistic resources • Low accuracy • Requires dictionaries that covers lot opinion words

and has showed to be very effective and benefic in finance, politics, e-commerce, but it can also be used in health, cybersecurity and point of view discovery.

In this paper, we presentend the field of sentiment analysis or opinion mining by covering utilized approaches based on three levels of granularity (document, sentence and aspect). Another important level related to sentiment analysis is the concept level which is being dealt with frequently. Concept-based approaches to sentiment analysis focus on a semantic analysis of text through the use of web ontologies or semantic networks (Cambria, 2013). This makes sentiment analysis at concept-level exciting and challenging and need more researches because of the lack of sentiment ontologies. As it can be remarked in the recent papers reviewed previously, researchers are following deep learning approaches to deal with SA tasks and challenges, and there is much more to be done using deep learning approaches.

Most of the researchers in SA are analyzing peoples opinions on social networks, e-commerce sites and other platforms where people can share there opinions, whereas they can also express their opinions outside the digital world. Graffiti are a way for people to express there opinions in an anonymous manner. Sentiment analysis can be applied to Graffiti for discovering several caracteristics and traits of society.

REFERENCES

Ahlgren, O. (2016). Research on sentiment analysis: The first decade. In *2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW)*, pages 890–899.

Al-Smadi, M., Al-Ayyoub, M., Jararweh, Y., and Qawasmeh, O. (2018). Enhancing aspect-based sentiment analysis of arabic hotels reviews using morphological, syntactic and semantic features. *Information Processing & Management*.

Alistair, K. and Diana, I. Sentiment classification of movie reviews using contextual valence shifters. *Computational Intelligence*, 22(2):110–125.

Bhatia, S., Sharma, M., and Bhatia, K. K. (2018). *Sentiment Analysis and Mining of Opinions*, pages 503–523. Springer International Publishing, Cham.

Cambria, E. (2013). An introduction to concept-level sentiment analysis. In Castro, F., Gelbukh, A., and González, M., editors, *Advances in Soft Computing and Its Applications*, pages 478–483, Berlin, Heidelberg. Springer Berlin Heidelberg.

Cambria, E., Poria, S., Gelbukh, A., and Thelwall, M. (2017). Sentiment analysis is a big suitcase. *IEEE Intelligent Systems*, 32(6):74–80.

Chao, A. F. and Yang, H.-L. (2018). Using chinese radical parts for sentiment analysis and domain-dependent seed set extraction. *Comput. Speech Lang.*, 47(C):194–213.

Chaturvedi, I., Cambria, E., Welsch, R. E., and Herrera, F. (2018). Distinguishing between facts and opinions for sentiment analysis: Survey and challenges. *Information Fusion*, 44:65 – 77.

Dou, Z.-Y. (2017). Capturing user and product information for document level sentiment analysis with deep memory network. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 521–526. Association for Computational Linguistics.

Feldman, R. (2013). Techniques and applications for sentiment analysis. *Commun. ACM*, 56(4):82–89.

Hemmatian, F. and Karim Sohrabi, M. (2017). A survey on classification techniques for opinion mining and sentiment analysis.

Hu, M. and Liu, B. (2004). Mining and summarizing customer reviews. In *Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '04, pages 168–177, New York, NY, USA. ACM.

Huang, M., Qian, Q., and Zhu, X. (2017). Encoding syntactic knowledge in neural networks for sentiment classification. *ACM Trans. Inf. Syst.*, 35(3):26:1–26:27.

Jung, H., Park, H.-A., and Song, T.-M. (2017). Ontology-based approach to social data sentiment analysis: Detection of adolescent depression signals. 19:e259.

Kalyani, Gupta, E., Rathee, G., Kumar, P., and Singh Chauhan, D. (2015). Mood swing analyser: A dynamic sentiment detection approach. 85:149–157.

Lee, D., Ju, H., Yu, H., Park, J.-m., and Kim, K.-Y. (2018). Dualsentinet: Dual prediction of word and document sentiments using shared word embedding. In *Proceedings of the 12th International Conference on Ubiquitous Information Management and Communication*, IMCOM '18, pages 34:1–34:9, New York, NY, USA. ACM.

Lin, B., Zampetti, F., Bavota, G., Di Penta, M., Lanza, M., and Oliveto, R. (2018). Sentiment analysis for software engineering: How far can we go? In *Proceedings of 40th International Conference on Software Engineering*.

Liu, B. (2012). *Sentiment Analysis and Opinion Mining*. Morgan & Claypool Publishers.

Liu, B. (2015). *Sentiment Analysis: Mining Opinions, Sentiments, and Emotions*. Cambridge University Press.

Ma, Y., Peng, H., and Cambria, E. (2018). Targeted aspect-based sentiment analysis via embedding commonsense knowledge into an attentive lstm. In *AAAI*.

Mantyla, M. V., Graziotin, D., and Kuutila, M. (2018). The evolution of sentiment analysisa review of research topics, venues, and top cited papers. *Computer Science Review*, 27:16 – 32.

Missen, M. M. S., Boughanem, M., and Cabanac, G. (2012). Opinion mining: reviewed from word to document level. *Social Network Analysis and Mining*, 3:107–125.

Muhammad, A., Wiratunga, N., and Lothian, R. (2016). Contextual sentiment analysis for social media genres. *Knowledge-Based Systems*, 108:92 – 101. New Avenues in Knowledge Bases for Natural Language Processing.

Musto, C., Semeraro, G., and Polignano, M. (2014). A comparison of lexicon-based approaches for sentiment analysis of microblog. 1314:59–68.

Najar, D. and Mesfar, S. (2017). Opinion mining and sentiment analysis for arabic on-line texts: application on the political domain. 20:1–11.

Pablos, A. G., Cuadros, M., and Rigau, G. (2017). W2VLDA: almost unsupervised system for aspect based sentiment analysis. *CoRR*, abs/1705.07687.

Peng, H., Ma, Y., Li, Y., and Cambria, E. (2018). Learning multi-grained aspect target sequence for chinese sentiment analysis. *Knowledge-Based Systems*, 148:167 – 176.

Pham, D.-H. and Le, A.-C. (2018). Learning multiple layers of knowledge representation for aspect based sentiment analysis. *Data & Knowledge Engineering*, 114:26 – 39. Special Issue on Knowledge and Systems Engineering (KSE 2016).

Rathan, M., Hulipalled, V., K R, V., and Patnaik, L. (2017). Consumer insight mining: Aspect based twitter opinion mining of mobile phone reviews.

Ravi, K. and Ravi, V. (2015). A survey on opinion mining and sentiment analysis. *Know.-Based Syst.*, 89(C):14–46.

Shams, M. and Baraani-Dastjerdi, A. (2017). Enriched lda (elda): Combination of latent dirichlet allocation with word co-occurrence analysis for aspect extraction. *Expert Systems with Applications*, 80:136 – 146.

Studer, R., Benjamins, V., and Fensel, D. (1998). Knowledge engineering: Principles and methods. *Data & Knowledge Engineering*, 25(1):161 – 197.

Sun, S., Luo, C., and Chen, J. (2017). A review of natural language processing techniques for opinion mining systems. *Information Fusion*, 36:10 – 25.

Tang, D., Qin, B., Wei, F., Dong, L., Liu, T., and Zhou, M. (2015). A joint segmentation and classification framework for sentence level sentiment classification. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 23(11):1750–1761.

Thakor, P. and Sasi, S. (2015). Ontology-based sentiment analysis process for social media content. *Procedia Computer Science*, 53:199 – 207. INNS Conference on Big Data 2015 Program San Francisco, CA, USA 8-10 August 2015.

Tripathy, A., Agrawal, A., and Rath, S. K. (2016). Classification of sentiment reviews using n-gram machine learning approach. *Expert Systems with Applications*, 57:117 – 126.

Turney, P. D. (2002). Thumbs up or thumbs down?: Semantic orientation applied to unsupervised classification of reviews. In *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics*, ACL '02, pages 417–424, Stroudsburg, PA, USA. Association for Computational Linguistics.

Yang, B. and Cardie, C. (2014). Context-aware learning for sentence-level sentiment analysis with posterior regularization. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 325–335. Association for Computational Linguistics.

Zhang, L., Wang, S., and Liu, B. (2018). Deep learning for sentiment analysis: A survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*.