**Deep Learning for Sentiment Analysis: A Survey**

**INTRODUCTION**

Sentiment analysis or opinion mining is the computational study of people’s opinions, sentiments, emotions, appraisals, and attitudes towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes.

In the supervised setting, early papers used all types of supervised machine learning methods (such as Support Vector Machines (SVM), Maximum Entropy, Na飗e Bayes, etc.) and feature combinations. Unsupervised methods include various methods that exploit sentiment lexicons, grammatical analysis, and syntactic patterns.

**WORD EMBEDDING**

Many deep learning models in NLP need **word embedding** results as input features. Word

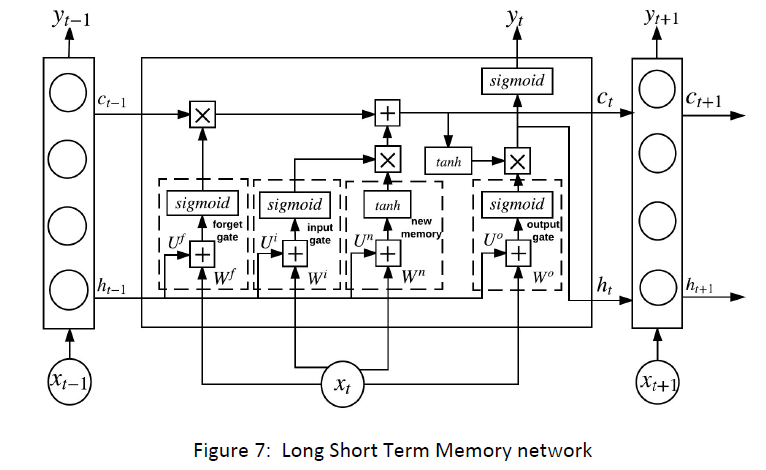
embedding is a technique for language modelling and feature learning, which transforms words in a vocabulary to vectors of continuous real numbers

**RECURRENT NEURAL NETWORK**

Bidirectional RNN is based on the idea that the output at each time may not only depend on the previous elements in the sequence, but also depend on the next elements in the sequence.

Deep bidirectional RNN is similar to bidirectional RNN. The only difference is that it has multiple layers per time step, which provides higher learning capacity but needs a lot of training data.

**LSTM NETWORK**



**ATTENTION MECHANISM WITH RECURRENT NEURAL NETWORK**

In NLP, the attention mechanism allows the model to learn what to attend to based on the input text and what it has produced so far, rather than encoding the full source text into a fixed-length vector like standard RNN and LSTM.

Note that each decoder output word 𝑦! depends on a weighted combination of all the input states, not just the last state as in the normal case.

**MEMORY NETWORK**

The four learnable/inference components function as follows: **I component** coverts the incoming input to the internal feature representation; **G component** updates old memories given the new input; **O** **component** generates output (also in the feature representation space); **R component** converts the output into a response format.

**SENTIMENT ANALYSIS TASKS**

Researchers have mainly studied sentiment analysis at three levels of granularity: document level, sentence level, and aspect level.

**Document level sentiment classification** classifies an opinionated document (e.g., a product review) as expressing an overall positive or negative opinion.

**Sentence level sentiment classification** classifies individual sentences in a document.

Compared with document level and sentence level sentiment analysis, aspect level sentiment analysis or **aspect-based sentiment analysis** is more fine-grained. Its task is to extract and summarize people’s opinions expressed on entities and aspects/features of entities, which are also called **targets**.

The whole task of aspect-based sentiment analysis consists of several subtasks such as **aspect extraction**, **entity** **extraction**, and **aspect sentiment classification**.

**DOCUMENT LEVEL SENTIMENT CLASSIFICATION**

**SENTENCE LEVEL SENTIMENT CLASSIFICATION**

**ASPECT LEVEL SENTIMENT CLASSIFICATION**

Given a sentence and a target aspect, aspect level sentiment classification aims to infer the sentiment polarity/orientation of the sentence toward the target aspect.

There are three important tasks in aspect level sentiment classification using neural networks. The first task is to represent the context of a target, where the context means the contextual words in a sentence or document.

The second task is to generate a target representation, which can properly interact with its context.

The third task is to identify the important sentiment context (words) for the specified target.

**ASPECT EXTRACTION AND CATEGORIZATION**

**OPINION EXPRESSION EXTRACTION**

**SENTIMENT COMPOSITION**

Sentiment composition claims that the sentiment orientation of an opinion expression is determined by the meaning of its constituents as well as the grammatical structure.

**OPINION HOLDER EXTRACTION**

**TEMPORAL OPINION MINING**

**SENTIMENT ANALYSIS WITH WORD EMBEDDING**

We first present the works of sentiment-encoded word embeddings.

Feature enrichment and multi-sense word embeddings are also investigated for sentiment analysis.

Multilinguistic word embeddings have also been applied to sentiment analysis.

**SARCASM ANALYSIS**

**EMOTION ANALYSIS**

Emotions are the subjective feelings and thoughts of human beings. The concept of emotion is closely related to sentiment.

**MULTIMODAL DATA FOR SENTIMENT ANALYSIS**

Multimodal data, such as the data carrying textual, visual, and acoustic information, has been used to help sentiment analysis as it provides additional sentiment signals to the traditional text features.

**RESOURCE-POOR LANGUAGE AND MULTILINGUAL SENTIMENT ANALYSIS**

**OTHER RELATED TASKS**

**Sentiment Intersubjectivity**

**Lexicon Expansion**

**Financial Volatility Prediction**

**Opinion Recommendation**

**Stance Detection**

**References**

[1] Liu B. Sentiment analysis: mining opinions, sentiments, and emotions. The Cambridge University Press, 2015.

[2] Liu B. Sentiment analysis and opinion mining (introduction and survey), Morgan & Claypool, May 2012.

[3] Pang B and Lee L. Opinion mining and sentiment analysis. Foundations and Trends in Information Retrieval, 2008. 2(1–2): pp. 1–135.

[4] Goodfellow I, Bengio Y, Courville A. Deep learning. The MIT Press. 2016.

[5] Glorot X, Bordes A, Bengio Y. Deep sparse rectifier neural networks. In *Proceedings of the International Conference on Artificial Intelligence and Statistics* (*AISTATS 2011*), 2011.

[6] Rumelhart D.E, Hinton G.E, Williams R.J. Learning representations by back-propagating errors. *Cognitive modelling,* 1988.

[7] Collobert R, Weston J, Bottou L, Karlen M, Kavukcuoglu K, and Kuksa P. Natural language processing (almost) from scratch. *Journal of Machine Learning Research*, 2011.

[8] Goldberg Y. A primer on neural network models for natural language processing. *Journal of Artificial Intelligence Research*, 2016.

[9] Bengio Y, Courville A, Vincent P. Representation learning: a review and new perspectives. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2013.

[10] Lee H, Grosse R, Ranganath R, and Ng A.Y. Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations. In *Proceedings of the International Conference on Machine Learning*

(*ICML 2009*), 2009.

[11] Bengio Y, Ducharme R, Vincent P, and Jauvin C. A neural probabilistic language model. *Journal of Machine Learning Research*, 2003.

[12] Morin F, Bengio Y. Hierarchical probabilistic neural network language model. In *Proceedings of the International Workshop on Artificial Intelligence and Statistics*, 2005.

[13] Mikolov T, Chen K, Corrado G, and Dean J. Efficient estimation of word representations in vector space. In *Proceedings of International Conference on Learning Representations* (*ICLR 2013*), 2013.

[14] Mikolov T, Sutskever I, Chen K, Corrado G, and Dean J. Distributed representations of words and phrases and their compositionality. In *Proceedings of the Annual Conference on* Advances in *Neural Information* *Processing Systems (NIPS 2013)*, 2013.

[15] Mnih A, Kavukcuoglu K. Learning word embeddings efficiently with noise-contrastive estimation. In *Proceedings of the Annual Conference on* Advances in *Neural Information Processing Systems (NIPS 2013)*, 2013.

[16] Huang E.H, Socher R, Manning C.D. and Ng A.Y. Improving word representations via global context and multiple word prototypes. In *Proceedings of the Annual Meeting of the Association for Computational* *Linguistics* (*ACL 2012*), 2012.

[17] Pennington J, Socher R, Manning C.D. GloVe: global vectors for word representation. In *Proceedings of the Conference on Empirical Methods on Natural Language Processing* (*EMNLP 2014*), 2014.

[18] Bengio Y, Lamblin P, Popovici D, and Larochelle H. Greedy layer-wise training of deep networks. In *Proceedings of the Annual Conference on* Advances in *Neural Information Processing Systems (NIPS 2006)*, 2006.

[19] Hinton G.E, Salakhutdinov R.R. Reducing the dimensionality of data with neural networks. *Science*, July 2006.

[20] Vincent P, Larochelle H, Bengio Y, and Manzagol P-A. Extracting and composing robust features with denoising autoencoders. In *Proceedings of the International Conference on Machine Learning* (*ICML 2008*), 2008.

[21] Sermanet P, LeCun Y. Traffic sign recognition with multi-scale convolutional networks. In *Proceedings of the International Joint Conference on Neural Networks* (*IJCNN 2011*), 2011.

[22] Elman J.L. Finding structure in time. *Cognitive Science*, 1990.

[23] Bengio Y, Simard P, Frasconi P. Learning long-term dependencies with gradient descent is difficult. *IEEE Transactions on Neural Networks*, 1994.

[24] Schuster M, Paliwal K.K. Bidirectional recurrent neural networks*. IEEE Transactions on Signal Processing*, 1997.

[25] Hochreiter S, Schmidhuber J. Long short-term memory. *Neural Computation*, 9(8): 1735-1780, 1997.

[26] Tai K.S, Socher R, Manning C. D. Improved semantic representations from tree-structured long short-term memory networks. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics (ACL* *2015)*, 2015.

[27] Cho K, Bahdanau D, Bougares F, Schwenk H and Bengio Y. Learning phrase representations using RNN encoder-decoder for statistical machine translation. In *Proceedings of the Conference on Empirical Methods in* *Natural Language Processing* (*EMNLP 2014*), 2014.

[28] Chung J, Gulcehre C, Cho K, Bengio Y. Empirical evaluation of gated recurrent neural networks on

sequence modelling. *arXiv preprint arXiv:1412.3555*, 2014.

[29] Bahdanau D, Cho K, Bengio Y. Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473*, 2014.

[30] Weston J, Chopra S, Bordes A. Memory networks. *arXiv preprint arXiv:1410.3916*. 2014.

[31] Sukhbaatar S, Weston J, Fergus R. End-to-end memory networks. In *Proceedings of the 29th Conference on Neural Information Processing Systems* (*NIPS 2015*), 2015.

[32] Graves A, Wayne G, Danihelka I. Neural Turing Machines. *preprint arXiv:1410.5401*. 2014.

[33] Qian Q, Tian B, Huang M, Liu Y, Zhu X and Zhu X. Learning tag embeddings and tag-specific composition functions in the recursive neural network. In *Proceedings of the Annual Meeting of the Association for* *Computational Linguistics* (*ACL 2015*), 2015.

[34] Moraes R, Valiati J.F, Neto W.P. Document-level sentiment classification: an empirical comparison between SVM and ANN. *Expert Systems with Applications*. 2013.

[35] Le Q, Mikolov T. Distributed representations of sentences and documents. In *Proceedings of the*

*International Conference on Machine Learning* (*ICML 2014*), 2014.

[36] Glorot X, Bordes A, Bengio Y. Domain adaption for large-scale sentiment classification: a deep learning approach. In *Proceedings of the International Conference on Machine Learning* (*ICML 2011*), 2011.

[37] Zhai S, Zhongfei (Mark) Zhang. Semisupervised autoencoder for sentiment analysis. In *Proceedings of AAAI Conference on Artificial Intelligence* (*AAAI 2016*), 2016.

[38] Johnson R, Zhang T. Effective use of word order for text categorization with convolutional neural networks. In *Proceedings of the Conference of the North American Chapter of the Association for Computational* *Linguistics: Human Language Technologies* (*NAACL-HLT 2015*), 2015.

[39] Tang D, Qin B, Liu T. Document modelling with gated recurrent neural network for sentiment classification. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing* (*EMNLP 2015*), 2015.

[40] Tang D, Qin B, Liu T. Learning semantic representations of users and products for document level

sentiment classification. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics (ACL 2015)*, 2015.

[41] Chen H, Sun M, Tu C, Lin Y, and Liu Z. Neural sentiment classification with user and product attention. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing* (*EMNLP 2016*), 2016.

[42] Dou ZY. Capturing user and product Information for document level sentiment analysis with deep memory network. In *Proceedings of the Conference on Empirical Methods on Natural Language Processing* (*EMNLP* *2017*), 2017.

[43] Xu J, Chen D, Qiu X, and Huang X. Cached long short-term memory neural networks for document-level sentiment classification. In *Proceedings of the Conference on Empirical Methods in Natural Language* *Processing* (*EMNLP 2016*), 2016.

[44] Yang Z, Yang D, Dyer C, He X, Smola AJ, and Hovy EH. Hierarchical attention networks for document classification. In *Proceedings of the Conference of the North American Chapter of the Association for* *Computational Linguistics: Human Language Technologies (NAACL-HLT 2016)*, 2016.

[45] Yin Y, Song Y, Zhang M. Document-level multi-aspect sentiment classification as machine comprehension. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing* (*EMNLP 2017*), 2017.

[46] Zhou X, Wan X, Xiao J. Attention-based LSTM network for cross-lingual sentiment classification. In

*Proceedings of the Conference on Empirical Methods in Natural Language Processing* (*EMNLP 2016*), 2016.

[47] Li Z, Zhang Y, Wei Y, Wu Y, and Yang Q. End-to-end adversarial memory network for cross-domain

sentiment classification. In *Proceedings of the International Joint Conference on Artificial Intelligence (IJCAI 2017)*, 2017.

[48] Wiebe J, Bruce R, and O’Hara T. Development and use of a gold standard data set for subjectivity

classifications. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics (ACL 1999)*, 1999.

[49] Socher R, Pennington J, Huang E.H, Ng A.Y, and Manning C.D. Semi-supervised recursive autoencoders for predicting sentiment distributions. In *Proceedings of the Conference on Empirical Methods in Natural* *Language Processing* (*EMNLP 2011*), 2011.

[50] Socher R, Huval B, Manning C.D, and Ng A.Y. Semantic compositionality through recursive matrix-vector spaces. In *Proceedings of the Conference on Empirical Methods on Natural Language Processing* (*EMNLP 2012*), 2012.

[51] Socher R, Perelygin A, Wu J. Y, Chuang J, Manning C.D, Ng A. Y, and Potts C. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the Conference on Empirical Methods* *on Natural Language Processing* (*EMNLP 2013*), 2013.

[52] Kalchbrenner N, Grefenstette E, Blunsom P. A convolutional neural network for modelling sentences. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics* (*ACL 2014*), 2014.

[53] Kim Y. Convolutional neural networks for sentence classification. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics* (*ACL 2014*), 2014.

[54] dos Santos, C. N., Gatti M. Deep convolutional neural networks for sentiment analysis for short texts. In *Proceedings of the International Conference on Computational Linguistics* (*COLING 2014*), 2014.

[55] Wang X, Liu Y, Sun C, Wang B, and Wang X. Predicting polarities of tweets by composing word embeddings with long short-term memory. In *Proceedings of the Annual Meeting of the Association for Computational* *Linguistics* (*ACL 2015*), 2015.

[56] Graves A, Schmidhuber J. Framewise phoneme classification with bidirectional LSTM and other neural network architectures. *Neural Networks*, 2005.

[57] Wang J, Yu L-C, Lai R.K., and Zhang X. Dimensional sentiment analysis using a regional CNN-LSTM model. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics (ACL 2016)*, 2016.

[58] Wang X, Jiang W, Luo Z. Combination of convolutional and recurrent neural network for sentiment analysis of short texts. In *Proceedings of the International Conference on Computational Linguistics* (*COLING* *2016*), 2016.

[59] Guggilla C, Miller T, Gurevych I. CNN-and LSTM-based claim classification in online user comments. In *Proceedings of the International Conference on Computational Linguistics* (*COLING 2016*), 2016.

[60] Huang M, Qian Q, Zhu X. Encoding syntactic knowledge in neural networks for sentiment classification. *ACM Transactions on Information Systems*, 2017

[61] Akhtar MS, Kumar A, Ghosal D, Ekbal A, and Bhattacharyya P. A multilayer perceptron based ensemble technique for fine-grained financial sentiment analysis. In *Proceedings of the Conference on Empirical Methods* *on Natural Language Processing* (*EMNLP 2017*), 2017.

[62] Guan Z, Chen L, Zhao W, Zheng Y, Tan S, and Cai D. Weakly-supervised deep learning for customer review sentiment classification. In *Proceedings of the International Joint Conference on Artificial Intelligence* (*IJCAI* *2016*), 2016.

[63] Teng Z, Vo D-T, and Zhang Y. Context-sensitive lexicon features for neural sentiment analysis. In

*Proceedings of the Conference on Empirical Methods in Natural Language Processing* (*EMNLP 2016*), 2016.

64] Yu J, Jiang J. Learning sentence embeddings with auxiliary tasks for cross-domain sentiment classification. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing* (*EMNLP 2016*), 2016.

[65] Zhao Z, Lu H, Cai D, He X, Zhuang Y. Microblog sentiment classification via recurrent random walk network learning. In *Proceedings of the Internal Joint Conference on Artificial Intelligence* (*IJCAI 2017*), 2017.

[66] Mishra A, Dey K, Bhattacharyya P. Learning cognitive features from gaze data for sentiment and sarcasm classification using convolutional neural network. In *Proceedings of the Annual Meeting of the Association for* *Computational Linguistics* (*ACL 2017*), 2017.

[67] Qian Q, Huang M, Lei J, and Zhu X. Linguistically regularized LSTM for sentiment classification. In

*Proceedings of the Annual Meeting of the Association for Computational Linguistics* (*ACL 2017*), 2017.

[68] Dong L, Wei F, Tan C, Tang D, Zhou M, and Xu K. Adaptive recursive neural network for target-dependent Twitter sentiment classification. In *Proceedings of the Annual Meeting of the Association for Computational* *Linguistics* (*ACL 2014*), 2014.

[69] Vo D-T, Zhang Y. Target-dependent twitter sentiment classification with rich automatic features. In *Proceedings of the Internal Joint Conference on Artificial Intelligence* (*IJCAI 2015*), 2015.

[70] Tang D, Qin B, Feng X, and Liu T. Effective LSTMs for target-dependent sentiment classification. In

*Proceedings of the International Conference on Computational Linguistics* (*COLING 2016*), 2016.

[71] Ruder S, Ghaffari P, Breslin J.G. A hierarchical model of reviews for aspect-based sentiment analysis. In *Proceedings of the Conference on Empirical Methods on Natural Language Processing* (*EMNLP 2016*), 2016.

[72] Zhang M, Zhang Y, Vo D-T. Gated neural networks for targeted sentiment analysis. In *Proceedings of AAAI Conference on Artificial Intelligence* (*AAAI 2016*), 2016.

[73] Wang Y, Huang M, Zhu X, and Zhao L. Attention-based LSTM for aspect-level sentiment classification. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing* (*EMNLP 2016*), 2016.

[74] Yang M, Tu W, Wang J, Xu F, and Chen X. Attention-based LSTM for target-dependent sentiment

classification. In *Proceedings of AAAI Conference on Artificial Intelligence* (*AAAI 2017*), 2017.

[75] Liu J, Zhang Y. Attention modeling for targeted sentiment. In *Proceedings of the Conference of the European Chapter of the Association for Computational Linguistics* (*EACL 2017*), 2017.

[76] Tang D, Qin B, and Liu T. Aspect-level sentiment classification with deep memory network. *arXiv preprint arXiv:1605.08900*, 2016.

[77] Lei T, Barzilay R, Jaakkola T. Rationalizing neural predictions. In *Proceedings of the Conference on Empirical Methods on Natural Language Processing (EMNLP 2016)*, 2016.

[78] Li C, Guo X, Mei Q. Deep memory networks for attitude Identification. In *Proceedings of the ACM International Conference on Web Search and Data Mining (WSDM 2017)*, 2017.

[79] Ma D, Li S, Zhang X, Wang H. Interactive attention networks for aspect-Level sentiment classification. In *Proceedings of the Internal Joint Conference on Artificial Intelligence* (*IJCAI 2017*), 2017.

[80] Chen P, Sun Z, Bing L, and Yang W. Recurrent attention network on memory for aspect sentiment analysis. In *Proceedings of the Conference on Empirical Methods on Natural Language Processing* (*EMNLP 2017*), 2017.

[81] Tay Y, Tuan LA, Hui SC. Dyadic memory networks for aspect-based sentiment analysis. In *Proceedings of the International Conference on Information and Knowledge Management* (*CIKM 2017*), 2017.

[82] Katiyar A, Cardie C. Investigating LSTMs for joint extraction of opinion entities and relations. In

*Proceedings of the Annual Meeting of the Association for Computational Linguistics (ACL 2016)*, 2016.

[83] Wang W, Pan SJ, Dahlmeier D, and Xiao X. Recursive neural conditional random fields for aspect-based sentiment analysis. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing* (*EMNLP 2016*), 2016.

[84] Wang W, Pan SJ, Dahlmeier D, and Xiao X. Coupled multi-Layer attentions for co-extraction of aspect and opinion terms. In *Proceedings of AAAI Conference on Artificial Intelligence* (*AAAI 2017*), 2017.

[85] Li X, Lam W. Deep multi-task learning for aspect term extraction with memory Interaction. In *Proceedings of the Conference on Empirical Methods on Natural Language Processing* (*EMNLP 2017*), 2017.

[86] He R, Lee WS, Ng HT, and Dahlmeier D. An unsupervised neural attention model for aspect extraction. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics* (*ACL 2017*), 2017.

[87] Zhang M, Zhang Y, Vo D-T. Neural networks for open domain targeted sentiment. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing* (*EMNLP 2015*), 2015.

[88] Zhou X, Wan X, Xiao J. Representation learning for aspect category detection in online reviews. In

*Proceeding of AAAI Conference on Artificial Intelligence* (*AAAI 2015*), 2015.

[89] Yin Y, Wei F, Dong L, Xu K, Zhang M, and Zhou M. Unsupervised word and dependency path embeddings for aspect term extraction. In *Proceedings of the International Joint Conference on Artificial Intelligence* (*IJCAI* *2016*), 2016.

[90] Xiong S, Zhang Y, Ji D, and Lou Y. Distance metric learning for aspect phrase grouping. In *Proceedings of the International Conference on Computational Linguistics* (*COLING 2016*), 2016.

[91] Poria S, Cambria E, Gelbukh A. Aspect extraction for opinion mining with a deep convolutional neural network*. Journal of Knowledge-based Systems*. 2016.

[92] Ying D, Yu J, Jiang J. Recurrent neural networks with auxiliary labels for cross-domain opinion target extraction. In *Proceedings of AAAI Conference on Artificial Intelligence* (*AAAI 2017*), 2017

[93] Irsoy O, Cardie C. Opinion mining with deep recurrent neural networks. In *Proceedings of the Conference on Empirical Methods on Natural Language Processing* (*EMNLP 2014*), 2014.

[94] Yang B, Cardie C. Extracting opinion expressions with semi-markov conditional random fields. In

*Proceedings of the Conference on Empirical Methods in Natural Language Processing* (*EMNLP 2012*), 2012.

[95] Liu P, Joty S, Meng H. Fine-grained opinion mining with recurrent neural networks and word embeddings. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing* (*EMNLP 2015*), 2015.

[96] Irsoy O, Cardie C. Deep recursive neural networks for compositionality in language. In *Proceedings of the Annual Conference on* Advances in *Neural Information Processing Systems (NIPS 2014)*, 2014.

[97] Zhu X, Guo H, Sobhani P. Neural networks for integrating compositional and non-compositional sentiment in sentiment composition. In *Proceedings of the Conference of the North American Chapter of the Association* *for Computational Linguistics: Human Language Technologies* (*NAACL-HLT 2015*), 2015.

[98] Yang B, Cardie C. Joint Inference for fine-grained opinion extraction. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics* (*ACL 2013*), 2013.

[99] Deng L, Wiebe J. Recognizing opinion sources based on a new categorization of opinion types. In

*Proceedings of the International Joint Conference on Artificial Intelligence* (*IJCAI 2016*), 2016.

[100] Chen C, Wang Z, Lei Y, and Li W. Content-based influence modelling for opinion behaviour Prediction. In *Proceedings of the International Conference on Computational Linguistics* (*COLING 2016*), 2016.

[101] Rashkin H, Bell E, Choi Y, and Volkova S. Multilingual connotation frames: a case study on social media for targeted sentiment analysis and forecast. In *Proceedings of the Annual Meeting of the Association for* *Computational Linguistics* (*ACL 2017*), 2017.

[102] Mass A. L, Daly R. E, Pham P. T, Huang D, Ng A. Y. and Potts C. Learning word vectors for sentiment analysis. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics* (*ACL 2011*), 2011.

[103] Bespalov D, Bai B, Qi Y, and Shokoufandeh A. Sentiment classification based on supervised latent n-gram analysis. In *Proceedings of the International Conference on Information and Knowledge Management* (*CIKM* *2011*), 2011.

[104] Labutov I, Lipson H. Re-embedding words. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics* (*ACL 2013*), 2013.

[105] Tang D, Wei F, Yang N, Zhou M, Liu T, and Qin B. Learning sentiment-specific word embedding for twitter sentiment classification. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics* *(ACL 2014)*, 2014.

[106] Tang D, Wei F, Qin B, Yang N, Liu T, and Zhoug M. Sentiment embeddings with applications to sentiment analysis. *IEEE Transactions on Knowledge and Data Engineering*, 2016.

[107] Wang L, Xia R. Sentiment Lexicon construction with representation Learning based on hierarchical sentiment Supervision. In *Proceedings of the Conference on Empirical Methods on Natural Language* *Processing* (*EMNLP 2017*), 2017.

[108] Yu LC, Wang J, Lai KR, and Zhang X. Refining word embeddings for sentiment analysis. In *Proceedings of the Conference on Empirical Methods on Natural Language Processing* (*EMNLP 2017*), 2017.

[109] Li J, Jurafsky D. Do multi-sense embeddings improve natural language understanding? In *Proceedings of the Conference on Empirical Methods in Natural Language Processing* (*EMNLP 2015*), 2015.

[110] Ren Y, Zhang Y, Zhang, M and Ji D. Improving Twitter sentiment classification using topic-enriched multi prototype word embeddings. In *Proceeding of AAAI Conference on Artificial Intelligence* (*AAAI 2016*), 2016.

[111] Zhou H, Chen L, Shi F, Huang D. Learning bilingual sentiment word embeddings for cross-language sentiment classification. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics* (*ACL 2015*), 2015.

[112] Barnes J, Lambert P, Badia T. Exploring distributional representations and machine translation for aspectbased cross-lingual sentiment classification. In *Proceedings of the 27th International Conference on* *Computational Linguistics* (*COLING 2016*), 2016.

[113] Zhang W, Yuan Q, Han J, and Wang J. Collaborative multi-Level embedding learning from reviews for rating prediction. In *Proceedings of the International Joint Conference on Artificial Intelligence* (*IJCAI 2016*), 2016.

[114] Sharma R, Somani A, Kumar L, and Bhattacharyya P. Sentiment intensity ranking among adjectives using sentiment bearing word embeddings. In *Proceedings of the Conference on Empirical Methods on Natural* *Language Processing* (*EMNLP 2017*), 2017.

[115] Zhang M, Zhang Y, Fu G. Tweet sarcasm detection using deep neural network. In *Proceedings of the International Conference on Computational Linguistics* (*COLING 2016*), 2016.

[116] Joshi A, Tripathi V, Patel K, Bhattacharyya P, and Carman M. Are word embedding-based features useful for sarcasm detection? In *Proceedings of the Conference on Empirical Methods on Natural Language* *Processing* (*EMNLP 2016*), 2016.

[117] Poria S, Cambria E, Hazarika D, and Vij P. A deeper look into sarcastic tweets using deep convolutional neural networks. In *Proceedings of the International Conference on Computational Linguistics* (*COLING 2016*) 2016.

[118] Peled L, Reichart R. Sarcasm SIGN: Interpreting sarcasm with sentiment based monolingual machine translation. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics* (*ACL 2017*),

2017.

[119] Ghosh A, Veale T. Magnets for sarcasm: making sarcasm detection timely, contextual and very personal. In *Proceedings of the Conference on Empirical Methods on Natural Language Processing* (*EMNLP 2017*), 2017.

[120] Van Hee C, Lefever E, Hoste V. Monday mornings are my fave:)# not exploring the automatic recognition of irony in english tweets. In *Proceedings of the International Conference on Computational Linguistics* (*COLING* *2016*), 2016.

[121] Chen WF, Lin FY, Ku LW. WordForce: visualizing controversial words in debates. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing* (*EMNLP 2016*), 2016.

[122] Wang Z, Zhang Y, Lee S, Li S, and Zhou G. A bilingual attention network for code-switched emotion prediction. In *Proceedings of the International Conference on Computational Linguistics* (*COLING 2016*), 2016.

[123] Zhou H, Huang M, Zhang T, Zhu X and Liu B. Emotional chatting machine: emotional conversation generation with internal and external memory. *arXiv preprint. arXiv:1704.01074,* 2017.

[124] Abdul-Mageed M, Ungar L. EmoNet: fine-grained emotion detection with gated recurrent neural

networks. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics* (*ACL 2017*), 2017.

[125] Felbo B, Mislove A, S鴊aard A, Rahwan I, and Lehmann S. Using millions of emoji occurrences to learn any-domain representations for detecting sentiment, emotion and sarcasm. In *Proceedings of the Conference* *on Empirical Methods on Natural Language Processing* (*EMNLP 2017*), 2017.

[126] Gui L, Hu J, He Y, Xu R, Lu Q, and Du J. A question answering approach to emotion cause extraction. In *Proceedings of the Conference on Empirical Methods on Natural Language Processing* (*EMNLP 2017*), 2017.

[127] Poria S, Cambria E, Gelbukh A. Deep convolutional neural text features and multiple kernel learning for utterance-level multimodal sentiment analysis. In *Proceedings of the Conference on Empirical Methods on* *Natural Language Processing* (*EMNLP 2015*), 2015.

[128] Bertero D, Siddique FB, Wu CS, Wan Y, Chan R.H, and Fung P. Real-time speech emotion and sentiment recognition for interactive dialogue systems. In *Proceedings of the Conference on Empirical Methods in Natural* *Language Processing* (*EMNLP 2016*), 2016.

[129] Fung P, Dey A, Siddique FB, Lin R, Yang Y, Bertero D, Wan Y, Chan RH, and Wu CS. Zara: a virtual

interactive dialogue system incorporating emotion, sentiment and personality recognition. In *Proceedings of the International Conference on Computational Linguistics* (*COLING 2016*), 2016.

[130] Wang J, Fu J, Xu Y, and Mei T. Beyond object recognition: visual sentiment analysis with deep coupled adjective and noun neural networks. In *Proceedings of the Internal Joint Conference on Artificial Intelligence* (*IJCAI 2016*), 2016.

[131] Yang J, Sun M, Sun X. Learning visual sentiment distributions via augmented conditional probability neural network. In *Proceedings of AAAI Conference on Artificial Intelligence* (*AAAI 2017*), 2017.

[132] Zhu X, Li L, Zhang W, Rao T, Xu M, Huang Q, and Xu D. Dependency exploitation: a unified CNN-RNN approach for visual emotion recognition. In *Proceedings of the Internal Joint Conference on Artificial* *Intelligence* (*IJCAI 2017*), 2017.

[133] You Q, Jin H, Luo J. Visual sentiment analysis by attending on local image regions. In *Proceedings of AAAI Conference on Artificial Intelligence* (*AAAI 2017*), 2017.

[134] Poria S, Cambria E, Hazarika D, Majumder N, Zadeh A, and Morency LP. Context-dependent sentiment analysis in user-generated videos. In *Proceedings of the Annual Meeting of the Association for Computational* *Linguistics* (*ACL 2017*), 2017.

[135] Tripathi S, Acharya S, Sharma RD, Mittal S, and Bhattacharya S. Using deep and convolutional neural networks for accurate emotion classification on DEAP dataset. In *Proceedings of AAAI Conference on Artificial* *Intelligence* (*AAAI 2017*), 2017.

[136] Zadeh A, Chen M, Poria S, Cambria E, and Morency LP. Tensor fusion network for multimodal sentiment analysis. In *Proceedings of the Conference on Empirical Methods on Natural Language Processing* (*EMNLP* *2017*), 2017.

[137] Long Y, Qin L, Xiang R, Li M, and Huang CR. A cognition based attention model for sentiment analysis. In *Proceedings of the Conference on Empirical Methods on Natural Language Processing* (*EMNLP 2017*), 2017.

[138] Wang H, Meghawat A, Morency LP, and Xing E.X. Select-additive learning: improving generalization in multimodal sentiment analysis. In *Proceedings of the International Conference on Multimedia and Expo* (*ICME* *2017*), 2017.

[139] Akhtar MS, Kumar A, Ekbal A, and Bhattacharyya P. A hybrid deep learning architecture for sentiment analysis. In *Proceedings of the International Conference on Computational Linguistics* (*COLING 2016*), 2016.

[140] Dahou A, Xiong S, Zhou J, Haddoud MH, and Duan P. Word embeddings and convolutional neural network for Arabic sentiment classification. In *Proceedings of the International Conference on Computational* *Linguistics* (*COLING 2016*), 2016.

[141] Singhal P, Bhattacharyya P. Borrow a little from your rich cousin: using embeddings and polarities of english words for multilingual sentiment classification. In *Proceedings of the International Conference on* *Computational Linguistics* (*COLING 2016*), 2016.

[142] Joshi A, Prabhu A, Shrivastava M, and Varma V. Towards sub-word level compositions for sentiment analysis of Hindi-English code mixed text. In *Proceedings of the International Conference on Computational* *Linguistics* (*COLING 2016*), 2016.

[143] Gui L, Xu R, He Y, Lu Q, and Wei Z. Intersubjectivity and sentiment: from language to knowledge. In *Proceedings of the International Joint Conference on Artificial Intelligence* (*IJCAI 2016*), 2016.

[144] Wang Y, Zhang Y, Liu B. Sentiment lexicon expansion based on neural PU Learning, double dictionary lookup, and polarity association. In *Proceedings of the Conference on Empirical Methods on Natural Language* *Processing* (*EMNLP 2017*), 2017.

[145] Rekabsaz N, Lupu M, Baklanov A, Hanbury A, Dür A, and Anderson L. Volatility prediction using financial disclosures sentiments with word embedding-based IR models. In *Proceedings of the Annual Meeting of the* *Association for Computational Linguistics* (*ACL 2017*), 2017.

[146] Wang Z, Zhang Y. Opinion recommendation using a neural model. In *Proceedings of the Conference on Empirical Methods on Natural Language Processing* (*EMNLP 2017*), 2017.

[147] Augenstein I, Rockt鋝chel T, Vlachos A, Bontcheva K. Stance detection with bidirectional conditional encoding. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing* (*EMNLP* *2016*), 2016.

[148] Du J, Xu R, He Y, Gui L. Stance classification with target-specific neural attention networks. In *Proceedings of the Internal Joint Conference on Artificial Intelligence* (*IJCAI 2017*), 2017.