



SYSTEMATIC LITERATURE REVIEW (SLR) AUTOMATION: A SYSTEMATIC LITERATURE REVIEW

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ABSTRACT

Context: A systematic literature review(SLR) is a methodology used to find and aggregate all relevant studies about a specific research question or topic of interest. Most of the SLR processes are manually conducted. Automating these processes can reduce the workload and time consumed by human.

Method: we use SLR as a methodology to survey the literature about the technologies used to automate SLR processes.

Result: from the collected data we found many work done to automate the study selection process but there is no evidence about automation of the planning and reporting process. Most of the authors use machine learning classifiers to automate the study selection process. From our survey, there are processes that are similar to the SLR process for which there are automatic techniques to perform them.

Conclusion: Because of these results, we concluded that there should be more research done on the planning, reporting, data extraction and synthesizing processes of SLR.

Keywords: *SLR, Automation, Planning, Reporting, Data Extraction, Synthesizing*

1. INTRODUCTION

A systematic literature review or a systematic review is a means of identifying, evaluating and interpreting all available research relevant to a particular research question, or topic area, or phenomenon of interest.[2]

The systematic literature review methodology has a well-defined methodological steps or protocol. The methodological steps, search strategy and research question are explicitly defined so that other researchers can reproduce the same protocol.[2]

There are many reasons for undertaking a systematic review. The most common reasons are: to summarize the existing evidence concerning a treatment or technology, to identify any gaps in current research in order to suggest areas for further investigation and to provide a framework/background in order to appropriately position new research activities.[3].

As described in Figure1, a systematic literature review (SLR) consists of several activities. These activities can be grouped into three phases, as follows:

- Planning the review
- Conducting the review
- Reporting the review

Systematic reviews require considerably more effort than traditional reviews, and currently, most of its activities are done manually. Automating the SLR process will reduce most if not all of the human effort and time consumed to conduct it.

The aim of our SLR is to see if there are any techniques, or methods or approaches in the literature that are used or can be used for SLR process automation in any of its phases and how effective they are.

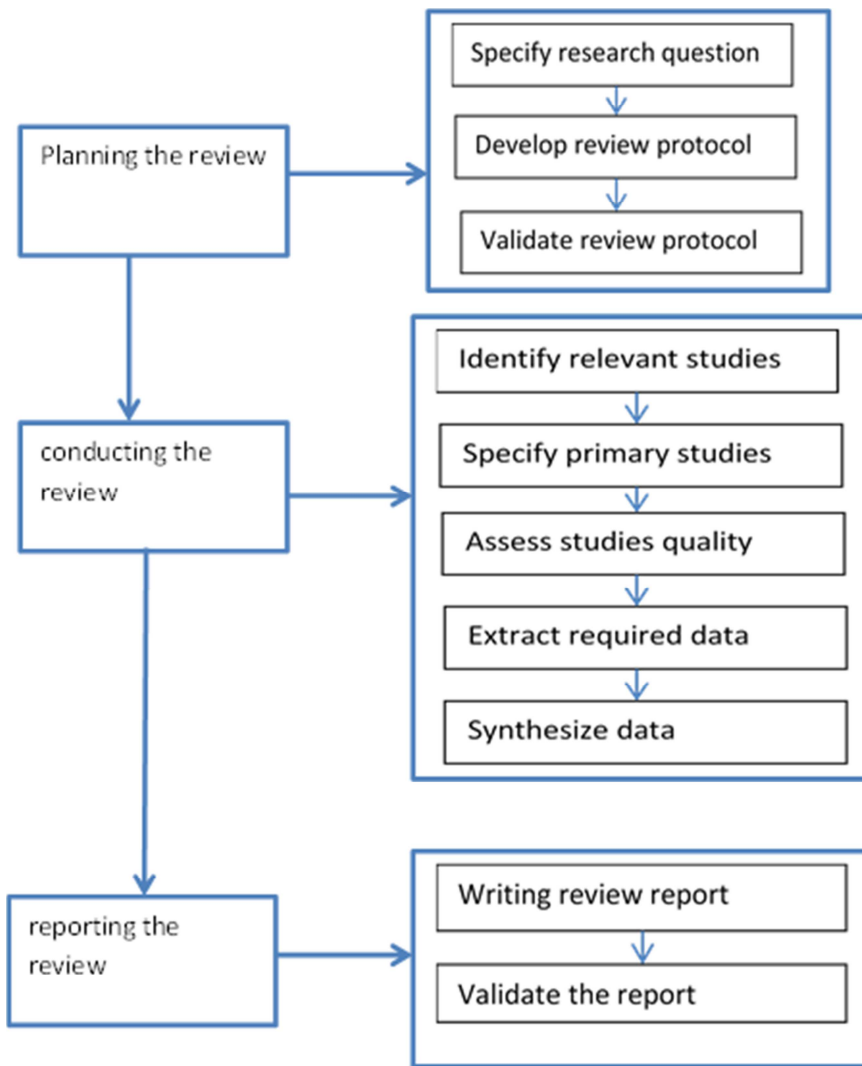


Figure1: Systematic literature review *process*[3].

2. METHOD

Research question

An approach used to formulate research questions is to use PICOC criteria. Using this approach the research question structured in: 1. population. 2. Intervention. 3. Comparison 4. Outcomes. 5. Context. The attributes of our research question are shown in table1.

Table1: PICOC Criteria For The Research Question

Population	Studies about SLR automation or any of its processes
Intervention	All possible techniques
Comparison	None
Outcome	Techniques that support to conduct SLR and to which SLR stage it is or can be applied.
Context	None



The research questions addressed by this study are as follows:

RQ1: what are the techniques that support SLR processes and how good they are?

RQ1.1: what are the SLR processes that have been done automatically?

RQ1.2: what are the techniques that support each process?

RQ1.2: how effective are they?

Here we want to know what are the processes of SLR that have been supported by computer and what are the techniques that support the different processes of the SLR and how they are effective.

RQ2: Is there any similar process to SLR in the literature? How it is supported by computer?

RQ2.1: what are the processes that similar to each SLR process?

RQ2.2: how it is supported by computer?

Here we want to see what are the processes that are similar to each SLR stage and how it can be done automatically or what are the techniques used for these processes.

Search strategy

The strategy used for searching is automatic search

Search Strings

For the search string we take terms from research questions, alternative terms and synonyms and join the string using AND, OR connectors.

Strings for RQ1:

(strategies/methods/supporting/facilitate/automate/technique/ approach/ supporting/searching/ relevant categorization/ classification/screening/ Reduce workload/ Data/knowledge/sentence/results/ information extraction/collection/ presentation/summarization) AND SLR OR (systematic reviews OR systematic literature review OR meta-analysis OR scoping review OR evidence based OR Mapping studies OR systematic mapping OR scoping review).

Strings for RQ2:

- 1- (searching OR grouping OR clustering) AND (relevant articles OR papers OR (similar articles OR papers)

- 2- (knowledge OR sentence OR information OR data) AND (extraction OR discovery OR mining)
- 3- Documents AND (classification OR categorization OR summarization OR clustering) AND (methods OR technique OR approach)

Data source

Databases to be searched for the primary studies are:

- 1- IEEE
- 2- ACM digital library
- 3- Science direct- Elsevier
- 4- Scopus – Elsevier
- 5- Wiley online library
- 6- Google scholar

Inclusion and exclusion criteria

Included studies

- 1- Journal and conference papers.
- 2- Publications written in English language.
- 3- That propose/implement/suggest methods/techniques to automate SLR complete process or automate any of SLR stages or similar process or sentence/knowledge/data extraction or documents classification/ categorization/ prioritization/ summarization
- 4- survey study about automatic SLR generation or any of it is stages.

Excluded studies

- 1- That describe theoretical aspects of SLR
- 2- Guidelines for doing SLR
- 3- SLR about other issues (not about SLR automation).
- 4- Studies that using manual techniques.

These criteria will be applied to the title, keywords, abstract and conclusion. This protocol will be reviewed by our supervisor.

Quality assessment



Table2: *Quality Assessment Criteria*

no	question	answer
1.	Is the technique or method used clearly stated?	Yes/no/partial
2.	Does the article address one of the research questions?	Yes/no/partial
3.	Does the article document the procedure used to validate its technique or method used?	Yes/no/partial
4.	Is it not a duplicate paper?	Yes/no/partial

Search process

The following table contain the results of the search on the specified databases using the search strings for RQ1 and RQ2, our search start 3/5/2013 and end 11/5/2013.

Table3: *Search Process Preliminary Results*

	Search results	Inclusion by title	Removing duplicates	Inclusion by abstract
RQ1 string	2922	251	211	50
RQ2 string	1183	192	190	66

Studies selection process

During this process we apply the inclusion and exclusion criteria to the full study, starting with 116 studies plus 3 from one of the included studies reference.

The initial screening end with 40 relevant studies. And a review process by the author started with the same population along with the quality assessment criteria. A weight assigned to each study according to this rule (yes=1,partial= 0.5 and no=0), including papers with the weight(2 to 4) only.

Data extraction process

Data extraction process was carried out on 26 papers that passes the inclusion/exclusion check and the quality check, the data extracted after

reading the full paper. Table1 and Table2 in appendix B summarize the data extraction process.

Data Synthesis process

For RQ1.1 synthesized data from all studies show that the study selection(initial screening and reviewing or validation of the selection process), data extraction and synthesizing have an automation support. The collected data show that the process which have more automatic support is the study selection process. It is very important to notes that there is no automatic support for the planning and the reporting phases of the SLR process.

For RQ1.2 the collected data show that For the study selection process the techniques used for the documents classification are the machine learning classifiers listed below:

- (1) Complement Naïve Bayes
- (2) Discriminative Multinomial Naïve Bayes
- (3) Alternating Decision Tree
- (4) AdaBoost (Logistic Regression)
- (5) AdaBoost (j48)
- (6) Support vector machine learning algorithm
- (7) A voting perceptron-based

In one paper graph representation is used as a technique to support the data extraction, for the search process a meta search is used in one paper and in another one the text mining is used to improve the search strategy by using an associative search and lastly a sentence extraction for multi documents summarization is used to support the data synthesis process

For RQ1.3 the collected data show that the reduction of the human workload between 20%-50%, the papers about study selection reporting that no loss of relevant data and no inclusion of irrelevant one.

For RQ2.1(what are the processes that similar to each SLR process?), there are processes that are similar to the study selection process: filtering spam emails, news articles classification and data loss prevention. For Data Synthesis, similar process is Research paper recommender system and for reporting the review the similar processes are summarization of multiple news documents and summarization of dissertation abstracts. But no



similar process for planning the review process and data extraction process.

For RQ2.2(how it is supported by computer?), from the collected data the processes that are similar to the study selection process supported by using a machine learning classifiers, the data synthesizing is supported by using SCuBA algorithm, and for reporting the review process sparse predictive classification framework is used in addition to the hierarchical variable-based framework.

3-Discussion of the results

From the obtained results there are processes in SLR(planning and reporting the review) that have not been supported by computer and more research on these processes needs to be undertaken.

From our survey there are similar processes to SLR processes and it is supported by computer, because of its effectiveness the technologies used can be applied to the SLR processes that have no computer support specially reporting the review process because it is the summary of the overall process.

4-Conclusion

In this paper we present a result of a systematic literature review aimed to investigate the use of computer to support systematic literature review processes, to identify the systematic literature processes that support by computer. The SLR study give us an identification of the current state of research and techniques to support research gaps and future work.

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APPENDIX A

the following are references for the included studies that referenced by S

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Appendix B

Form1 : to answer research question1(RQ1): what are the techniques that support SLR processes and how good they are?

Study Id	Author(s)	SLR process	Date	Method/technique	Performance measurements	Effectiveness
S1	Cohen, A., Hersh, W., Peterson, K., & Yen, P.	Study selection	2006	Machine learning based classifier : A voting perceptron-based automated citation classification	Recall , precision and F-measure	Reduction in the number of articles needing manual review(3 for each 15(20%))
S2	Tomassetti, F., Rizzo, G., Vetro, A., & Ardito, L.	Study selection	2011	Extending technologies in the field of the linked data and text mining(Naive Bayes classifier)	Recall	Improving the second step in SLR by filtering the possible studies and automatically discarding non relevant ones
S3	Felizardo, K. R., Andery, G. F., Paulovich, F. V., Minghim, R., & Maldonado, J. C.	Study selection (review or validation)	2012	Visual text mining (VTM): 1- Content map 2- Citation map		The results have shown that employment of VTM techniques can successfully assist in the Selection Review task, speeding up the entire SLR process in comparison to the conventional approach.
S4	Bekhuis, T., Demner-Fushman, D	Study selection (the initial screening phase)	2010	Supervised machine learning Three types of classifiers: 1.decision trees. 2.EovSVM 3. weightily averaged one-dependence estimator (WAODE)	Mean recall , mean precision and harmonic mean of equally-weighted precision and recall (F1);	EvoSVM with a radial or Epanechnikov kernel may be an appropriate classifier when observational studies are eligible for inclusion in a systematic review.
S5	Wallace, B. C., Trikalinos, T. a, Lau, J., Brodley, C., Schmid, C. H.	Study selection (citation screening)	2010	Machine learning – support victor machine(SVM) Active learning strategy		The algorithm is able to reduce the number of citations that must be screened manually by nearly half in two of these, and by around 40% in the third, without excluding any of the citations eligible for the systematic review.



S6	Ananiadou, S., Rea, B.	Searching, Screening and Synthesizing	2009	-Text mining improves the search strategy by using an associative search which discovers the set of documents most similar to a given document. -Document classification using support vector machine(SVM) -Adaptable multi-document summarization	micro-average F1-measure and the multi-topic accuracy	
S7	Cohen, A. M.	Study selection	2008	-machine learning techniques -documents classifications (classification including feature systems unigram, n-gram, MeSH, and natural language processing (NLP) feature)	“AUC” using the area under the receiver operating curve as a measure of goodness.	The best feature set used a combination of n-gram and MeSH features. NLP-based features were not found to improve performance.
S8	Cohen, A. M., Adams, C. E., Davis, J. M., Yu, C., Yu, P. S., Meng, W., Duggan, L., et al.	- searching - study selection	2010	-meta-search -classifier(SVM based) clustering -ranking	time and effort measurements (comparing	the text mining-based pipeline for accelerating systematic reviews in evidence-based medicine will decrease the manual burden of systematic reviewers during the literature collection and review process, and increase the proportion of reviewer time spent synthesizing evidence, performing meta-analyses, and considering results.
S9	Cohen, A. M., Ambert, K., & McDonagh, M. (n.d.).	study selection	2009	- support vector machine learning algorithm was evaluated with cross-validation	“AUC” using the area under the receiver operating curve as a measure of goodness.	On average, the method improves performance by about 20%, when the amount of topic-specific training data are scarce.



S10	Felizardo, K. R., Nakagawa, E. Y., Feitosa, D., Minghim, R., Mapping, S., & Mining, V. T.	study selection	2009	Visual text mining (VTM)		Effort reduction to conduct systematic mapping can be achieved, since the approach is automated using a supporting tool.
S12	Frunza, O., Inkpen, D., Matwin, S.	Study selection	2010	machine learning technique- CNB (Complement Naïve Bayes) classifier	Recall, precision	Our goal of improving the recall level from the first level of screening is achieved, since when both the classifier and the human judge are integrated in the workflow, the recall level jumps from 79.7% to 92.7%.
S13	Kouznetsov, A., Matwin, S., Inkpen, D., Razavi, A. H.	Study selection	2009	machine learning technique- a committee of classifiers: (1)Complement Naïve Bayes (2) Discriminative Multinomial Naïve Bayes (3) Alternating Decision Tree (4) AdaBoost (Logistic Regression) (5) AdaBoost (j48)	Recall, precision	1-The experiments demonstrate that a committee of machine learning classifiers can rank biomedical research abstracts with a confidence level similar to human experts. 2- The ranking approach allows selecting abstracts that are classified as relevant or non-relevant with high level of prediction confidence 3- We tried our approach on data used in a real case systematic review. The papers selected with our ranking method are classified by the machine learning technique with a



						recall of 91.6% and a precision of 84.3% for the class of interest.
S14	Malheiros, V., Hohn, E., Pinho, R., Mendonca, M., Maldonado, J. C.	Study selection	2007	Visual text mining(VTM)	Precision	precision of 83.87%
S15	Matwin, S., Kouznetsov, A., Inkpen, D., Frunza, O., O'Blenis, P.	Study selection	2010	factorized version of the complement naive Bayes (FCNB) classifier	(WSS) at no less than a 95% recall was	The minimum workload reduction for a systematic review for one topic, achieved with a FCNB/WE classifier, was 8.5%; the maximum was 62.2% and the average over the 15 topics was 33.5%. This is 15.0% higher than the average workload reduction obtained using a voting perceptron-based automated citation classification system.
S16	Rizzo, G., Tomassetti, F., Ardito, L., Torchiano, M., & Morisio, M.	Study selection	2012	an automated pre-selection approach based on text mining and semantic enrichment techniques.		Results show a reduction of the manual workload of 18% that a human researcher has to spend. As baseline, we compared the enriched approach with one based on a normal Multinomial Naive Bayes classifier. The improvements range from 2.5% to 5% depending on the dimension of the trained model.
S11	Felizardo, K. R., Riaz,	Data extraction	2011	Graph representation		- Graphs were more efficiently



	M., Sulayman, M., Mendes, E., MacDonell, S. G., & Maldonado, J. C.					understood - there is reduction in time
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Form2 : to answer research question2 (RQ2): Is there any similar process to SLR in the literature? How it is supported by computer ?

Study Id	Author(S)	date	SLR process	Similar process	Techniques/methods
S17	Miratrix, L., Gawalt, B., Yu, B., Ghaoui, L. El, Berkeley, U. C.	2011	Reporting the review	summarization of multiple news documents	sparse predictive classification framework
S24	Ou, S., Khoo, C. S. G., & Goh, D. H.	2005	Reporting the review	summarization of dissertation abstracts	hierarchical variable-based framework to integrate four kinds of information—research concepts, relationships between variables, contextual relations, and research methods extracted from different documents, and gives the user a map or overview of a specific topic which the user can explore and zoom in for more details.
S18	Agarwal, N., Haque, E., Liu, H., & Parsons, L.	2006	Data Synthesizing	Research paper recommender systems	a scalable subspace clustering algorithm(SCuBA)
S19	Androutopoulos, I., Koutsias, J., Chandrinou, K. V., & Spyropoulos, C. D.	2000	Study selection	Anti-Spam Filtering	Naive Bayesian classifier
S20	Hart, M., Manadhata, P. K., Johnson, R., & Manadhata, P.	2011	Study selection	Data loss prevention	Support vector machine(SVM)
S21	Pandey, U., Chakraverty, S., Juneja, B., Arora, A., & Jain, P.	2011	Study selection	News groups classification	lexical chaining +a triangular fuzzy membership function
S22	Youn, S., & Mcleod, D.	2007	Study selection	Spam email classification	Adaptive ontology-J48
S23	Ramdass, D., & Seshasai, S.	2009	Study selection	Newspaper Articles Classification	Naive Bayesian classifier, Maximum Entropy Classification and Probabilistic Grammar Classification
S25	Diao, Y., Lu, H., & Wu, D.	2000	Study selection	personal e-mail filtering	naive Bayesian classifier and decision tree based classifier was
S26	El-Halees, A.	2009	Study selection	Filtering Spam E-Mail	maximum entropy, decision trees, artificial neural nets, naive Bayesian , support vector machines and k-nearest neighbor.