# A Survey on Sentiment Classification Methods and Challenges

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**Abstract**

Sentiment classification (SC) is an important natural language processing (NLP) task that aims to determine the sentiment or emotional tone in a given text. With the increasing pervasiveness of internet-based applications and social media, massive amounts of unstructured data are generated daily, elevating the opportunity and challenges associated with automated sentiment extraction for tasks such as customer feedback analysis, social media monitoring, and opinion mining. In this review paper, we provide an update on the state of the art in sentiment analysis, including an overview of and classification methods leveraging machine learning and deep learning methods.

**Keywords**— *Sentiment classification, Machine learning, Survey, Text pre-processing*

## Introduction

The number of users actively involved in social media has increased rapidly and millions of people express their sentiments regarding any fields that affect companies, governments, and organizations. Therefore, SC is necessary to quantify the opinion of texts such as reviews, feedback, and news articles by involving statistical, machine learning, and deep learning techniques to classify the sentiments of the text. Most of the surveys have concentrated specific areas in SC like Deep learning-based SC (Bhatia, Ji, and Eisenstein 2015), Gated recurrent Neural Networks (Yang et al. 2016), different languages and genres in sentiment analysis (Yang and Cardie 2014), and emotion detection from text (Behdenna, Barigou, and Belalem 2018a). Different from these surveys, the point of this paper is to cover substantial and widespread approaches that are presented recently in the field of SC.

## Sentiment Analysis Levels

### Document Level sentiment classification

Document-level SC is assigned a sentiment label such as positive, negative, or neutral on a whole document. It can be used to classify the words and phrases of pages or chapters of a book by considering both supervised and unsupervised learning approaches to classify the document (Bhatia, Ji, and Eisenstein 2015). TOPICDOC2VEC a new topic-document embedding outperforms the DOC2VEC embedding to gain the polarity of a document by using CBOW, SkipGram, Word2Vec, GloVe and FastText(Mitroi et al. 2020).

### Sentence Level sentiment classification

When a document has a wide range of sentiments associated with it, the document-level classification is complicated,so, sentence-level will be considered independently (Rao et al. 2018). Hence at this level, sentences are classified into objective and subjective sentences. (Behdenna, Barigou, and Belalem 2018b).

### Aspect-Level sentiment classification

Aspect-level SC is performed fine-grained analysis and it is called feature-entity-based sentiment classification. This task includes the relation of features or aspects in a sentence, then categorizing the features by 3-way decision model (Yao 2009) as positive, negative, or neutral (Chen et al. 2022).

## Data Collection and Feature Extraction

The process of sentiment classification involves multiple tasks in Fig1, including data collection, pre-processing, feature selection and extraction, model development, and evaluation. In the data collection stage, text data can be collected and combined with other types of data. The raw form of text data needs to be pre-processed to remove noise, clean, and reduce dimensionality to improve the accuracy and efficiency of the classification model (Zhang and Liu 2012). There are several tools and libraries available for NLP tasks, including tokenization, normalization, removing stop words, part of speech tagging, and stemming and lemmatization. Feature selection involves selecting the most appropriate input variables to increase the accuracy of sentiment classification models, and there are three supervised feature selection models: filter methods, wrapper methods, and intrinsic methods. Feature extraction involves converting raw text data into numerical representations, and common techniques for feature extraction in NLP include Bag of Words (BoW)(Bandhakavi et al. 2017), N-gram, TF-IDF (Ahuja et al. 2019), and neural network-based word embedding methods like Word2Vec, GloVe, and BERT.

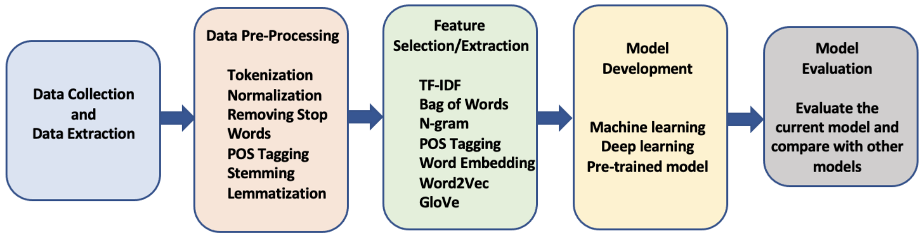


Figure 1: Step-by-step sentiment classification process

# Methodology

## Machine Learning-based Approach

Sentiment classification in machine learning involves dividing a text dataset into training and testing sets, training a model on a labeled dataset, and predicting labels for new instances. **Naive Bayes** is a commonly used algorithm for sentiment classification that assumes feature independence. It is suitable for high-dimensional inputs and has been shown to improve accuracy on the FakeNews dataset in (Adiba et al. 2020). **Support Vector Machine (SVM)** is a non-probabilistic supervised learning algorithm used for classification and regression to find the best decision boundary that separates data points into different classes. In (KESHTKAR and INKPEN 2012) the method described in this source is a hierarchy-based mood classification for blogs that uses sentiment orientation features. The classification is based on the number of positive and negative words in blog posts, and a support vector machine (SVM) is used for classification. The approach outperforms flat classification. **Decision Tree(DT)** recursively divides text data based on their features until all data is classified to the same class. Random Forest improves accuracy by combining multiple DTs. **Logistic Regression** predicts one of two classes by multiplying input value with a weight value and achieved highest accuracy in (Shah et al. 2020) with considering TF-IDF vectorizer. **Maximum Entropy(ME)** is a probabilistic exponential classifier that selects the most likely label for a feature set and, combined with PLSA, extracts emotion words for input into the model. K-fold is used to divide the training and test sets (Xie et al. 2019).

## Deep Learning-Based Approach

Deep learning methods are popular for SC due to their high performance and automated feature extraction. CNNs, RNNs (including GRU and LSTM), Recursive Neural Networks, Transformer Networks, and Language Models are commonly used in NLP tasks. CNNs are used for one-dimensional convolution by converting text to vectors. RNNs process sequential data and overcome the vanishing gradient problem faced by traditional RNNs with GRU and LSTM architectures (Sherstinsky 2020). Recursive Neural Networks are designed to learn tree structures. A Bidirectional Gated Temporal Convolution Attention model was presented in (Ren et al. 2021) to improve temporal feature extraction.

## Aspect Based Sentiment Analysis

Aspect-based sentiment analysis (ABSA) aims to identify the sentiment expressed towards a particular aspect in a text. Aspect extraction is a crucial stage in ABSA, which can be explicit or implicit, depending on whether the aspect term is explicitly mentioned or inferred from the context (Maitama et al. 2020). Pre-trained models like GPT-2 and BERT can be used to classify the corresponding sentiment in ABSA, given the challenges of aspect extraction.

## Transfer Learning

The challenge of extracting valuable information from text data can be solved by transfer learning, which applies knowledge from a source task to a similar target task. Pre-trained models like Open AI GPT (Radford et al. 2018), BERT (Devlin et al. 2018), and ELMo (Peters et al. 2018) are popular choices for transfer learning, providing accurate results with less training time (Alyafeai, AlShaibani, and Ahmad 2020). ELMo creates context-dependent word embeddings from a bidirectional language model, while GPT uses a multi-layer transformer decoder and fine-tuning, and BERT jointly conditions left and right context in all layers. ELMo is semi-bidirectional, GPT is unidirectional, and BERT is bi-directional.

# Challenges

The increasing amount of text data in the internet era poses challenges for SC, including irony, sarcasm, slang, and subjective emotional intensity. Unstructured data from social media posts, reviews, and emails also contain noise and irrelevant information. (Khalid et al. 2020) A voting classifier gradient boosted SVM has been proposed to tackle this challenge by considering different datasets with term frequency and TF-IDF. Adversarial attacks is another challenge in SC that can manipulate the output of the classifier.

# Conclusion

This review paper discusses different techniques for SC, data preparation, and classification methods. Machine learning methods such as SVM, RF and Naive Bayes are effective for SC, but deep learning approaches like LSTM and Bert are preferred due to their ability to handle complex problems with large datasets. SC is still an unexplored area of study and we will expanding the comparison of deep learning methods in future work.

## References


Adiba, F. I.; Islam, T.; Kaiser, M. S.; Mahmud, M. A. P.; and Rahman, M. A. 2020. Effect of corpora on classification of fake news using naive bayes classifier.

Ahuja, R.; Chug, A.; Kohli, S.; Gupta, S.; and Ahuja, P. 2019. The impact of features extraction on the sentiment analysis. *Procedia Computer Science* 152:341–348. International Conference on Pervasive Computing Advances and Applications- PerCAA 2019.

Alyafeai, Z.; AlShaibani, M. S.; and Ahmad, I. 2020. A survey on transfer learning in natural language processing.

Bandhakavi, A.; Wiratunga, N.; Padmanabhan, D.; and Massie, S. 2017. Lexicon based feature extraction for emotion text classification. *Pattern Recognition Letters* 93:133–142. Pattern Recognition Techniques in Data Mining.

Behdenna, S.; Barigou, F.; and Belalem, G. 2018a. Document level sentiment analysis: A survey. *EAI Endorsed Transactions on Context-aware Systems and Applications* 4(13):e2.

Behdenna, S.; Barigou, F.; and Belalem, G. 2018b. Document level sentiment analysis: A survey. *EAI Endorsed Transactions on Context-aware Systems and Applications* 4(13).

Bhatia, P.; Ji, Y.; and Eisenstein, J. 2015. Better document-level sentiment analysis from rst discourse parsing.

Chen, J.; Chen, Y.; He, Y.; Xu, Y.; Zhao, S.; and Zhang, Y. 2022. A classified feature representation three-way decision model for sentiment analysis. *Applied Intelligence* 52(7):7995–8007.

Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

KESHTKAR, F., and INKPEN, D. 2012. A hierarchical approach to mood classification in blogs. *Natural Language Engineering* 18(1):61–81.

Khalid, M.; Ashraf, I.; Mehmood, A.; Ullah, S.; Ahmad, M.; and Choi, G. S. 2020. Gbsvm: Sentiment classification from unstructured reviews using ensemble classifier. *Applied Sciences* 10(8).

Maitama, J. Z.; Idris, N.; Abdi, A.; Shuib, L.; and Fauzi, R. 2020. A systematic review on implicit and explicit aspect extraction in sentiment analysis. *IEEE Access* 8:194166–194191.

Mitroi, M.; Truică, C.-O.; Apostol, E.-S.; and Florea, A. M. 2020. Sentiment analysis using topic-document embeddings. In *2020 IEEE 16th international conference on intelligent computer communication and processing (ICCP)*, 75–82. IEEE.

Peters, M. E.; Neumann, M.; Iyyer, M.; Gardner, M.; Clark, C.; Lee, K.; and Zettlemoyer, L. 2018. Deep contextualized word representations. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, 2227–2237. New Orleans, Louisiana: Association for Computational Linguistics.

Radford, A.; Narasimhan, K.; Salimans, T.; Sutskever, I.; et al. 2018. Improving language understanding by generative pre-training.

Rao, G.; Huang, W.; Feng, Z.; and Cong, Q. 2018. Lstm with sentence representations for document-level sentiment classification. *Neurocomputing* 308:49–57.

Ren, J.; Wu, W.; Liu, G.; Chen, Z.; and Wang, R. 2021. Bidirectional gated temporal convolution with attention for text classification. *Neurocomputing* 455:265–273.

Shah, K.; Patel, H.; Sanghvi, D.; and Shah, M. 2020. A comparative analysis of logistic regression, random forest and KNN models for the text classification. *Augmented Human Research* 5(1):12.

Sherstinsky, A. 2020. Fundamentals of recurrent neural network (rnn) and long short-term memory (lstm) network. *Physica D: Nonlinear Phenomena* 404:132306.

Xie, X.; Ge, S.; Hu, F.; Xie, M.; and Jiang, N. 2019. An improved algorithm for sentiment analysis based on maximum entropy. *Soft Computing* 23(2):599–611.

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)*, 325–335. Baltimore, Maryland: Association for Computational Linguistics.

Yang, Z.; Yang, D.; Dyer, C.; He, X.; Smola, A.; and Hovy, E. 2016. Hierarchical attention networks for document classification. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 1480–1489. San Diego, California: Association for Computational Linguistics.

Yao, Y. 2009. Three-way decision: An interpretation of rules in rough set theory. In *Rough Sets and Knowledge Technology*.

Zhang, L., and Liu, B. 2012. Sentiment analysis and opinion mining. In *Encyclopedia of Machine Learning and Data Mining*.