Machine Learning for Software Engineering: a Bibliometric Analysis from 2015 to 2019

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Abstract

The increase of computer processor speed and the ubiquitous availability of data coming from a diversity of sources (e.g., version control systems, software developers forums, operating system logs, etc.) have boosted the interest in applying machine learning to software engineering. Accordingly, the research literature on this topic has increased rapidly. This paper provides a comprehensive overview of that literature for the last five years. To do so, it examines 1,312 records gathered from Elsevier Scopus, identifying (i) the most productive authors and their collaboration networks, (ii) the countries and institutions that are leading research, (iii) the journals that are publishing the most papers, and (iv) the most important research themes and the highest impacted articles for those themes.

1. Introduction

The volume of data captured and stored from software applications, version control systems, software developers forums, operating system logs, application reviews, etc. grows incessantly. Machine Learning (ML) opens the possibility of processing that data for a variety of purposes.

For instance, the failures reported on existing software systems may be used for training a ML algorithm to predict potential failures in new systems according to some code features (e.g., cyclomatic complexity, lines of code, etc.) [1, 2, 3, 4]. Likewise, ML can be used to estimate software development cost/effort [5, 6], to trace dependencies between software artifacts [5, 6], to refactor code [7], to classify application reviews [8], to detect malware [9], etc.

According to Elsevier Scopus, the number of publications on ML for software engineering has grown from 110 papers in 2015 to 485 articles in 2019 (i.e., a 340.91% increment). This paper aims to provide a systematic analysis of the increasing large literature that is being generated about this topic. Thus, supporting the

identification of the research with the highest potential for industry and future investigations.

In particular, this paper targets the following *Research Questions*:

- RQ1: How fast is the number of publications growing?
- RQ2: Who are the most productive authors, and how do they collaborate?
- RQ3: What countries and institutions are leading research?
- RQ4: What journals have published most articles?
- RQ5: What are the most relevant themes of research, and what are the highest impacted papers for those themes?

To answer these questions, a sample of 1,312 articles retrieved from Elsevier Scopus is examined. Analyzing such a huge sample by hand would be difficult and error-prone. Alternative automated procedures are preferable [10, 11]. Consequently, we have used two widespread bibliometric methods [12]: *performance analysis* and *science mapping*, which have been successfully applied in recent studies (e.g., [13, 14, 15]) since they complement each other thoroughly: performance analysis determines the significance of the bibliometric elements, and science mapping models how those elements are interrelated.

The remaining of this paper is organized as follows: Section 2 describes the materials and methods used to perform the analysis; Section 3 summarizes and discusses the most relevant results; finally, Section 4 provides some concluding remarks and points directions for future research.

2. Materials and Methods

This section describes the systematic methodology we have followed to gather and analyze a representative

bibliometric corpus of articles dealing with the application of ML to software engineering from 2015 to 2019.

2.1. Bibliometric workflow

According to the recommendations given by Cobo et al. [10], PRISMA [16], and Börner et al. [17], we followed a workflow composed of the following stages:

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1 TITLE=ABS=KEY("Machine Learning" OR (supervised W/O learning)
2 OR (unsupervised W/O learning) OR (Support W/O Vector W/O
3 Machine) OR (Latent W/O Dirichlet W/O Allocation) OR (Deep W/O
4 Learning) OR (Neural W/O Network) OR (k W/O nearest W/O
5 neighbors) OR (naive W/O bayes) OR (decision W/O trees) )
6 AND SRCTITLE("Agile Conf." OR "Aspect-Oriented Softw.
7 Development" OR "Asia-Pacific Softw. Engineer. Conf." OR
8 "IEEE/ACM Int. Conf. on Automated Softw. Engineer." OR
9 "Component-Based Softw. Engineer." OR "European Conf. on Softw.
10 Maintenance and ReEngineer." OR "Int. Conf. on Evaluation and
11 Assessment in Softw. Engineer." OR "European Conf. on
12 Object-Oriented Programming" OR "European Conf. on Softw.
13 Architecture" OR "ACM Sigsoft Conf. on the Foundations of
14 Softw. Engineer." OR "Int. Symposium on Empirical Softw.
15 Engineer. and Measurement" OR "Int. Conf. on Generative
16 Programming and Component Engineer." OR "IEEE Int. Conf. on
17 Engineer. of Complex Computer Systems" OR "Int. Conf. on
18 Formal Engineer. Methods" OR "Int. Conf. on Softw. Engineer."
19 OR "IEEE Int. Conf. on Softw. Maintenance" OR "IEEE Int. Conf.
20 on Softw. Reuse" OR "Int. Conf. on Softw. Testing, Verification
21 and Validation" OR "Int. Symposium on Empirical Softw.
22 Engineer." OR "Int. Symposium on Softw. Reliability Engineer."
23 OR "Int. Symposium on Softw. Testing and Analysis" OR "Int.
24 Workshop on Principles of Softw. Evolution" OR "ACM/IEEE Int.
25 Conf. on Model-Driven Engineer. Languages and Systems" OR
26 "IEEE Int. Working Conf. on Mining Softw. Repositories" OR
27 "ACM Conf. On Object Oriented Programming Systems Languages
28 and Applications" OR "Int. Conf. on Quantitative Evaluation
29 of Systems" OR "Int. Conf. on Quality Softw." OR "IEEE Int.
30 Requirements Engineer. Conf." OR "Int. Workshop on
31 Requirements Engineer.: Foundation for Softw. Quality" OR
32 "Simposio Brasileiro de Engenharia de Softw." OR "Euromicro
33 Conf. on Softw. Engineer. and Advanced Applications" OR "Int.
34 Symposium on Softw. Engineer. for Adaptive and Self-Managing
35 Systems" OR "IEEE Int. Conf. on Softw. Engineer. and formal
36 Methods" OR "Int. Conf. on Softw. Engineer. and Knowledge
37 Engineer." OR "Softw. Visualization" OR "Softw. Product Line
38 Conf." OR "ACM Sigsoft Working Conf. on Softw. Reusability" OR
39 "Technology of Object-Oriented Languages and Systems" OR "IEEE
40 Working Conf. on Reverse Engineer." OR "Working IEEE/IFIP Conf.
41 on Softw. Architecture" OR "ACM Transactions on Programming
42 Languages and Systems" OR "ACM Transactions on Softw. Engineer.
43 and Methodology" OR "Automated Softw. Engineer." OR "Empirical
44 Softw. Engineer." OR "IEEE Softw." OR "IEEE Transactions on
45 Softw. Engineer." OR "IET Softw." OR "Information and Softw.
46 Technology" OR "Int. Journal on Softw. Tools for Technology
47 Transfer" OR "Journal of Softw.: Evolution and Process" OR
48 "Journal of Systems and Softw." OR "Requirements Engineer."
49 OR "Softw. and Systems Modeling" OR "Softw. Quality Journal"
50 OR "Softw. Testing Verification and Reliability" OR "Softw.:
51 Practice and Experience" OR "Int. Journal of Softw. Engineer.
52 and Knowledge Engineer.")
53 AND (LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018)
54 OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016)
55 OR LIMIT-TO (PUBYEAR , 2015))
56 AND (LIMIT-TO (DOCTYPE , "cp") OR LIMIT-TO (DOCTYPE , "ar")
57 OR LIMIT-TO (DOCTYPE , "re"))
58 AND (LIMIT-TO (SUBJAREA , "COMP"))
59 AND (LIMIT-TO (LANGUAGE , "English"))

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Figure 1: Query to gather the paper sample.

1. *Data retrieval.* Gathering the complete population of all research literature published about a given topic is usually unrealistic [18, 19]. In other words, *exhaustiveness* has to be substituted

by *representativeness*. To obtain an unbiased publication sample that represents the population satisfactorily, the query in Figure 1 was executed on Elsevier Scopus, gathering 1,312 documents. Lines 1-5 specify the topic (i.e., *machine learning*); Lines 6-52 set the publication sources (40 conferences and 17 journals on software engineering); Lines 53-55 constraint the query to the period 2015-2019; Lines 56-57 limit the type of publication to conference paper (*cp*), journal article (*ar*), and review (*re*); Line 58 constraints the search to the computer science subject area; and Line 59 filters the results to documents written in English. It is worth noting that the query was iteratively polished until a good balance between completeness and absence of false-positives was reached.

2. *Data normalization.* Bibliographic data often includes typos and ambiguities [10, 11, 20]; e.g., an author may appear in several records with slightly changed names, or the same concept may correspond to different keywords. As these problems can bias the analysis, we standardized the bibliographic data manually.

3. *Data analysis.* The normalized data was examined using performance analysis (publication counts and citations) combined with a bibliometric technique called *science mapping*.

2.2. Science mapping

The *Scimat* tool¹ was used to identify the most relevant topics and their role in the area by using two complementary techniques: *thematic network* clustering and *strategic diagrams*.

To recognize the most important research topics, the *equivalence index* [21] between each pair of keywords i and j was calculated as $e_{ij} = c_{ij}^2 / c_i c_j$, where c_i stands for the number of documents that include i , and c_{ij} accounts for the number of documents that contain both i and j . Then, the topics were identified with the *simple center* clustering algorithm [21], which searches for highly tied keywords according to their e_{ij} . Thus each topic corresponds to a group of keywords, i.e., to a *thematic network*.

The role of a thematic network is characterized in function of two measures [21]:

- *Centrality* calculates the degree of interaction of a thematic network with the remaining ones as $c = 10 \sum e_{io}$, where i and o are keywords inside and outside the network.

¹<https://sci2s.ugr.es/scimat/>

- *Density* characterizes the network internal consistency as $d = 100 \sum e_{ij} / w$, where i and j are every pair of keywords inside the network, and w is the total number of keywords the network has.

Strategic diagrams help to visualize both centrality and density distributions. To do so, the centrality and density *normalized rankings* are calculated as $\text{rank}(c_i)/n$ and $\text{rank}(d_i)/n$, where $\text{rank}(c_i)$ and $\text{rank}(d_i)$ are the positions of the theme i in the centrality and density rankings sorted in ascending order, respectively. Notice that $\text{rank}(c_i)$ and $\text{rank}(d_i)$ are divided by the total number of themes n to normalize their values into the interval $[0,1]$. The strategic diagram x -axis and y -axis account for the centrality and density normalized rankings, respectively. Figure 2 shows the possible roles a thematic network may have according to the strategic diagram quadrant where it is placed.

Figure 2: Strategic diagram quadrants.

2.3. Material

In accordance with *open science*'s good practices, the data we have analyzed, together with a detailed report of the results, are publicly available at:

<https://github.com/rheradio/ML-SE-BibAnalysis>

3. Results and discussion

This section reports the most significant results of our article bibliometric corpus analysis.

3.1. How fast is the number of publications growing? (RQ1)

Figure 3 shows the distribution of the analyzed paper sample over time. In the period this article is focused,

2015-2019, there has been an explosion of interest in applying machine learning techniques to tackle software engineering problems.

Figure 3: Number of publications per year.

3.2. Who are the most productive authors, and how do they collaborate? (RQ2)

A total of 2,862 researchers have co-authored the 1,312 papers that this article analyzes. Most of them are causal authors, as 75.99% have published a single paper, and only 3.33% have published five or more papers. This is consistent with one of the fundamental laws in bibliometrics, called *Lotka's law* [22], which states that the number of authors with n papers is usually inversely proportional to n^2 . In our case, 2175 authors have written one article, so Lotka's law predicts that the number of authors that have published n papers should be $\frac{2175}{n^2}$. Figure 4 compares the empirical distribution found in the sample with the distribution predicted by Lotka's law.

Figure 4: Authorship distribution fits Lotka's law.

Figure 5 shows the collaboration networks among the most prolific researchers that have published at least five papers. There is an edge between two researchers whenever they have co-authored some paper. Node sizes and edge widths are proportional to the number of published articles and the equivalence indices between authors, respectively. The graph is colored according to the clusters of collaborating authors identified with the Leiden algorithm [23].

Figure 5: Collaboration networks of the authors that have published at least five papers.

3.3. What countries and institutions are leading research? (RQ3)

Figure 6 highlights the countries that have contributed with the most papers: China (27.81% of all published papers), USA (15.23%), Canada (7%), and Germany (4.17%). Figure 7 summarizes the institutions whose researchers have published the greatest number of papers.

Figure 6: Most prolific countries.

Figure 7: Most prolific institutions.

3.4. What journals have published the most articles? (RQ4)

Figure 8 shows the journals that have published the highest number of papers.

Figure 8: Most prolific journals.

3.5. What are the most relevant themes of research, and what are the highest impacted papers for those themes? (RQ5)

Our science mapping analysis reveals five thematic networks, whose role is represented in the strategic diagram in Figure 9 (the size of each network is proportional to its number of associated articles). There are two motor topics (*classification* and *defect prediction*), one traversal topic (*genetic algorithms*), one emerging topic (*topic modeling*), and one developed but isolated topic (*security*).

Figure 9: Strategic diagram.

Figures 10-14 detail each thematic network. Node sizes reflect the number of papers that include the corresponding keywords. There is an edge connecting two keywords whenever they co-occur in some paper. The edge width is proportional to the keywords equivalence index.

Table 1 summarizes the papers that have received the highest number of citations in each thematic network. The last column follows the notation [reference]_{#citations}, e.g., [24]₁₃₂ means that [24] has been cited 132 times since its publication in 2015. It is

worth noting that some papers deal with different topics, and thus they appear several times in the table (e.g., [24] encompasses *classification* and *defect prediction*). A more exhaustive list of articles per topic is available at this paper public repository (see Section 2.3).

Table 1: H-index and highest impacted papers per thematic network.

Thematic network	H-index	Top-10 Papers
CLASSIFICATION	29	[24] ₁₃₂ , [25] ₁₃₁ , [26] ₁₂₈ , [27] ₁₁₆ , [28] ₉₇ , [29] ₇₃ , [8] ₆₁ , [30] ₆₁ , [31] ₅₈ , [32] ₅₄ , [33] ₅₃ , [34] ₅₁
DEFECT-PREDICTION	24	[24] ₁₃₂ , [27] ₁₁₆ , [35] ₁₁₅ , [36] ₇₀ , [37] ₆₅ , [38] ₅₈ , [39] ₅₁ , [40] ₄₅ , [41] ₄₃ , [42] ₄₀
GENETIC-ALGORITHMS	21	[26] ₁₂₈ , [43] ₇₉ , [29] ₇₃ , [9] ₅₅ , [44] ₄₅ , [45] ₄₃ , [46] ₄₃ , [47] ₃₉ , [48] ₃₅ , [49] ₃₄
TOPIC-MODELING	21	[25] ₁₃₁ , [50] ₈₃ , [29] ₇₃ , [51] ₆₂ , [38] ₅₈ , [34] ₅₁ , [52] ₄₈ , [53] ₄₈ , [54] ₄₄ , [55] ₄₃
SECURITY	10	[31] ₅₈ , [45] ₄₃ , [48] ₃₅ , [56] ₃₀ , [57] ₂₈ , [58] ₂₆ , [59] ₂₀ , [60] ₁₆ , [61] ₁₃ , [62] ₁₁

3.5.1. Thematic Network 1: Classification (Figure 10). 44.28% of the papers in the sample deal with *classification*, thus being the most common ML application in the software engineering field. For example, ML approaches are used (i) to distinguish between potentially defective and correct software components [24, 27, 29, 52], (ii) to identify code clones, caused by copying & pasting code fragments instead of using software abstractions that favor maintenance [25], (iii) to classify software application reviews [8, 53], (iv) to distinguish relevant knowledge published on forums about software development (e.g., *Stack Overflow*) [30], (v) to detect if a given code fragment is vulnerable from a security point of view [31], (vi) to extract traceability links between software artifacts coming from different life-cycle stages [32], (vii) to classify requirements into functional and non-functional [63], etc.

For that, different techniques are used, e.g., support vector machines (SVMs) [24], neural networks [25, 26,

28, 29, 30, 32], natural language processing (NLP) [29, 8, 30], k nearest neighbors (k-NN) [52], naive Bayes [63], feature selection [64], etc.

Figure 10: Thematic network CLASSIFICATION.

3.5.2. Thematic Network 2: Defect Prediction (Figure 11). As software complexity increases, more rigorous quality control procedures are required to guarantee application correctness. However, the scarcity of human and financial resources makes it desirable to automate quality control as much as possible. Accordingly, much research analyzes existing projects to learn the symptoms that will help to identify error-prone components in future projects [24, 27, 35, 36, 37, 38, 39], or artifacts that will require a major development and maintenance effort [39, 65, 66].

Figure 11: Thematic network DEFECT-PREDICTION.

3.5.3. Thematic Network 3: Genetic Algorithms (Figure 12). A bio-inspired technique, known as *mutation testing*, tries to assess the capacity of a test suite to detect errors by slightly modifying a program [67, 68]. Other bio-inspired approaches look for automatizing fault debugging by learning how to rank software components according to their likelihood of being the cause of a given problem [49]. Also, some genetic programming approaches try to sort bugs according to their severity by examining bug reports [46].

Other ML techniques are used to target different issues, such as (i) refactoring code to fix design problems, improving this way software quality and maintenance [43, 69], or (ii) predicting the future behavior of cloud systems to adjust the resources they may need in advance [47].

Figure 12: Thematic net. GENETIC-ALGORITHMS.

3.5.4. Thematic Network 4: Topic Modeling (Figure 13). NLP techniques, such as topic modeling, typically Latent Dirichlet Allocation (LDA), and sentiment analysis, are used for various purposes: (i) to extract information from developers' discussion forums to complement and improve API documentation [50, 51], (ii) to classify application reviews [53], (iii) to assign bugs to the most convenient developers for fixing them [55], (iv) to classify, cluster and rank tweets about software applications [70, 71], (v) to adjust software maintenance by classifying changes into corrective and adaptive [72], etc.

Figure 13: Thematic network TOPIC-MODELING.

3.5.5. Thematic Network 5: Security (Figure 14).

Another important ML application field is software security. For instance, to repeatedly test an application with modified inputs for finding vulnerabilities [31, 60], to detect malware [45], to recognize run-time system anomalies [59], to complement firewalls by detecting network intrusions [62], etc. It is worth noting that many of these applications are validated on the Android operating system [45, 48].

Figure 14: Thematic network SECURITY.

4. Conclusions

In the last five years, there has been an explosion of articles about ML for software engineering, being mostly published by Chinese and American researchers.

Although ML is applied to a variety of software engineering problems, most literature is focused on software testing and security, including fault/vulnerability detection, localization, and prediction. To do so, neural networks are typically

used, particularly *deep* neural networks. Other common techniques are SVMs, decision trees, naive Bayes, k-NN, Bayesian networks, and genetic algorithms.

As an emerging line of research, NLP and text mining techniques, such as topic modeling (e.g., LDA) and sentiment analysis, have begun to be used for analyzing developers forums (e.g., Stack Overflow), application reviews, *commits* and *issues* from version control systems (e.g., GitHub), etc. Then, the extracted knowledge is applied to handle different questions, such as supporting software maintenance, improving API documentation, predicting defects, estimating software cost, etc.

The reduced number of articles reporting the use of other popular ML techniques, such as regression methods (e.g., multivariate linear regression, logistic regression, regression trees, and model trees), or rule induction algorithms (e.g., decision rules and association rules) is striking. Perhaps this points a direction for future research. Anyway, we believe ML can contribute to many other software engineering areas, such as requirement analysis, design validation, code generation, etc. Consequently, we think that this research field will keep growing in the future.

Our study provides a general perspective obtained with the automated analysis of an extensive article corpus. This overview might be complemented with more in-depth reviews focused on more specific topics, such as software failure prediction, artifact traceability, support for highly configurable software systems, etc.

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