Is the Rush to Machine Learning Jeopardizing Safety?
Results of a Survey

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Abstract. Machine learning (ML) is finding its way into safety-critical systems (SCS). Current safety standards and practice were not designed to cope with ML techniques, and it is difficult to be confident that SCSs that contain ML components are safe. Our hypothesis was that there has been a rush to deploy ML techniques at the expense of a thorough examination as to whether the use of ML techniques introduces safety problems that we are not yet adequately able to detect and mitigate against. We thus conducted a targeted literature survey to determine the research effort that has been expended in applying ML to SCSs compared with that spent on evaluating the safety of SCSs that deploy ML components. This paper presents the (surprising) results of the survey.

Keywords: Literature Survey · Safety-critical · Machine learning · Safety.

1 Introduction

Machine learning (ML) is rapidly being incorporated in the design of safety-critical systems (SCS) for many different purposes such as object recognition, computer vision, and navigation. The ability to solve complex problems while improving performance is a primary reason for the prevalent and ever-growing use of ML.

Working in the safety domain, we have an uneasy feeling about this rapid shift, since the current practices and regulations in various domains (such as ISO 26262 for road vehicles and ISO 10218 for robotic systems) are not adequate to tackle the complexities and data-driven nature of ML based systems, as they are not developed based on requirements, design trace-ability or functional needs. We started by exploring the existing literature on safety and ML. Our initial findings escalated our uneasiness, because we inferred that more research was done on integrating ML in safety-critical systems (SCS) compared with assessing the safety of those integrated components. Thus, we decided to perform a targeted literature review to determine whether or not this is true. This paper reports the results of our literature review.

Our evaluation of the current state of the art suggests three main research directions in the domain of ML and SCSs: (C1) ML for the design of SCSs, (C2) the safety of systems that contain ML components, and (C3) using ML techniques to analyse the safety of SCSs that may or may not embed ML components. The three classes are not
strictly separable and overlap in different ways. In particular, C1 and C3 are similar in that they both discuss the application of ML in SCSs, while C2 is about coping with ML components that are already embedded in SCSs. In our analysis we found papers that, regardless of the super/sub class relationships of the three classes, tackle the issues that are covered in more than one of them (see Table 3.)

We provide statistical analysis on the current research directions and compare the dedicated attention to C1, C2, and C3. In particular – and this may be seen as a limitation of this research – we chose a set of relevant venues as a statistical population and investigated the number of publications in each of them (see Table 1). We hoped to see, despite our intuition, that the same amount of effort applied to all of them.

| Acronym | Venue Name                                                                 | Safety                                                                 | Software Engineering and Model-Driven Engineering | Machine Learning                                                                 | Transportation |
|---------|-----------------------------------------------------------------------------|------------------------------------------------------------------------|---------------------------------------------------|--------------------------------------------------------------------------------|----------------|
| SAFECOMP| Int. Conference on Computer Safety, Reliability, and Security               | SAFECOMP Int. Conference on Computer Safety, Reliability, and Security | MODELS Int. Conference on Model Driven Engineering Languages and Systems | ICML Int. Conference on Machine Learning | IV IEEE Intelligent Vehicles Symposium |
| ISSRE   | IEEE Int. Symposium on Software Reliability Engineering                     | ISSRE IEEE Int. Symposium on Software Reliability Engineering          | JSS Journal of Systems and Software                | ICMLA Int. Conference on Machine Learning and Applications | ITSC Int. Conference on Intelligent Transportation Systems |
| RESS    | Reliability Engineering & System Safety Journal                             | RESS Reliability Engineering & System Safety Journal                    | ASE Automated Software Engineering                 | IJCAI Int. Joint Conference on Artificial Intelligence | |
| ICVES   | Int. Conference on Vehicular Electronics and Safety                        | ICVES Int. Conference on Vehicular Electronics and Safety              | TSE IEEE Transactions on Software Engineering      | NeurIPS Neural Information Processing Systems | |
| SS      | Journal of Safety Science                                                  | SS Journal of Safety Science                                            | ICSE - SEAMS Int. Symp. on Software Engineering for Adaptive and Self-Managing Systems | ICLR Int. Conference on Learning Representations | |

Table 1. Targeting publication venues. We evaluated ECMFA, other ICSE tracks, and EASE but did not find relevant papers. ICMLA 2020 proceedings are not available as up to Feb. 2020.
2 Research Method

We first precisely defined our research questions, then we defined a methodology to explore the state of the art with a predefined paper inclusion criteria.

**Research Questions:** Our main research questions are: (RQ1) How many papers discuss C1, C2, and C3 respectively? (RQ2) Is there a large gap between the answers to RQ1? and (RQ3) How have each of the three directions grown or shrunk over the years, and is a larger gap between them plausible in the near future?

**Paper Selection and Criteria:** Typically, systemic literature reviews conduct a query with certain keywords over one of the reliable academic research databases such as Google Scholar or Scopus. However, we saw one big issue in proceeding as such, and that was choosing a comprehensive enough set of keywords; We could have searched for combinations of “safety” and “machine learning” in titles and abstracts of papers, however the ML domain has several sub-domains (e.g., NN, DL,...) and simply searching for ML could lead to missing out on papers that directly discuss those sub-domains. Besides, listing all the keywords that reflect the sub-domains of ML might be a challenge. So, we decided to select a collection of high quality venues in ML, safety and software engineering domains and to inspect their published papers in the last six years (2015 - 2020). We manually examined the proceedings and volumes of the selected venues listed in Table 1 and analyzed the abstract and introduction section of any paper with a title that contained one of the following keywords:

(“Safety” OR “Certification” OR “Assurance” OR “Risk”) AND (Any ML Keyword including “Bayesian Networks”, “Deep learning”, “Supervised learning”, “Markov Process”)

We suspected that there might be relevant work that does not contain ML keywords in their title, abstract or keywords, so we added those we knew of to the set of our search results, even if they were not a result of our query. Note that we chose venues of Table 1 such that our results would not reflect a single domain. The last two venues were not included in our first round of exploration. Later, in Section 3, we explain why we added two domain specific venues and what we obtained by doing that.

**Data Extraction and Analysis:** We manually analyzed the proceedings and volumes of the venues listed in Table 1 by searching our query in DBLP and journal homepages. After pruning them based on title and abstraction, we further pruned them by reading their introduction sections. We then fully scanned the remaining papers to confirm their relevance. Figure 2 shows our process steps, and the number of papers analysed in each step, excluding key-notes, posters, invited talks, oral presentations, and reviews.

**Ontology:** We visualize the ontology of the domain in Figure 1 we envision using this as part of a road-map for possible future research directions. The yellow boxes depict ML used in SCS design. ML algorithms use the execution log histories, accident documentation, performance reports, etc., as the training dataset to create models of the system or components within the system, and to extract uncertainty parameters or draw safety constraints. The red boxes, inspired by Faria et. al., [34], reflect the challenges of ML that potentially affect the safety and reliability of ML systems. Qualifications of the training dataset (i.e., its size, validity, distribution and distributional shift) and how feature selection is performed on it, notoriously affect the driven model and constraints, and might cause over-fitting. Moreover, any mismatch between the generalization and the reality could lead to safety cracks directly or indirectly (i.e., generalizing inadequate
policies or inefficient safety values for safe exploration). The orange boxes show which safety analysis processes could be implemented via ML techniques [132].

![Fig. 1. The ontology of the interdisciplinary area of ML and Safety.](image)

### 3 Search Results

After applying the methodology explained in Section 2, we found a total of 140 relevant papers (Figure 2), created Table 3 and found the following answers to our questions:

![Fig. 2. The number of papers filtered out during different phases of the adopted research method. The numbers exclude venues IV and ITCS.](image)

| Community  | Order of focus          |
|------------|-------------------------|
| Safety     | C3(51) > C2(15) > C1(14) |
| Software Eng. | C3(14) > C2(7) > C1(4) |
| ML         | C1(23) > C2(19) > C3(11) |

**RQ1**: There were 38, 36, and 74 papers for C1, C2, and C3 respectively.

**RQ2**: The results show a large focus on C3. Note that the number of papers for C3 is almost twice that of C1 or C2 (see Table 3), which means that ML is more often used as an external tool to analyze safety rather than as a safety-critical component. Despite the possible relationship between C2 and C3, there is not a single work that treats them both. Surprisingly, we do not see a large gap between C1 and C2. This is good news – however too good to be true. We suspected that the reason that we did not find more
C1 papers with our query is that many papers discuss the use of ML in a system that is potentially safety critical, or part of a safety critical system, but the main focus of the paper is not safety. Hence, they do not even use “safety-critical” to describe their system of interest. To verify this theory, we decided to pick a couple of venues that are particular to safety critical systems and search only for ML keywords in them with the justification that the importance of “safety” is inherent in those works. We chose IEEE Intelligent Vehicles Symposium (IV) and International Conference on Intelligent Transportation Systems (ITSC) for this purpose. This time, we were not surprised to see that there is a large gap between C1 and C2. In fact, we did not even find one instance of C2 in the last six years of IV, and detected only a couple in proceedings of ITSC. We provided the numbers of papers found in IV and ITSC in Figure 4 and Figure 3 respectively but could not include all the citations due to the space limit.

In the light of this observation and also the results shown in Table 2, we can conclude that: i) there is a large gap between C1 and C2 at least in transportation and autonomous vehicles domains; ii) the same gap might exist in several other safety critical domains which requires a different research scope from the one we chose (i.e., more concentrated on one single domain); iii) ML and software engineering research communities tend to ignore the impact of ML on safety; and iv) the safety community tends to be more cautious about the safety of ML systems, yet focuses more on C3 rather than C2.

**RQ3:** Figure 5 shows the number of papers about each research direction per year. It is evident that the focus on C3 has been increasing, while the number of C1 and C2 papers has fluctuated over the last six years. Figure 5 shows that there is still a gap between C1 and C2, but it is decreasing over time, indicating that the importance of C2 is being recognized by the community. In particular, in 2020 there was a rise in publications discussing C2. Section 3 also shows that C2 is the second focus of the three communities and has been the focus of more papers than C1. However, as discussed for RQ2, Figure 4 and Figure 3 which are domain specific venues, draw a different picture of the situation where C2 hardly appears. As a further observation, the prevalence of the targeted application domains impacted the most by ML are shown in Figure 6.
Fig. 5. Numbers of papers regarding C1 (blue), C2 (red), and C3 (yellow) per year.

Fig. 6. Distribution of results of our search over various application domains.

| Safety | SAFECOMP | C3 | [74, 24], [144, 39] |
|        | C2 | [18, 40], [15, 83], [97, 66], [12, 100], [129, 127] |
|        | C1 | [101, 88], [16] |
|        | ISSRE | C2 | [15] |
|        | C3 | [2] |
|        | RESS | C3 | [31, 4, 140], [149, 39], [107, 33, 131, 56, 72, 143, 26, 748, 133, 31, 141, 145, 50, 45, 43, 40, 72] |
|        | C2 | [130] |
|        | C1 | [89], [138] |
|        | C1 & C3 | [54] |
|        | ICVES | C3 | [56] |
|        | C1 | [20] |
|        | SS | C3 | [85], [42], [86], [13], [25], [28], [36], [136], [134], [84] |
|        | C1 | [33], [19], [39] |

| Software Engineering | MODELS | C3 | [99] |
|                     | C1 | [42] |
|                     | C2 | [42], [15] |
|                     | C3 | [137], [61] |
|                     | C1 & C3 | [60] |
|                     | JSS | C3 | [3] |
|                     | C2 | [8], [42] |
|                     | C3 & C1 | [52] |
|                     | ASE | C3 | [3] |
|                     | C2 | [22] |
|                     | C1 | [122] |
|                     | C3 & C1 | [55] |
|                     | TSE | C3 | [112], [113], [103] |
|                     | [106] |
|                     | SEAMS | C2 | [69, 83] |
|                     | C3 | [93] |

| Machine Learning | ICML | C3 | [109, 13], [110, 47], [43], [78] |
|                  | C1 | [4] |
|                  | ICMLA | C3 & C1 | [4], [98] |
|                  | JICAI | C3 | [130], [78], [17], [79], [45] |
|                  | C2 | [140], [40], [28] |
|                  | C1 | [92], [108] |
|                  | C3 & C1 | [92] |
|                  | NeurIPS | C2 & C1 | [81], [119], [26], [24], [149], [14] |
|                  | [111] |
|                  | ICLR | C2 | [102] |
|                  | C1 | [104], [9] |
|                  | C3 & C1 | [30] |
|                  | LOD | C3 | [20] |
|                  | C1 | [20] |
|                  | C2 | [9], [116], [105] |
|                  | C3 & C1 | [20] |

Table 3. The list of venues and 140 papers found over 2015-20, excluding IV and ITSC.
4 Conclusions

This paper provides a targeted literature survey and an analysis of the past six years of published research related to ML and SCS. We targeted highly regarded and relevant conferences and journals to reduce the scope of the survey, but also to be able to make statements about how various research communities have fared regarding ML and SCS. Our original idea was to draw attention to the lack of research on the safety of SCSs that rely on ML components. An interesting outcome of the survey is that our original hypothesis would have been true prior to 2020. It is encouraging that in many application domains, research related to safety of SCSs with embedded ML components is now getting the attention it should. A disconcerting result is that in the automotive domain, if our selected publication venues are representative, almost all the effort is going into ML usage in design of SCSs or in evaluation of safety using ML technology.

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