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A PATH FOR HORIZING YOUR INNOVATIVE WORK

STATE OF THE ART IN SENTIMENT ANALYSIS: TAXONOMY, REVIEW, RESEARCH ISSUES AND CHALLENGES

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Abstract: - Sentiment Analysis (SA) is defined as an efficient method of extracting wide scope of opinions and views from consumers. Obtaining meaningful information from the feedbacks and categorizing it into different dimensions of individual development remains the prominent components for comprehensive growth. The concept of sentiment analysis is highly useful in managing this problem. S.A is a primary phase in the Artificial Intelligence research and has a prominent role in the polarity determination procedure. The analysis presents a key opportunity for obtaining the opinions of individuals, consumers and reviewers with respect to different dimensions such as choice of goods, share market estimates, brand recognition, support to government policies etc. In particular, in the domain of NLP, SA is believed to be an emerging solution. The growth of ICT and networking platforms is found to be an ideal stage enabling users to quickly interchange opinions, ideas etc. A robust growth in the operative computing and opinion mining areas can be found, which provides influence with respect to computer- manual interaction, and data recovery in the context of infinite and voluminous networking information. This manuscript provides the current scenario of different approaches to SA used for opinion-mining such as ML techniques, lexicon based techniques are presented. Multiple methods suggested for efficient SA are analyzed in the research work by presenting an assessment of the works. Further, the research work also depicts the usefulness of previous works in the context. The research paper can also be used by next studies to gain knowledge on available gaps in contemporary studies in the field of SA.

Keywords: Hybrid Approaches * Sentiment Analysis * Affective computing * Five eras of the Web * Jumping NLP curves.

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INTRODUCTION

Analysing the user engendered content has become an integral prerequisite for the modern-day management of the organizations sentiment analysis is vital as one of the resourceful factors that support in the mining process.

Analysis of user's opinions plays a critical role in the decision making of the companies as they offer significant factors that determine the way people have an opinion and the way market perceives such opinion. Opinion from one user is not an effective for decision making and there is imperative need for considering and gaining insights from the opinions of distinct range of customers. Evaluating the overall opinions in a structured manner can lead to insights about divergent views [1].

Since a decade of time, opinion mining and sentiment analysis has gained profound importance in the field of NLP [2] [3] and is vividly focused upon in the case of data mining, social media analytics and web mining.

The contribution depicted in [3] denoted the opinion asfive folds and they are

a. entity (E) [1] [4] such as an individual, an organization, an event, a product, a concept, or a service,

b. entity aspect (A) such as usefulness of a good, person or an organization, quality of a service, or result of an event,

c. sentiment (S)such as positive, negative, neutral, rated, or ranked related to the aspect of the entity,

d. Representative such a customer, reviewer, or decision maker who maintains the expression (H),

e. Opinion articulated time (T) that denotes the context of period the expression is presented.

Concerning this definition, it is significant to quote that the aim of SA discovers one or more of these five folds, which further categorizes to depict the overall opinion of the target representatives.The majority of the SAtechniques presented in the contemporary studies are machine-learning approaches,which focused on the first four of the aforesaid quintuple (fivefold) description.

The process of feature representation significantly impacts the efficiency of the machine learning approaches [5], there is imperative need for contributions pertaining to feature selection strategies which is envisaged from the review of contemporary literature [6] [7]. The learning mechanisms are very significant in terms of choosing discriminative features [8], ensemble of learners [9] that increases the scope of learning from the chosen data at varied levels, and it can denote deep learning.

In the next chapters of the research work, focus is given on analyzing existing studies corresponding to attribute selection mechanisms in the S.A context.

SENTIMENT ANALYSIS: THE NOMENCLATURE

1. Sentimental analysis explored at various levels [10].

2. In the document level analysis, the primary problem is to categorize the opinion text as anencouraging or discouraging text. In the process, it is presumed that each document depicts the opinion of an entity. The process of document sentiment classification results in understanding if the opinion is encouraging or discouraging. However, any kind of extraction or study of information is not feasible with the document and the task is termed as document-level sentiment classification.

3. The basic task in a sentence evaluation is to understand if the sentence expressed is a neutral opinion or a positive or a negative one. Such study is significantly associated with the process of sentiment extraction, classification and subjectiveness classification, opinion spam detection and other such factors [11]. It targets in investigating people sentiment, opinions, emotions, attitudes etc for varied range of elements like services, topics, products, and organizations [12].

4. Sentiment level classification of sentiment is very identical process to the document sentiment classification as profoundly the sentences are considered as smalltexts. However the crux is that the opinion categorization is highly complex as the information in a distinctive sentence is much lower than the ones in a document.

5. Also, in the case of sentiment analysis, neutral class has to be considered as there is varied range of factual sentences which depicts hardly any type of encouraging or discouraging opinion in the opinion document process. Usually in the case of document classification, the neutral class are not considered.

1. In the context of dimension level SA, the opinion of individual targets are analysed, wherein the aforesaid document, and sentence level analysis reflects upon the state of sentiment but shall target any kind of sentiment. Aspect level sentiment analysis is profoundly used for understanding the opinion targets. For instance, the statement defining "Both the price and performance are high" has more ambiguity in the statement and do not reflect either positivity or negativity. If the sentiment states like "Both the cost of car and also the performance are high", there is clear defining in the statement pertaining positive opinion.

2. Unless the targets are any kind of positive or negative sentiment they are hardly of any use. It is authoritative that more than the document or sentence level sentiment classification, aspect sentiment classification can be more resourceful.

3. The other form in which the sentence level is depicted is the sarcasm which might reflect the actual sentiment in a sarcastic manner. Such opinions and statement increase the complexity in analysing the sentiment as it needs common sense and also profound levels of discourse analysis [13] [14].

4. Analysis at a sentence level is very critical in the case of subjective and objective expressions that are discussed in sentences. Opinion words that are used at the subjective expressions indicate neither positive nor negative sentence. For instance, a statement like "I prefer to buy a car which offers good mileage" is a clear and subjective analysis which indicates advocating to a specific scenario.

5. Even in the case of objective expressions, expel sentence comprising an opinion word as objective expression is *"dust covered over the car can be ineffective for starting the engine*". Such sentence is not depicting any sentiment class and it only denotes observation. Effectively such subjective or objective expression can depict the sentiment wherein the subject or object is desirable.

6. In the other dimension sentiment analysis is carried out by comparative sentences. Unlike the opinion sentences that are regular, in the case of comparative sentence details a relation reliant on similarities or the variations in any entity. In the English language evaluations are generally discussed based on the comparative or superlative forms. In the case of comparative mining, aspect sentiment analysis is very essential due to its sensibility in terms of classifying sentence as positive, neutral or negative sentiment [15] [16].

Prevalent Sentiment Analysis Methods

1. Rule Based Approach: In this model, various rules for formulated for extracting opinions. Tokenizing each sentence in the documents and the tokens are assessed for the presence of any opinions. In case of any input sentence do not find the words that are in the databases, it can facilitate them in terms of moving the picture review and such words are usually included to the database. It is often supervised learning within the system to ensure if any new words are to be trained.

2. Machine Learning Models: In this approach, machine learning model is used for training algorithm comprising predefined datasets whilst applying them to the actual datasets. Machine learning methods initially trains the algorithm comprising specific inputs constituting known outputs which enables in handing the unknown data in the future analysis.

3. Lexical Based Approach: Lexicon based techniques focus on assumption that collective priority in a sentence or documents is the cumulative of polarities for individual phrases or the contexts.

RELATED WORK

In the recent past, numerous articles depicting varied types of solutions designed for SA in English documents has come up. Few of the models are subjectivity detection, objectivity detection, polarity classification, opinion identification, entity or aspect-based sentiment classification etc. Recent contributions [2], [17] and [18] emphasize the aforesaid factors.

Sentiment Analysis at Document Level

Sentimentcategorization regarded as a niche scenario of text classification problem by the Corpus based methods [19]. It develops the opinion classification model from the phrases utilizing the listedopinion polarity and the opinion supervision can effectively annotate or systematically gathered by sentiment signals like the human ratings over the reviews [20] or emoticons in tweets [21].

In [19], the researchers have exploitedopinion categorization of reviews from the dimension of text classification problem. Few other contemporary models like NB feature that is enhanced by SVM [22], that depicts feature weights by Information Retrieval Weight Functions [23], feature selection by lexicons and POS tagging [24] [6], polar shifting and conditional random fields [25] have targeted on learning effective features for attaining better performance for opinion mining.

Supervised learning models are profoundly utilized for document stageopinion analysis, which reflects on class of encouraging and discouraging or any type of predefined rankings. Certain benchmark classifiers like the NB and SVM can be espoused directly. Diversification of classification results which influence the features chosen in the learning process [3].

Researchers observed that the sentiment classification that is supervised are profoundly domain sensitive and a classification model trained through the expression texts from one sector might be yielding quality results in one application while for the other cases it might deliver poor results from the process. Simply such developments can be assigned to the terms that areput to use in vivid domains to express views and opinions, which can be different. In a different manner, one word could be positive for one domain but might yield adverse results in the other domain. In [26], [27], [3], domain incorporation or the transfer training approaches engaged for addressing the issues.

Significant contributions pertaining to unsupervised learning moethodsconversed in the literature signifies the importance of labels corresponding to opinion groups. In [1], [28], [29], [30] lexicon based technique have been detailed which focus on syntactic pattern of opinion words like the good, bad, beautiful, awful, awesome and other such related synonyms, hyponyms and hypernyms of the words that are class labels.

Sentence Level S.A

Document sentiment classification techniques are mainlyincorporated in the context of phrase sentiment grouping. In [31], certain sentence-specific approaches were proposed. Also, the researchers found that varied types of sentences are vital for different range of classification methods like the integrative sentences and conditional sentences [3].

For instance, a conditional sentence details implication in terms of hypothetical scenarios and its related implications. Such sentences comprise two clauses- condition and consequent, which are inner-dependent. Association has most important affect regarding it the phrase presents an encouraging or discouraging opinion. In [32] supervised learning methodprovisions in handling the linguistic features like phrases, locations, tense patterns, and some sort of conditional connectives.

Aspect level SA

Irrespective of the fact that the supervised training can be useful for aspect classification, still the attributes, which are engaged may not be sufficient as such features do not consider opinion targets. It leads to amiss of target an opinion focus upon. To address such issues, opinion targets are to be considered in the learning. One of way of learning is to focus on set of features which rely on outlook target in the sentence and the second way is to evaluate the application scope for every sentiment expression by determining if they cover the target over a sentence. Predominantly the first approach used in majority of them, but also it has flavour of second approach [24].

Due to limited listings, unsupervised techniques present a vital role on fine-tuned level S.A. For dimension identification, the relation-mining program is adapted. Further, language understanding, such as metonym- discriminators [33] and partial/ complete structures [34], are considered. Double propagation coding suggested for an integrated sentiment terms and dimensions obtaining [35]. In addition, rule-specific approaches are also efficient for identification of potential elements and dimensions [36]. Comparison phrases utilized for identification of implied dimensions [37]. Clause patterns explored for dividing texts into phrases that are resourceful for dimension identification [38].

LDA topic method and its variations used for dimension identification [39] and combined aspect and opinion identification [40], [41].

An aspect grouping mechanism that includes explicit understanding, is put forward for partially-supervised aspect identification [42].

Lexicons and Sentiment Analysis

In [29] [30] authors have relied on repository of sentimental words that constitutes sentiment polarity, intensification, and negation incorporation for computation of sentiment polarity in every sentence. The method of representative lexicon oriented method that is adapted in [29] profoundly has three steps. Extraction phase is implemented in the first phase where the postages affirm the patterns based on predefined conditions. Secondary phase comprise the process of PMI that computes the extent of dependency amidst two terms. In the final phase, average of polarity for all phrases of a review are evaluated and treated as sentiment polarity.

In [43], the authors have targeted negation words to improve the performance of lexicon-based methods. In [30], the authors have focused on integration of intensifications and discouraging terms in opinion lexicons, which are listed with sentiment power and its polarity. In [44], Senti strength developed using lexicons that related to lexicons and the language rules for defining strength of sentiments in tweets. In [45], a rule based system to address sentiment analysis issues in twitter were proposed, which adapts hand-written rules wherein pattern that suits words or sequence of words are considered.

In the lexicon based approaches, sentiment orientation for a target is computed for a sentence by considering sentiment aggregation function, which relies on distances of sentiment expression and opinion target in the sentence, for finding application scope of every sentiment expression. At a higher level, the approach adapts lexicon of sentiment expressions comprising sentiment words, composition rules, phrases and idioms. And the other element is usage of set of rules to address varied language constructs and varied types of sentences. In addition, a sentiment aggregation function, the associated relationship amidst them generate parse tree for detecting sentiment-orientation for each test entity [43] [3].

Deep Learning Strategies for Sentiment Analysis

Feature engineering has significant importance despite of labour-intensiveness. Hence it is essential to identify explanatory features from the dataand guarantees that the training programs are relatively less variable with extensive attribute engineering. Swiftprogressin deep learning models [5] [46] for contemporary literature relying on learning small-dimensional and the vectors that are real-valued which hastext attributes for S.A, without any type of attribute engineering mechanism.

Certaindeep learning approachesfor S.A through categorization consists of two. In the first phase, embedding word using the text corpus shall be learnt by the algorithm [47] [48] and in second stage, word embedding's are adapted for producing representation of phrases or textswith respect to semantic alignment [49].

Various existing composition learning practices are generally dependent on the facets of compositionality [50] that defines the implication of lengthier opinion arousing from the implications of components andstandards for uniting them. In [51], the authors initialized term integrating through latent S.A and it presents each text as a linear and wieighted of n-gram vectors for categorization.

In [52], the authors used stacked de noising auto encoder adapts unsupervised manner on the basis of rebuilding andadapt them for the level of domain level learning. Auto encoder is neural network solution which optimizes reconstruction of input by itself. It usually masks the values of feed information on random basis and aims to rebuild any type of noisy feed information.

In [7], certain recursive deep neutral models that constituting MN-RNN [53], [54], RAE and RNTM [7] were adapted to develop composition of varied length phrases which signifies depiction of the child nodes. Specifically, the RAE usually learns the sentence's structure in an unsupervised reconstruction mechanism and based on compositionality of learned tree pattern.

At RAE each term is encoded as vector and the computer shall become the matrix multiplication of a non-linear level of hyperbolic tangent function. In MV-RVN, all the words are associated to a matrix reflection that results in creation of tree structure using the external parser.

RNN is among the effective models developed in NLP segment and it has extended models in the form of global feed backward [55], deep recursive layer [56], feature weight tuning [57], Combinatory Categorical Grammar [58], Hermann ete.al [58], Combinatory Categorical Auto encoders develop adaptive RNN which relies on over one composition problems and select them on the basis of feed vectors. In [57], extended RNN was proposed by handling the feature weight to regulateone particular entity, which adds to next level detailing.

CNN discussed in [59], which is one of the emphatic models of neural network concerned with semantic composition [59]. In [60], the authors for improvement in learning sentence representation discussed DCNN. In [61], [62] authors contributed by exploring the CNNs and attaining varied range of performances pertaining to certain benchmark level datasets towards sentiment classification and the word order is handled in an appropriate manner.

Sequential model based solutions and LSTM oriented solutions were considered as very effective to address semantic composition. The method handles processing of sentences in sequential manner and focusing on one term at any time. NNs consisting shared parameters are selected for estimation. The fundamental computational system can be an elementary matrix compounding or even complicated LSTM unit. In [63], efficacy of RNN and the other models were explored and in [64], [65] the tree structured LSTM were explored for understanding the semantic composition patterns.

A few of the works have exploited the document level semantic composition [66], [67] while few of them have evaluated the relationship amidst lines in the solutions designed for text level S.A. In [68], specific phrase reflections on textreflectionsin a serial manner have focus upon. The model depicted in [69] considered RST discourse-parser and combine parsed outcomesconsisting RNN textstage S.A.

CONCLUSION

This research work provided a detailed analysis of different studies of S.A. The complexity involved in information representation and dimensionality, different utilization needs, the S.A evolved as prominent research target over the past ten years. This work identified the classification of SA procedure, analysis of ML technique driven S.A methods observed in the contemporary literature, careful comparison of different approaches through prominent study objectives for next scholars. This work depicts that all the SA processes are highly challenging and awareness of the task and possible solutions are largely restricted. The primary cause behind this is the task being an NLP task that is further complicated amidst unavailability of proper prototypes. But, the research presented prominent works in contemporary studies, it is clear to convey that the S.A is consisting prospect scope for additional research and is presenting the scope of emerging soft-computing approaches and the integration of these approaches for attribute choosing to categorize the opinion.

REFERENCES

1. Hu, Minqing, and Bing Liu. "Mining and Summarizing Customer Reviews." (2004).

2. Pang, Bo, and Lillian Lee. "Opinion Mining and Sentiment Analysis." Information Retrieval 2.1-2 (2008): 1-135.

3. Liu, Bing. "Sentiment Analysis and Opinion Mining." (2012): 167.

4. Deng, Lingjia, and Janyce Wiebe. "MPQA 3.0: An Entity/Event-Level Sentiment Corpus." HLT-NAACL. 2015.

5. Bengio Y, Goodfellow IJ, Courville A. Deep Learning. Cambridge, MA: MIT Press (in preparation); 2015.

6. Mohammad, Saif M., Svetlana Kiritchenko, and Xiaodan Zhu. "NRC-Canada: Building the state-of-the-art in sentiment analysis of tweets." arXiv preprint arXiv:1308.6242 (2013).

7. Yang, Bishan, and Claire Cardie. "Extracting opinion expressions with semi-Markov conditional random fields." Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning. Association for Computational Linguistics, 2012.

8. Bengio, Yoshua, Aaron Courville, and Pascal Vincent. "Representation learning: A review and new perspectives." IEEE transactions on pattern analysis and machine intelligence 35.8 (2013): 1798-1828.

9. LeCun, Yann, YoshuaBengio, and Geoffrey Hinton. "Deep learning." Nature 521.7553 (2015): 436-444.

10. Hussein, DoaaMohey El-Din Mohamed. "A survey on sentiment analysis challenges." Journal of King Saud University-Engineering Sciences (2016).

11. Dwivedi, Sanjay Kumar, and Bhupesh Rawat. "A review paper on data pre-processing: A critical phase in web usage mining process." Green Computing and Internet of Things (ICGC IoT), 2015 International Conference on. IEEE, 2015.

12. Pradhan, Vidisha M., Jay Vala, and PremBalani. "A survey on Sentiment Analysis Algorithms for opinion mining." International Journal of Computer Applications 133.9 (2016).

13. Tsur, Oren, Dmitry Davidov, and Ari Rappoport. "ICWSM–A Great Catchy Name: Semi-Supervised Recognition of Sarcastic Sentences in Online Product Reviews." (2010).

14. Riloff, Ellen, et al. "Sarcasm as contrast between a positive sentiment and negative situation." 2013 Conference on Empirical Methods in Natural Language Processing, EMNLP 2013. Association for Computational Linguistics (ACL), 2013.

15. Jindal, Nitin, and Bing Liu. "Mining comparative sentences and relations." 21st National Conference on Artificial Intelligence and the 18th Innovative Applications of Artificial Intelligence Conference, AAAI-06/IAAI-06. 2006.

16. Liu, Bing. "Sentiment analysis: Mining opinions, sentiments, and emotions." (2015).

17. Liu, Bing, and Lei Zhang. "A Survey of Opinion Mining and Sentiment Analysis." Mining Text Data (2012): 415-463.

18. Mohammad, Saif M. "Sentiment analysis: Detecting valence, emotions, and other affectual states from text." Emotion measurement (2015): 201-238.

19. Pang, Bo, Lillian Lee, and ShivakumarVaithyanathan. "Thumbs up? sentiment classification using machine learning techniques." Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10. Association for Computational Linguistics, 2002.

20. Maas, Andrew L., et al. "Learning word vectors for sentiment analysis." Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1. Association for Computational Linguistics, 2011.

21. Zhao, Jichang, et al. "Moodlens: an emoticon-based sentiment analysis system for chinese tweets." Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 2012.

22. Wang, Sida, and Christopher D. Manning. "Baselines and bigrams: Simple, good sentiment and topic classification." Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Short Papers-Volume 2. Association for Computational Linguistics, 2012.

23. Paltoglou, Georgios, and Mike Thelwall. "A study of information retrieval weighting schemes for sentiment analysis." in Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics. 2010.

24. Jiang, Long, et al. "Target-dependent twitter sentiment classification." Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1. Association for Computational Linguistics, 2011.

25. Nakagawa, Tetsuji, Kentaro Inui, and SadaoKurohashi. "Dependency tree-based sentiment classification using CRFs with hidden variables." Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics. Association for Computational Linguistics, 2010.

26. Blitzer, John, Mark Dredze, and Fernando Pereira. "Biographies, Bollywood, Boom-boxes and Blenders: Domain Adaptation for Sentiment Classification." ACL 2007 (2007): 440.

27. Pan, SinnoJialin, et al. "Cross-domain sentiment classification via spectral feature alignment." Proceedings of the 19th international conference on World wide web. ACM, 2010.

28. Kim, Soo-min, and Eduard Hovy. "Determining the sentiment of opinions." In Proceedings of the 20th International Conference on Computational Linguistics COLING’04. 2004.

29. Turney, P. D. Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews. No. cs. LG/0212032. cs/0212032, 2002.

30. Taboada, Maite, et al. "Lexicon-based methods for sentiment analysis." Computational linguistics 37.2 (2011): 267-307.

31. Mcdonald, Ryan, et al. "Structured Models for Fine-to-Coarse Sentiment Analysis." Proceedings of the 45th Annual Meeting of the Association of Computational Linguistics. 2007.

32. Narayanan, Ramanathan, Bing Liu, and Alok Choudhary. "Sentiment analysis of conditional sentences." Association for Computational Linguistics, 2009.

33. Popescu, Ana-Maria, and Orena Etzioni. "Extracting product features and opinions from reviews." Natural language processing and text mining. Springer, London, 2007. 9-28.

34. Zhang, Lei, et al. "Extracting and ranking product features in opinion documents." 23rd International Conference on Computational Linguistics, Coling 2010. 2010.

35. Qiu, Guang, et al. "Expanding Domain Sentiment Lexicon through Double Propagation." Twenty-First International Joint Conference on Artificial Intelligence. 2009.

36. Gindl, Stefan, Albert Weichselbraun, and Arno Scharl. "Rule-based Opinion Target and Aspect Extraction to Acquire Affective Knowledge." (2013): 557-563.

37. Ding, Xiaowen, Bing Liu, and Lei Zhang. "Entity Discovery and Assignment for Opinion Mining Applications." (2009).

38. Thet, TunThura, Jin-Cheon Na, and Christopher SG Khoo. "Aspect-based sentiment analysis of movie reviews on discussion boards." Journal of Information Science 36.6 (2010): 823-848.

39. Brody, Samuel. "An Unsupervised Aspect-Sentiment Model for Online Reviews." (2010).

40. Lazaridou, Angeliki, Ivan Titov, and Caroline Sporleder. "A Bayesian Model for Joint Unsupervised Induction of Sentiment, Aspect and Discourse Representations." ACL (1). 2013.

41. Wang, F. Linlin, et al. "Sentiment-Aspect Extraction based on Restricted Boltzmann Machines." (2015).

42. Zhai, Zhongwu, et al. "Clustering Product Features for Opinion Mining." (2011).

43. Ding, Xiaowen, Bing Liu, and S. Yu Philip. "A Holistic Lexicon-Based Approach to Opinion Mining." (2008).

44. Thelwall, Mike, Kevan Buckley, and Georgios Paltoglou. "Sentiment strength detection for the social web." Journal of the American Society for Information Science and Technology 63.1 (2012): 163-173.

45. Reckman, Hilke, et al. "Linnea Micciulla, SaratenduSethi, and FruzsinaVeress SAS Institute 10 Fawcett Street Cambridge, MA 02138, USA." Atlanta, Georgia, USA (2013): 513.

46. Hinton, Geoffrey E., and Ruslan R. Salakhutdinov. "Reducing the dimensionality of data with neural networks." science 313.5786 (2006): 504-507.

47. Mikolov, Tomas, et al. "Distributed Representations of Words and Phrases and their Compositionality." arXiv preprint arXiv:1310.4546 (2013).

48. Tang, Duyu, et al. "Learning Sentiment-Specific Word Embedding for Twitter Sentiment Classification." ACL (1). 2014.

49. Mitchell, Jeff, and Mirella Lapata. "Composition in Distributional Models of Semantics." Cognitive Science 8.34 (2010): 1388-1429.

50. Frege, Gottlob. "On sense and nominatum." (1949).

51. Bespalov, Dmitriy, et al. "Sentiment Classification Based on Supervised Latent n-gram Analysis." (2011).

52. Glorot, Xavier, Antoine Bordes, and YoshuaBengio. "Domain Adaptation for Large-Scale Sentiment Classification: A Deep Learning Approach." (2011).

53. Socher, Richard, et al. "Semi-supervised recursive autoencoders for predicting sentiment distributions." In Proceedings of the Conference on Empirical Methods in Natural Language Processing, (pp. 151–161). Association for Computational Linguistics. 2011.

54. Socher, Richard, et al. "Semantic compositionality through recursive matrix-vector spaces." Proceedings of the 2012 joint conference on empirical methods in natural language processing and computational natural language learning. Association for Computational Linguistics, 2012.

55. Paulus, Romain, Richard Socher, and Christopher D. Manning. "Global belief recursive neural networks." Proceedings of the 27th International Conference on Neural Information Processing Systems. MIT Press, 2014.

56. Cardie, Claire. "Deep recursive neural networks for compositionality in language." In Advances in Neural Information Processing Systems. 2014.

57. Li, Jiwei. "Feature Weight Tuning for Recursive Neural Networks." arXiv preprint arXiv:1412.3714 (2014).

58. Hermann, Karl Moritz, and Phil Blunsom. "The Role of Syntax in Vector Space Models of Compositional Semantics." In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics. 2013.

59. Severyn, Aliaksei, and Alessandro Moschetti. "Twitter sentiment analysis with deep convolutional neural networks." Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval. ACM, 2015.

60. Kalchbrenner, Nal, Edward Grefenstette, and Phil Blunsom. "A convolutional neural network for modelling sentences." arXiv preprint arXiv:1404.2188 (2014).

61. Kim, Yoon. "Convolutional neural networks for sentence classification." arXiv preprint arXiv:1408.5882 (2014).

62. Johnson, Rie, and Tong Zhang. "Effective Use of Word Order for Text Categorization with Convolutional Neural Networks." arXiv preprint arXiv:1412.1058 (2014).

63. Li, Jiwei, et al. "When are tree structures necessary for deep learning of representations?." arXiv preprint arXiv:1503.00185 (2015).

64. Tai, Kai Sheng, Richard Socher, and Christopher D. Manning. "Improved Semantic Representations from Tree-Structured Long Short-Term Memory Networks." (2015).

65. Zhu, Xiaodan, ParinazSobhani, and Hongyu Guo. "Long short-term memory over recursive structures." Proceedings of the 32nd International Conference on International Conference on Machine Learning-Volume 37. JMLR. org, 2015.

66. Le, Quoc, and Tomas Mikolov. "Distributed Representations of Sentences and Documents." International Conference on Machine Learning. 2014.

67. Li, Jiwei, Minh-Thang Luong, and Dan Jurafsky. "A hierarchical neural autoencoder for paragraphs and documents." arXiv preprint arXiv:1506.01057 (2015).

68. Tang, Duyu, Bing Qin, and Ting Liu. "Document Modeling with Gated Recurrent Neural Network for Sentiment Classification." EMNLP. 2015.

69. Bhatia, Parminder, Yangfeng Ji, and Jacob Eisenstein. "Better Document-level Sentiment Analysis from RST Discourse Parsing." arXiv preprint arXiv:1509.01599 (2015).