

# Discussion

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We propose a new integrated framework to help researchers collect and screen scientific publications characterised by high performance and versatility, joining the growing field of systematic review automation (SRA) and helpers (SRH) tools (Ananiadou et al., 2009; A. M. Cohen et al., 2010, 2006; O’Mara-Eves et al., 2015). This framework joins standard approaches and uses ad-hoc solutions to deal with common SRA issues. By freely sharing the tool as an open-source R package and by following a modular design, we tried to adopt some of the so-called Vienna Principles advocated by the International Collaboration for the Automation of Systematic Reviews (ICASR) (Beller et al., 2018).

The framework consists of four main components: 1) an integrated query-based citation search and management engine, 2) a text-to-feature extractor module, 3) a Bayesian active machine learning-based citation classifier, and 4) a data-driven search query generation algorithm.

The framework’s search engine module is capable of automatically collecting citation data from three well-known scientific databases (i.e. Pubmed, Web of Science, and the database of the Institute of Electrical and Electronics Engineers) as well as process manually downloaded results from both the mentioned and other (SCOPUS, EMBASE) databases. In comparison, most SRH tools, commercial or free to use, rely either on internal databases (e.g., Mendeley <https://www.mendeley.com/>) sometimes focusing just on a particular topic (Visser, 2010) or on a single external data source (Poulter et al., 2008; Soto et al., 2019; Thomas & Brunton, 2007).

Mixing different databases is fundamental to have a more comprehensive view of the literature (Bajpai et al., 2011; Wilkins et al., 2005; Woods & Trewheellar, 1998): in our results, 18.7% of the positive matches found were unique for one of the different data sources, and no positive record was present in all of them (data not shown).

The online search algorithms are efficient enough to manage tens of thousands of search results, using various expedients to overcome the limitations of the queried databases in terms of traffic and download quota. The results are then automatically organized, deduplicated and arranged by “simple query ordering” in a uniform corpus. The preliminary ordering allow to increase the positivity rate in the initial training set (Wallace, Small, et al., 2010).

The feature extractor module uses modern NLP techniques (Ananiadou & McNaught, 2006; K. B. Cohen & Hunter, 2008) to transform text into input data for machine learning. We did not include classical n-grams (Schonlau & Guenther, 2017), but we used network analysis to find non-consecutive frequently associated terms, a generalisation of n-grams relaxing the term adjacency assumption. A similar network approach was applied to merge redundant terms to make model estimation more efficient and reduce noise.

The use of concurrency network-driven modelling of text is not new (Ohsawa et al., 1998; François Rousseau et al., 2015; Francois Rousseau, 2015; Violos et al., 2016) and is a valuable tool to extract semantic information not evident in one-word or consecutive n-gram models.

The framework’s record classification module implements an active machine learning approach Miwa et al. (2014) and is based on Bayesian Additive Regression Trees (BART) (Chipman et al., 2010; Kapelner & Bleich, 2013). When implementing our algorithm we adopted best practices from other SRA studies, bringing improvements at various levels.

As with other boosted trees algorithms (Hastie et al., 2009), BART can explore complex non-linearities,

perform variable selection, manage missing data while sporting high performance in predictive power. However, its Bayesian foundation provides further benefits: less sensitivity on hyperparameter choices, natural regularisation through priors, and, especially, predictive distributions as output in place of point-wise predictions (Joo et al., 2020; Jospin et al., 2020; Soria-Olivas et al., 2011). By selecting relatively tight prior distributions, we discouraged excessively deep trees, long sequences of trees, or extreme predicted probabilities, to decrease the risk of overfitting.

The algorithm runs multiple replications of the model and averages their predictive distributions creating an “ensemble”; this technique has been shown to improve out-of-sample predictive performance (Dietterich, 2000; Zhou, 2021), as we were able to confirm during the hyperparameter evaluation (Supplemental Material S2). Ensembling reduces the uncertainty in the predictive distribution tails related to the randomness in the MCMC fit (Robert et al., 2004), generating a shift of probability mass towards the distribution centre and stabilising it (i.e., decreasing variance without impacting bias). On the other hand, just imposing robust uninformative priors against extreme predictions would have decreased variance but also shifted the distribution towards a non-decision zone, increasing bias (Hansen & others, 2000).

Since the number of model replications significantly impacts computation times, we decided to use ten replicas, the lower value after which showed performance stabilisation during the hyperparameter evaluation. We also investigated whether bootstrapping between replications (Breiman, 1996) would improve performance, but, contrary to theory (Díez-Pastor et al., 2015), it was demonstrated to be slightly detrimental (Supplemental Material S2) compared to simple ensembling.

A low rate of relevant matches (class imbalance) is typical in literature reviews (O’Mara-Eves et al., 2015; Sampson et al., 2011; Wallace, Trikalinos, et al., 2010), and such strong imbalance between positive and negative records can affect sensitivity (Chawla et al., 2004; Khoshgoftaar et al., 2010).

To overcome the problem, we oversampled (Batista et al., 2004) the positive records ten times before model fitting. Our hyperparameter analysis showed that together with model ensembling, the oversampling rate was the parameter with the highest impact on performance.

A known risk with positive oversampling is the misclassification of negative records (Ramezankhani et al., 2016). However, since all predicted positives get manually reviewed in our approach, we are always ensured to achieve 100% specificity/positive predictive value: the only price for the increased sensitivity due to oversampling is a larger number of records to review.

An alternative to oversampling would be applying different weights and/or cost to the classes (Abd Elrahman & Abraham, 2013; Díez-Pastor et al., 2015), but the BART implementation we used did not have this feature; also, using simple oversampling permits broader compatibility with different modelling engines (Galar et al., 2011; Roshan & Asadi, 2020).

Finally, ordering the records by query term frequency (simple query ordering) generates a far higher rate of relevant records in the initial training set (17.2%) compared to the overall data (0.11%), and this boosts the sensitivity of the model.

One of the central innovations we introduced is the concept of “uncertainty zone,” whose implementation is possible thanks to the Bayesian foundation of the classification model. This construct guides the selection of the records to review, dynamically updating and shrinking after every CR iteration, as more uncertain predictions are evaluated (Supplemental Material S2 Fig. 1).

This approach overcomes the usual requirement of dataset-specific hard thresholds in active machine learning, and also allows to review multiple items at once between iterations (Laws & Schütze, 2008; Miwa et al., 2014; Zhu et al., 2010). The parameters our algorithm needs are instead quite general and non task-specific, like the PPD intervals based on which the uncertainty zone is built, and the maximum number of iterations with no positive matches after which a session is concluded; the hyperparameter evaluation shows that the algorithm is robust against variations in these parameters and we expect the default values to perform well on most datasets.

Since researchers are asked to review both records with a positive predicted label and those inside the uncertainty zone, this method can be considered as a unifying synthesis of the “certainty” and “uncertainty” paradigms of active learning (Miwa et al., 2014).

We evaluated performance as the capability of the screening procedure (automatic classification plus manual review) to find the largest number of relevant records while reviewing as few of them as possible (i.e., sensitivity  $\times$  efficiency).

We avoided the classic out-of-sample approaches like train-test sampling, out-of-bag bootstrapping or cross-validation (James et al., 2013; Kohavi & others, 1995). Such methods primarily assume that the rate of positivity is equal on average in every random subset of the data (Tashman, 2000); this uniformity is broken by how the initial training set and the subsequent reviewed records are selected by the query-based ordering and the active learning algorithm, determining a lower positivity rate in the unlabelled records (Fig. 2). Also, a literature corpus is unique per search query/database combination, and therefore any out-of-sample performance estimate is not replicable since no new data can be acquired related to the current corpus.

Instead, to estimate overall sensitivity, we employed simple Bayesian regression (surrogate model) on the manually reviewed data to abstract the classification model predictions and achieve a maximum entropy (Harremoës & Topsøe, 2001) estimate of the number of missed positive matches among the unreviewed records in the whole dataset. This simple surrogate model fitted the data very well ( $R^2$  consistently above 97%) using just the lower 98% PrI bound of the PPDs as predictor, indicating predictive consistency in the classification model. The surrogate model posterior predictive distribution could be exploited to explore worse case scenarios in terms of sensitivity.

Our framework achieved very high sensitivity by screening a markedly small fraction of all records, bringing a sensible reduction in workload.

Based on the surrogate model, we predicted a predicted median sensitivity of 100% [93.5%, 100%] in the first session (screening 4.29% of records) and of 97.3% [73.8%, 100%] in the second (screening 1.34% of records): efficiency increased significantly in the second session since only a few new positive matches were found, but given the large number of records, uncertainty regarding sensitivity also expectedly increased.

Both results are above the usual performance in the field (O’Mara-Eves et al., 2015) and in line with the 92% average sensitivity estimated after human-only screening (Edwards et al., 2002). In one interesting case, the model spotted a human-made misclassification error, demonstrating its robustness and value as a second screener, a role already suggested for SRA tools by previous studies (Bekhuis & Demner-Fushman, 2010, 2012; Frunza et al., 2010). Finally, albeit the simple query ordering already concentrated most of the relevant matches in the first 20-25 thousand records, without the tool support some relevant records would have required almost the complete data set to be manually checked to be found.

The model took ~5-20 minutes per iteration to perform predictions in session 1 (17,755 documents) and 20-40 minutes in session 2 (98,371 documents) on an eight-core, 2.5 GHz, 16 GB RAM laptop from 2014; including manual record review, one session required 1-3 days of work, for a total of 1-2 weeks for the whole process (including record collection). That is a considerable saving of time compared to the multiple months usually required for the screening phase of systematic reviews (Allen & Olkin, 1999; Bannach-Brown et al., 2019; Borah et al., 2017). To our knowledge, the amount of data processed (~100.000 records) were larger than what is typical in most SRA studies (O’Mara-Eves et al., 2015; Olorisade et al., 2016), emphasising the reliability of the tool in real-world scenarios.

The last module of our framework is a data-driven query generation algorithm. Creating an efficient and efficacious search query is a complex task (Hammerstrøm et al., 2010; Lefebvre et al., 2011) since it requires building a combination of positive and negative terms to maximise the number of relevant search results while minimising the total number of records to review. Our solution joins a sensitivity-driven subquery proposal engine based on concurrent decision trees (Blanco-Justicia & Domingo-Ferrer, 2019; Moore et al., 2018) built on the BART ensemble PPD with a human review step and an efficiency-driven query builder. The aim is to generate a second query that helps find records missed during the first session search. The generated query allowed indeed to retrieve few more positive matches not found in session 1, but at the cost of a significant increase in the number of documents.

One interesting aspect of this functionality is that it provides a human-readable overview of the classification rules learned by the classification model, showing which combination of terms was particularly relevant and

even spotting authors and geographical locations associated with the study topic. The generated query, therefore, acted as a tool for machine learning explainability (Bhatt et al., 2020; Burkart & Huber, 2021), a feature useful to understand and spot bias in black-box classification algorithms (Malhi et al., 2020); explainability is often required or even legally mandatory for high-stake machine learning applications (Bibal et al., 2020, 2021).

It is important to note that this process is entirely data-driven. The algorithm is only aware of the “world” defined by the data set used as input, which is generated by a specific search query focused on a particular topic. Therefore, the new query may not be specific enough once applied to an unbounded search domain, returning an unmanageable amount of unrelated results. The solution we found was to add another component to the query, specifying the general topic (antimicrobial resistance and healthcare-associated infections) of our research.

As reported, our framework builds on modularity. We designed it to easily implement complete independence of the main modules in future iterations, making it possible for users to add custom features like citation search and parsing for other scientific databases, alternative text processing algorithms or machine learning modules. We deem such interoperability extremely relevant because the main strength of our tool is the composition of many solutions and the general idea of Bayesian active machine learning and uncertainty zone. However, each of its components could benefit considerably from the recent improvements in text mining.

For example, our text processing approach is quite simple, based on the boolean bag-of-words paradigm, and indeed could be improved by more nuanced text representations. It could be evaluated if feature transformations like TF-IDF (Ananiadou & McNaught, 2006; Baeza-Yates et al., 1999) would be advantageous, even if we hypothesise that tree-based classification algorithms like BART are robust enough not to need such operations. Word embedding could be worth exploring: this technique transforms terms in semantic vectors derived from the surrounding text Minaee et al. (2021) and could be used to eliminate semantically redundant terms or differentiate identical terms with different meanings given the context. Another option would be to employ unsupervised learning models like Latent Dirichlet Analysis, Latent Semantic Analysis (Q. Chen et al., 2016; Landauer et al., 1998; Pavlinek & Podgorelec, 2017) or graph-of-word techniques (Ohsawa et al., 1998; Francois Rousseau, 2015) to extract topics to enrich the feature space.

Our classification algorithm can be implemented with any Bayesian supervised machine learning method that provides full PPDs; therefore alternative classification models could be evaluated, like Gaussian Processes which are known for their flexibility (S.-H. Chen et al., 2015; Jayashree & Srijith, 2020). Even more interesting would be to test advanced learning algorithms that surpass the bag-of-words approach, taking into consideration higher-level features in the text like term context and sequences, long-distance term relationships, semantic structures, etc., (Cheng et al., 2019; Farkas, 1995; Lai et al., 2015; Li et al., 2020; Minaee et al., 2021; Yang et al., 2020), given that a Bayesian implementation of such algorithms is available (for example C. Chen et al. (2018)).

Finally, a natural improvement would be to provide a graphical user interface to make the framework easy to use also for less technical users.

The field of literature review automation is maturing rapidly, and we expect an increasing use of such technologies to manage the ever-faster rate of scientific production. We believe it is appreciable that a multiplicity of tools are being made available to let researchers and policymakers find the instrument that better fits their needs.

We contribute to this field with an innovative framework that provide excellent performance and easy integration with existing systematic review pipelines. The value of this work lies not only in the framework itself, which we provide as open-source software, but in the set of methodologies we developed to solve various SRA issues and that can be used to improve already existing solutions.

Abd Elrahman, S. M., & Abraham, A. (2013). A review of class imbalance problem. *Journal of Network and Innovative Computing*, 1(2013), 332–340.

Allen, I. E., & Olkin, I. (1999). Estimating time to conduct a meta-analysis from number of citations retrieved. *Jama*, 282(7), 634–635.

202 Ananiadou, S., & McNaught, J. (2006). *Text mining for biology and biomedicine*. Citeseer.

203 Ananiadou, S., Rea, B., Okazaki, N., Procter, R., & Thomas, J. (2009). Supporting systematic reviews using  
204 text mining. *Social Science Computer Review*, 27(4), 509–523.

205 Baeza-Yates, R., Ribeiro-Neto, B., & others. (1999). *Modern information retrieval* (Vol. 463). ACM press  
206 New York.

207 Bajpai, A., Davuluri, S., Haridas, H., Kasliwal, G., Deepti, H., Sreelakshmi, K., Chandrashekar, D., Bora, P.,  
208 Farouk, M., Chitturi, N., & others. (2011). In search of the right literature search engine (s). *Nature*  
209 *Precedings*, 1–1.

210 Bannach-Brown, A., Przybyła, P., Thomas, J., Rice, A. S., Ananiadou, S., Liao, J., & Macleod, M. R. (2019).  
211 Machine learning algorithms for systematic review: Reducing workload in a preclinical review of animal  
212 studies and reducing human screening error. *Systematic Reviews*, 8(1), 1–12.

213 Batista, G. E., Prati, R. C., & Monard, M. C. (2004). A study of the behavior of several methods for  
214 balancing machine learning training data. *ACM SIGKDD Explorations Newsletter*, 6(1), 20–29.

215 Bekhuis, T., & Demner-Fushman, D. (2010). Towards automating the initial screening phase of a systematic  
216 review. *MEDINFO 2010*, 146–150.

217 Bekhuis, T., & Demner-Fushman, D. (2012). Screening nonrandomized studies for medical systematic reviews:  
218 A comparative study of classifiers. *Artificial Intelligence in Medicine*, 55(3), 197–207.

219 Beller, E., Clark, J., Tsafnat, G., Adams, C., Diehl, H., Lund, H., Ouzzani, M., Thayer, K., Thomas, J.,  
220 Turner, T., & others. (2018). Making progress with the automation of systematic reviews: Principles of  
221 the international collaboration for the automation of systematic reviews (ICASR). *Systematic Reviews*,  
222 7(1), 1–7.

223 Bhatt, U., Andrus, M., Weller, A., & Xiang, A. (2020). Machine learning explainability for external  
224 stakeholders. *arXiv Preprint arXiv:2007.05408*.

225 Bibal, A., Lognoul, M., De Streel, A., & Frénay, B. (2021). Legal requirements on explainability in machine  
226 learning. *Artificial Intelligence and Law*, 29(2), 149–169.

227 Bibal, A., Lognoul, M., Streel, A. de, & Frénay, B. (2020). Impact of legal requirements on explainability in  
228 machine learning. *arXiv Preprint arXiv:2007.05479*.

229 Blanco-Justicia, A., & Domingo-Ferrer, J. (2019). Machine learning explainability through comprehensible  
230 decision trees. *International Cross-Domain Conference for Machine Learning and Knowledge Extraction*,  
231 15–26.

232 Bollegala, D., Maehara, T., & Kawarabayashi, K. (2015). Embedding semantic relations into word represen-  
233 tations. *Twenty-Fourth International Joint Conference on Artificial Intelligence*.

234 Borah, R., Brown, A. W., Capers, P. L., & Kaiser, K. A. (2017). Analysis of the time and workers needed  
235 to conduct systematic reviews of medical interventions using data from the PROSPERO registry. *BMJ*  
236 *Open*, 7(2), e012545.

237 Breiman, L. (1996). Bagging predictors. *Machine Learning*, 24(2), 123–140.

238 Burkart, N., & Huber, M. F. (2021). A survey on the explainability of supervised machine learning. *Journal*  
239 *of Artificial Intelligence Research*, 70, 245–317.

240 Chawla, N. V., Japkowicz, N., & Kotcz, A. (2004). Special issue on learning from imbalanced data sets. *ACM*  
241 *SIGKDD Explorations Newsletter*, 6(1), 1–6.

242 Chen, C., Lin, X., & Terejanu, G. (2018). An approximate bayesian long short-term memory algorithm for  
243 outlier detection. *2018 24th International Conference on Pattern Recognition (ICPR)*, 201–206.

244 Chen, Q., Yao, L., & Yang, J. (2016). Short text classification based on LDA topic model. *2016 International*  
245 *Conference on Audio, Language and Image Processing (ICALIP)*, 749–753.

- Chen, S.-H., Lee, Y.-S., Tai, T.-C., & Wang, J.-C. (2015). Gaussian process based text categorization for healthy information. *2015 International Conference on Orange Technologies (ICOT)*, 30–33. <https://doi.org/10.1109/ICOT.2015.7498487>
- Cheng, Y., Ye, Z., Wang, M., & Zhang, Q. (2019). Document classification based on convolutional neural network and hierarchical attention network. *Neural Network World*, 29(2), 83–98.
- Chipman, H. A., George, E. I., McCulloch, R. E., & others. (2010). BART: Bayesian additive regression trees. *The Annals of Applied Statistics*, 4(1), 266–298.
- Cohen, A. M., Adams, C. E., Davis, J. M., Yu, C., Yu, P. S., Meng, W., Duggan, L., McDonagh, M., & Smalheiser, N. R. (2010). Evidence-based medicine, the essential role of systematic reviews, and the need for automated text mining tools. *Proceedings of the 1st ACM International Health Informatics Symposium*, 376–380.
- Cohen, A. M., Hersh, W. R., Peterson, K., & Yen, P.-Y. (2006). Reducing workload in systematic review preparation using automated citation classification. *Journal of the American Medical Informatics Association*, 13(2), 206–219.
- Cohen, K. B., & Hunter, L. (2008). Getting started in text mining. *PLoS Computational Biology*, 4(1), e20.
- Dietterich, T. G. (2000). Ensemble methods in machine learning. *International Workshop on Multiple Classifier Systems*, 1–15.
- Díez-Pastor, J. F., Rodríguez, J. J., García-Osorio, C. I., & Kuncheva, L. I. (2015). Diversity techniques improve the performance of the best imbalance learning ensembles. *Information Sciences*, 325, 98–117.
- Edwards, P., Clarke, M., DiGuseppi, C., Pratap, S., Roberts, I., & Wentz, R. (2002). Identification of randomized controlled trials in systematic reviews: Accuracy and reliability of screening records. *Statistics in Medicine*, 21(11), 1635–1640.
- Farkas, J. (1995). Document classification and recurrent neural networks. *Proceedings of the 1995 Conference of the Centre for Advanced Studies on Collaborative Research*, 21.
- Frunza, O., Inkpen, D., & Matwin, S. (2010). Building systematic reviews using automatic text classification techniques. *Coling 2010: Posters*, 303–311.
- Galar, M., Fernandez, A., Barrenechea, E., Bustince, H., & Herrera, F. (2011). A review on ensembles for the class imbalance problem: Bagging-, boosting-, and hybrid-based approaches. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 42(4), 463–484.
- Hammerstrøm, K., Wade, A., Jørgensen, A.-M. K., & Hammerstrøm, K. (2010). Searching for studies. *Education*, 54(11.3).
- Hansen, L. K., & others. (2000). Bayesian averaging is well-tempered. *Proceedings of NIPS*, 99, 265–271.
- Harremoës, P., & Topsøe, F. (2001). Maximum entropy fundamentals. *Entropy*, 3(3), 191–226.
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). Boosting and additive trees. In *The elements of statistical learning* (pp. 337–387). Springer.
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning* (Vol. 112). Springer.
- Jayashree, P., & Sriji, P. (2020). Evaluation of deep gaussian processes for text classification. *Proceedings of the 12th Language Resources and Evaluation Conference*, 1485–1491.
- Joo, T., Chung, U., & Seo, M.-G. (2020). Being bayesian about categorical probability. *International Conference on Machine Learning*, 4950–4961.
- Jospin, L. V., Buntine, W., Boussaid, F., Laga, H., & Bennamoun, M. (2020). Hands-on bayesian neural networks—a tutorial for deep learning users. *arXiv Preprint arXiv:2007.06823*.

- Kapelner, A., & Bleich, J. (2013). bartMachine: Machine learning with bayesian additive regression trees. *arXiv Preprint arXiv:1312.2171*.
- Khoshgoftaar, T. M., Van Hulse, J., & Napolitano, A. (2010). Comparing boosting and bagging techniques with noisy and imbalanced data. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, 41(3), 552–568.
- Kohavi, R., & others. (1995). A study of cross-validation and bootstrap for accuracy estimation and model selection. *Ijcai*, 14, 1137–1145.
- Lai, S., Xu, L., Liu, K., & Zhao, J. (2015). Recurrent convolutional neural networks for text classification. *Twenty-Ninth AAAI Conference on Artificial Intelligence*.
- Landauer, T. K., Foltz, P. W., & Laham, D. (1998). An introduction to latent semantic analysis. *Discourse Processes*, 25(2-3), 259–284.
- Laws, F., & Schütze, H. (2008). Stopping criteria for active learning of named entity recognition. *Proceedings of the 22nd International Conference on Computational Linguistics (Coling 2008)*, 465–472.
- Lefebvre, C., Manheimer, E., Glanville, J., Higgins, J., & Green, S. (2011). Searching for studies (chapter 6). *Cochrane Handbook for Systematic Reviews of Interventions Version*, 510.
- Li, Q., Peng, H., Li, J., Xia, C., Yang, R., Sun, L., Yu, P. S., & He, L. (2020). A survey on text classification: From shallow to deep learning. *arXiv Preprint arXiv:2008.00364*.
- Malhi, A., Knapic, S., & Främling, K. (2020). Explainable agents for less bias in human-agent decision making. *International Workshop on Explainable, Transparent Autonomous Agents and Multi-Agent Systems*, 129–146.
- Minaee, S., Kalchbrenner, N., Cambria, E., Nikzad, N., Chenaghlu, M., & Gao, J. (2021). Deep learning-based text classification: A comprehensive review. *ACM Computing Surveys (CSUR)*, 54(3), 1–40.
- Miwa, M., Thomas, J., O’Mara-Eves, A., & Ananiadou, S. (2014). Reducing systematic review workload through certainty-based screening. *Journal of Biomedical Informatics*, 51, 242–253.
- Moore, A., Murdock, V., Cai, Y., & Jones, K. (2018). Transparent tree ensembles. *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval*, 1241–1244.
- O’Mara-Eves, A., Thomas, J., McNaught, J., Miwa, M., & Ananiadou, S. (2015). Using text mining for study identification in systematic reviews: A systematic review of current approaches. *Systematic Reviews*, 4(1), 1–22.
- Ohsawa, Y., Benson, N. E., & Yachida, M. (1998). KeyGraph: Automatic indexing by co-occurrence graph based on building construction metaphor. *Proceedings IEEE International Forum on Research and Technology Advances in Digital Libraries-ADL’98*, 12–18.
- Olorisade, B. K., Quincey, E. de, Brereton, P., & Andras, P. (2016). A critical analysis of studies that address the use of text mining for citation screening in systematic reviews. *Proceedings of the 20th International Conference on Evaluation and Assessment in Software Engineering*, 1–11.
- Pavlinek, M., & Podgorelec, V. (2017). Text classification method based on self-training and LDA topic models. *Expert Systems with Applications*, 80, 83–93.
- Poulter, G. L., Rubin, D. L., Altman, R. B., & Seoighe, C. (2008). MScanner: A classifier for retrieving medline citations. *BMC Bioinformatics*, 9(1), 1–12.
- Ramezankhani, A., Pournik, O., Shahrabi, J., Azizi, F., Hadaegh, F., & Khalili, D. (2016). The impact of oversampling with SMOTE on the performance of 3 classifiers in prediction of type 2 diabetes. *Medical Decision Making*, 36(1), 137–144.
- Robert, C. P., Casella, G., & Casella, G. (2004). *Monte carlo statistical methods* (Vol. 2). Springer.

332 Roshan, S. E., & Asadi, S. (2020). Improvement of bagging performance for classification of imbalanced  
333 datasets using evolutionary multi-objective optimization. *Engineering Applications of Artificial Intelligence*,  
334 87, 103319.

335 Rousseau, Francois. (2015). *Graph-of-words: Mining and retrieving text with networks of features* [PhD  
336 thesis]. Ph. D. dissertation.

337 Rousseau, François, Kiagias, E., & Vazirgiannis, M. (2015). Text categorization as a graph classification  
338 problem. *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the*  
339 *7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 1702–1712.

340 Sampson, M., Tetzlaff, J., & Urquhart, C. (2011). Precision of healthcare systematic review searches in a  
341 cross-sectional sample. *Research Synthesis Methods*, 2(2), 119–125.

342 Schonlau, M., & Guenther, N. (2017). Text mining using n-grams. *Schonlau, M., Guenther, N. Sucholutsky,*  
343 *I. Text Mining Using n-Gram Variables. The Stata Journal*, 17(4), 866–881.

344 Settles, B. (2009). *Active learning literature survey*.

345 Soria-Olivas, E., Gomez-Sanchis, J., Martin, J. D., Vila-Frances, J., Martinez, M., Magdalena, J. R., &  
346 Serrano, A. J. (2011). BELM: Bayesian extreme learning machine. *IEEE Transactions on Neural Networks*,  
347 22(3), 505–509.

348 Soto, A. J., Przybyła, P., & Ananiadou, S. (2019). Thalia: Semantic search engine for biomedical abstracts.  
349 *Bioinformatics*, 35(10), 1799–1801.

350 Tashman, L. J. (2000). Out-of-sample tests of forecasting accuracy: An analysis and review. *International*  
351 *Journal of Forecasting*, 16(4), 437–450.

352 Thomas, J., & Brunton, J. (2007). *EPPI-reviewer: Software for research synthesis*.

353 Turian, J., Ratinov, L., & Bengio, Y. (2010). Word representations: A simple and general method for  
354 semi-supervised learning. *Proceedings of the 48th Annual Meeting of the Association for Computational*  
355 *Linguistics*, 384–394.

356 Violos, J., Tserpes, K., Psomakelis, E., Psychas, K., & Varvarigou, T. (2016). Sentiment analysis using  
357 word-graphs. *Proceedings of the 6th International Conference on Web Intelligence, Mining and Semantics*,  
358 1–9.

359 Visser, E. (2010). Performing systematic literature reviews with researchr: Tool demonstration. *Technical*  
360 *Report Series TUD-SERG-2010-010*.

361 Wallace, B. C., Small, K., Brodley, C. E., & Trikalinos, T. A. (2010). Active learning for biomedical citation  
362 screening. *Proceedings of the 16th ACM SIGKDD International Conference on Knowledge Discovery and*  
363 *Data Mining*, 173–182.

364 Wallace, B. C., Trikalinos, T. A., Lau, J., Brodley, C., & Schmid, C. H. (2010). Semi-automated screening of  
365 biomedical citations for systematic reviews. *BMC Bioinformatics*, 11(1), 1–11.

366 Wilkins, T., Gillies, R. A., & Davies, K. (2005). EMBASE versus MEDLINE for family medicine searches:  
367 Can MEDLINE searches find the forest or a tree? *Canadian Family Physician*, 51(6), 848–849.

368 Woods, D., & Trewheellar, K. (1998). Medline and embase complement each other in literature searches.  
369 *BMJ: British Medical Journal*, 316(7138), 1166.

370 Yang, J., Bai, L., & Guo, Y. (2020). A survey of text classification models. *Proceedings of the 2020 2nd*  
371 *International Conference on Robotics, Intelligent Control and Artificial Intelligence*, 327–334.

372 Zhou, Z.-H. (2021). Ensemble learning. In *Machine learning* (pp. 181–210). Springer.

373 Zhu, J., Wang, H., Hovy, E., & Ma, M. (2010). Confidence-based stopping criteria for active learning for  
374 data annotation. *ACM Transactions on Speech and Language Processing (TSLP)*, 6(3), 1–24.