|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |

**Figure 1 Representation of Text Classification methods**

* Ahmad, S., Lavin, A., Purdy, S., & Agha, Z. (2017). Unsupervised real-time anomaly detection for streaming data. *Neurocomputing*, *262*(1), 134-147.https://doi.org/10.1016/j.neucom.2017.04.070
* Aliwy, A. H., & Ameer, E. (2017). Comparative study of five text classification algorithms with their improve-ments. *International Journal of Applied Engineering Research, 12*, 4309-4319.
* Allahyari, M., Pouriyeh, S. A., Assefi, M., Safaei, S., Trippe, E. D., Gutierrez, J. B., &Kochut, K. J. (2017). A brief survey of text mining: classification, clustering and extraction techniques. *CoRR*, abs/1707.02919.
* Altınel, B., & Ganiz, M. C. (2016). A new hybrid semi-supervised algorithm for text classification with class-based semantics. *Knowledge-Based Systems, 108*, 50–64.https://doi.org/10.1016/j.knosys.2016.06.021
* Altınel, B., Ganiz, M. C., &Diri, B. (2015). A corpus-based semantic kernel for text classification by using meaning values of terms. *Engineering Applications of Artificial Intelligence, 43*, 54–66. https://doi.org/10.1016/j.engappai.2015.03.015
* An, Y., Tang, X., & Xie, B. (2017). Sentiment analysis for short Chinese text based on character-level methods. *Proceedings of the 9th international conference on knowledge and smart technology (KST).* IEEE. Chonburi. Thailand. https://doi.org/10.1109/KST.2017.7886093
* Arar, O. F., & Ayan, K. (2017). A feature dependent Naive Bayes approach and its application to the software defect prediction problem. *Applied Soft Computing, 59*, 197-209. https://doi.org/10.1016/j.asoc.2017.05.043
* Asadi, S., &Shahrabi, J. (2016). ACORI: A novel ACO algorithm for rule induction. *Knowledge-Based Systems, 97,* 174-187. https://doi.org/10.1016/j.knosys.2016.01.005
* Asadi, S., & Shahrabi, J. (2017). Complexity-based parallel rule induction for multiclass classification. *Information Sciences, 380*, 53–73. https://doi.org/10.1016/j.ins.2016.10.047
* Aseervatham, S., Antoniadis, A., Gaussier, E., Burlet, M., &Denneulin, Y. (2011). A sparse version of the ridge logistic regression for large-scale text categorization. *Pattern Recognition Letters, 32,* 101–106. https://doi.org/10.1016/j.patrec.2010.09.023
  + Benites, F., & Sapozhnikova, E. (2017). Improving scalability of ART neural networks. *Neurocomputing*, *230*, 219–229. <https://doi.org/10.1016/j.neucom.2016.12.022>
* Brindha, S., Sukumaran, S., & Prabha, K. (2016). A survey on classification techniques for text mining. *Proceed-ings of the 3rd International Conference on Advanced Computing and Communication Systems*. IEEE. Coimbatore, In-dia. https://doi.org/10.1109/ICACCS.2016.7586371
* Brownlee, J. (2016). Parametric and non-parametric machine learning algorithms. Retrieved on March 14 from http://machinelearningmastery.com/parametric-and-nonparametric-machine-learning-algorithms
* Cerchiello, P., & Giudici, P. (2012). Non parametric statistical models for on-line text classification. *Advanced Data Analysis and Classification*, *6*, 277–288. https://doi.org/10.1007/s11634-012-0122-2
* Cerri, R., Barros, R. C., & Carvalho, A. (2014). Hierarchical multi-label classification using local neural net-works. *Journal of Computer and System Sciences, 80*, 39–56. https://doi.org/10.1016/j.jcss.2013.03.007
* Demidova, L., Klyueva, I., Sokolova, Y., Stepanov, N., &Tyart, N. (2017). Intellectual approaches to improve-ment of the classification decisions quality on the base of the SVM classifier. *Procedia Computer Science, 103*, 222-230. https://doi.org/10.1016/j.procs.2017.01.070
* Deshmukh, J. S., & Tripathy, A. K. (2017). Text classification using semi-supervised approach for multi domain. *Proceedings of the International Conference on Nascent Technologies in Engineering (ICNTE)*.IEEE. Navi Mumbai, India. https://www.doi.org/10.1109/ICNTE.2017.7947982
* Diab, M., & El Hindi, K. (2017).Using differential evolution for fine tuning Naive Bayesian classifiers and its application for text classification. *Applied Soft Computing*, *54*, 183-199. https://doi.org/10.1016/j.asoc.2016.12.043
* Du, J. (2017). Automatic text classification algorithm based on gauss improved convolutional neural network. *Journal of Computational Science, 21,* 195-200. https://doi.org/10.1016/j.jocs.2017.06.010
* Dwivedi, S. K., & Arya, C. (2010). Automatic text classification in information retrieval: A survey. *Proceedings of the Second International Conference on Information and Communication Technology for Competitive Strategies.* ACM. Udaipur, India. https://doi.org/10.1145/2905055.2905191
* Gomez, J. C., Boiy, E., & Moens, M. F. (2012). Highly discriminative statistical features for email classification. *Knowledge Information Systems, 31,* 23–53.https://doi.org/10.1007/s10115-011-0403-7
* Goudjil, M., Koudil, M., Bedda, M., & Ghoggali, N. (2016). A novel active learning method using SVM for text classification. *International Journal of Automation and Computing,* 1-9. Springer. https://doi.org/10.1007/s11633-015-0912-z
* Hiew, B. Y., Tan, S. C., & Lim, W. S. (2016). Intra-specific competitive co-evolutionary artificial neural network for data classification. *Neurocomputing*, *185*, 220–230. https://doi.org/10.1016/j.neucom.2015.12.051
* Jiang, L., Li, C., Wang, S., & Zhang, L. (2016). Deep feature weighting for Naive Bayes and its application to text classification. *Engineering Applications of Artificial Intelligence*, *52*, 26–39. https://doi.org/10.1016/j.engappai.2016.02.002
* Jiang, L., Wang, S., Li, C., & Zhang, L. (2016). Structure extended multinomial Naive Bayes. *Information Sciences, 329*, 346–356. https://doi.org/10.1016/j.ins.2015.09.037
* Karabadji, N. I., Seridi, H., Bousetouane, F., Dhifli, W., &Aridhi, S. (2017). An evolutionary scheme for decision tree construction. *Knowledge-Based Systems, 119*, 166–177. https://doi.org/10.1016/j.knosys.2016.12.011
* Khan, A., Baharudin, B., Lee, L. H., & Khan, K. (2010). A review of machine learning algorithms for text-documents classification*. Journal of Advances in Information Technology, 1*, 4-20.
* Korde, V., & Mahender, N. C. (2012). Text classification and classifiers: a survey. *International Journal of Artificial Intelligence & Applications, 3*(2), 85-99. https://doi.org/10.5121/ijaia.2012.3208
* Kotsiantis, S. B. (2013). Decision trees: A recent overview. *Artificial Intelligence Review, 39*, 261–283. https://doi.org/10.1007/s10462-011-9272-4
* Liu, B. (2011).Supervised learning. In B. Liu, *Web data mining: Exploring hyperlinks, contents, and usage data* (pp. 63-132). Springer. <https://doi.org/10.1007/978-3-642-19460-3_3>
* Liu, H., Cheng, J., & Wang, F. (2017). Sequential subspace clustering via temporal smoothness for sequential data segmentation. *IEEE Transactions on Image Processing, 27*(2), 866-878. https://doi.org/10.1109/TIP.2017.2767785
* Liu, X., Wang, J., Yin, M., Edwards, B., & Xu, P. (2017). Supervised learning of sparse context reconstruction coefficients for data representation and classification. *Neural Computing & Applications, 28*, 135–143. https://doi.org/10.1007/s00521-015-2042-5
* Liu, Y., Ni, X., Sun, J., & Chen, Z. (2011). Unsupervised transactional query classification based on webpage form understanding. *Proceedings of the 20th ACM International Conference on Information and Knowledge Manage-ment.* Glasgow, Scotland, UK. https://doi.org/10.1145/2063576.2063590
* Maalouf, M., & Siddiqi, M. (2014). Weighted logistic regression for large-scale imbalanced and rare events data. *Knowledge-Based Systems, 59*, 142–148. https://doi.org/10.1016/j.knosys.2014.01.012
* Maillo, J., Ramfrez, S., Triguero, I., & Herrera, F. (2016). kNN-IS: An iterative spark-based design of the k-nearest neighbors classifier for big data. *Knowledge-Based Systems, 117,* 3-15. https://doi.org/10.1016/j.knosys.2016.06.012
* Merinopoulou, E., Ramagopalan, S., Malcolm, B., & Cox, A. (2017). RM3 - Methods for extracting treatment patterns for renal cell carcinoma (RCC) from social media (SM) forums using natural language processing (NLP) and machine learning (ML). *Value in Health*, *20*(9), A402. https://doi.org/10.1016/j.jval.2017.08.021
* Mirzamomen, Z.,& Kangavari, M.R. (2017). Evolving fuzzy min–max neural network based decision trees for data stream classification. *Neural Processing Letters, 45*(1), 341–363. https://doi.org/10.1007/s11063-016-9528-8
* Nguyen, T. T., Nguyen, H., Wu, Y., & Li, M. J. (2015). Classifying gene data with regularized ensemble trees. *Proceedings of the International Conference on Machine Learning and Cybernetics (ICMLC).* IEEE. Guangzhou. Chi. https://doi.org/10.1109/ICMLC.2015.7340911
* Nidhi & Gupta, V. (2011). Recent trends in text classification techniques. *International Journal of Computer Applica-tions, 35*(6), 45-51.
* Nie, Q., Jin, L., Fei, S., & Ma, J. (2015). Neural network for multi-class classification by boosting composite stumps. *Neurocomputing*, *149,* 949–956. https://doi.org/10.1016/j.neucom.2014.07.039
* Park, J. (2018). Simultaneous estimation based on empirical likelihood and general maximum likelihood estima-tion. *Computational Statistics & Data Analysis, 117*, 19-31. https://doi.org/10.1016/j.csda.2017.08.003
* Pavlinek, M., & Podgorelec, V. (2017). Text classification method based on self-training and LDA topic models. *Expert System with Applications*, *80*, 83-93. https://doi.org/10.1016/j.eswa.2017.03.020
* Pereira, J. M., Basto, M., & Silva, A. F. (2016). The logistic lasso and ridge regression in predicting corporate failure. *Procedia Economics and Finance, 39,* 634-641. https://doi.org/10.1016/S2212-5671(16)30310-0
* PhD projects. (2016). *PhD research topic in text mining*. Retrieved on October 3 from http://phdprojects.org/phd-research-topic-text-mining
* Ramesh, B., & Sathiaseelan, J. G. R. (2015). An advanced multi class instance selection based support vector machine for text classification. *Procedia Computer Science*, *57,* 1124-1130. https://doi.org/10.1016/j.procs.2015.07.400
* Ranjan, N. M., & Prasad, R. S. (2017).*Automatic text classification using BPLion-neural network and semantic word pro-cessing*. https://doi.org/10.1080/13682199.2017.1376781
* Rasane, S., &Patil, D. V. (2016).Handling various issues in text classification: a review. *International Journal on Emerging Trends in Technology*, *3,* 4076-4082.
* Reamy, T. (2012). *Future directions in text analytics*. Retrieved on September 27 from http://www.textanalyticsworld.com/pdf/Future\_directions.pdf
* Reitmaier, T., Calma, A., & Sick, B. (2016). Semi-supervised active learning for support vector machines: A novel approach that exploits structure information in data. *Cornell University Library,* arXiv :1610.03995 [stat.ML]. 1-35.
* Rubin, T. N., Chambers, A., Smyth, P., & Steyvers, M. (2012). Statistical topic models for multi-label document classification. *Machine Learning, 88*, 157–208. https://doi.org/10.1007/s10994-011-5272-5
* Santos, A., & Canuto, A. (2014). Applying semi-supervised learning in hierarchical multi-label classification. *Expert Systems with Applications*, *41,* 6075–6085. https://doi.org/10.1016/j.eswa.2014.03.052
* Savas, S. K., & Nasibov, E. (2017). Fuzzy ID3 algorithm on linguistic dataset by using WABL defuzzification method. *Proceedings of the IEEE International Conference on Fuzzy Systems (FUZZ-IEEE),* Naples. Italy. https://doi.org/10.1109/FUZZ-IEEE.2017.8015502
* Shafiabady, N., Lee, L. H., Rajkumar, R., Kallimani, V. P., Akram, N. A., & Isa, D. (2016). Using unsupervised clustering approach to train the support vector machine for text classification. *Neurocomputing, 211,* 4–10. https://doi.org/10.1016/j.neucom.2015.10.137
* Shi, L., Ma, X., Xi, L., Duan, Q., & Zhao, J. (2011). Rough set and ensemble learning based semi-supervised algorithm for text classification. *Expert Systems with Applications, 38,* 6300–6306. https://doi.org/10.1016/j.eswa.2010.11.069
* Srivastava, T. (2015). *Difference between machine learning & statistical modeling*. Retrieved on September 28 from https://www.analyticsvidhya.com/blog/2015/07/difference-machine-learning-statistical-modeling/
* Stas, J., Juhar, J., & Hladek, D. (2014). Classification of heterogeneous text data for robust domain-specific lan-guage modeling. *EURASIP Journal on Audio, Speech, and Music Processing*, *14*, 1-12.
* Sucar, L.E. (2015). Bayesian classifiers. In L. E. Sucar, *Probabilistic graphical models* (pp. 41-62). Springer. https://doi.org/10.1007/978-1-4471-6699-3\_4
* Sun, Z., Ye, Y., Deng, W., & Huang, Z. (2011). A cluster tree method for text categorization. *Procedia Engineering, 15*, 3785-3790. https://doi.org/10.1016/j.proeng.2011.08.709
* Tang, X., & Xu, A. (2016). Multi-class classification using kernel density estimation on K-nearest neighbours. *Electronics Letters*, *52*(8), 600–602. https://doi.org/10.1049/el.2015.4437
* Tbarki, K., Said, S. B., Ksantini, R., &Lachiri, Z. (2017). One-class SVM for landmine detection and discrimina-tion. *Proceedings of the International Conference on Control Automation and Diagnosis (ICCAD).* IEEE. Hammam-et. Tunisia. https://doi.org/10.1109/CADIAG.2017.8075676
* Tsai, C. F., & Chang, C. W. (2013). SVOIS: Support vector oriented instance selection for text classification. *Information Systems, 38*, 1070–1083. https://doi.org/10.1016/j.is.2013.05.001
* Tsangaratos, P., & Ilia, I. (2016). Comparison of a logistic regression and Naïve Bayes classifier in landslide susceptibility assessments: The influence of models complexity and training dataset size. *Catena, 145*, 164–179. https://doi.org/10.1016/j.catena.2016.06.004
* Vasa, K. (2016). Text classification through statistical and machine learning methods: A survey. *International Journal of Engineering Development and Research, 4*, 655-658.
* Vieira, A .S., Borrajo, L., & Iglesias, E. L. (2016). Improving the text classification using clustering and a novel HMM to reduce the dimensionality. *Computer Methods and Programs in Biomedicine, 136*, 119-130. https://doi.org/10.1016/j.cmpb.2016.08.018
* Wang, J., & Park, E. (2017). Active learning for penalized logistic regression via sequential experimental design. *Neurocomputing, 222*, 183–190. https://doi.org/10.1016/j.neucom.2016.10.013
* Wu, J., Pan, S., Zhu, X., Cai, Z., Zhang, P., & Zhang, C. (2015). Self-adaptive attribute weighting for Naive Bayes classification. *Expert Systems with Applications, 42*, 1487–1502. https://doi.org/10.1016/j.eswa.2014.09.019
* Yan, W., Zhang, B., Ma, S., & Yang, Z. (2017). A novel regularized concept factorization for document cluster-ing. *Knowledge-Based Systems, 135*(1), 147-158. https://doi.org/10.1016/j.knosys.2017.08.010
* Yen, S., Lee, Y., Ying, J., & Wu, Y. (2011). A logistic regression-based smoothing method for Chinese text cate-gorization. *Expert Systems with Applications, 38,* 11581–11590. https://doi.org/10.1016/j.eswa.2011.03.036
* Yi, W., Lu, M., & Liu, Z. (2011). Multi-valued attribute and multi-labeled data decision tree algorithm. *Interna-tional Journal of Machine Learning and Cybernetics*, *2*(2), 67-74. <https://doi.org/10.1007/s13042-011-0015-2>
* Zamil, M., & Can, A. B. (2011). ROLEX-SP: Rules of lexical syntactic patterns for free text categorization. *Knowledge-Based Systems, 24*, 58–65. https://doi.org/10.1016/j.knosys.2010.07.005
* Zhang, L., Jiang, L., Li, C., & Kong, G. (2016). Two feature weighting approaches for Naive Bayes text classifi-ers. *Knowledge-Based Systems, 100,* 137–144. https://doi.org/10.1016/j.knosys.2016.02.017
* Zhang, W., Tang, X., & Yoshida, T. (2015). TESC: An approach to text classification using semi-supervised clustering. *Knowledge-Based Systems*, *75,* 152–160. https://doi.org/10.1016/j.knosys.2014.11.028
* Zhang, X., Li, Y., Kotagiri, R., Wu, L., Tari, Z., & Cheriet, M. (2017). KRNN: K rare-class nearest neighbour classification. *Pattern Recognition*, *62,* 33–44. https://doi.org/10.1016/j.patcog.2016.08.023
* Zhoua, L., Pana, S., Wanga, J., Athanasios, V., & Vasilakos. (2017). Machine learning on big data: opportunities and challenge. *Neurocomputing, 237*, 350–361. https://doi.org/10.1016/j.neucom.2017.01.026