A Requirements Engineering Process for Machine Learning Innovation Projects

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Abstract. Despite the increasing development of Machine Learning (ML) applications, Requirements Engineering (RE) activities face challenges in this new data-intensive paradigm, e.g., the high dependence on data availability and quality and the continuous adaptation to changing environments. In this context, we have identified a lack of an integrated view of the RE process of ML applications in the literature. This paper proposes an RE process tailored to ML application projects, covering requirements elicitation, analysis, specification, validation, and management. The process development methodology includes the ISO/IEC 12207 standard and Design Thinking. Our solution combines problem study and formulation supported by the state of the art in research. The solution proposal follows three evaluation formats: laboratory, static, and dynamic validation. We expect the process to improve RE practice and thus improve ML-based systems development with higher quality deliveries and easier maintenance.

Keywords: Requirements Engineering · Machine Learning · ISO/IEC 12207 · Software Process · Design Thinking · Technology Transfer Model.

1 Introduction

In Machine learning (ML), one acquires knowledge by extracting patterns from raw data and solving specific problems using this knowledge [7]. The ML lifecycle structures activities required to develop, train, and deploy models. Improvements throughout the ML cycle can improve the performance of ML applications [7].However, the success of ML systems in the real world is still below expectations [17]. According to research by Herzberg et al. [14], only 36% of participants stated that ML projects go beyond the pilot phase.

RE is considered the most challenging activity in ML projects [16]. Requirements are uncertain, new quality properties (e.g., explainability) emerge, goals are ambitious, and development features a high degree of iterative experimentation. Villamizar et al. [23] pointed out that the state of the art of RE for ML-enabled systems is limited, which makes application difficult. Furthermore, literature and practice do not clarify issues regarding requirements for this domain. According to Ahmad et al. [2], RE research interacting with ML primarily

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focuses on using ML approaches to assist requirements activities rather than the other way around. E Alves et al. declared from a survey with data scientists that the most challenging activity in developing ML systems is understanding the problem [5].

We carried out a study on the state of RE practice in ML projects in an innovation scenario [18] that conducts research, development and innovation (RDI) projects. When conducting interviews with coordinators of different projects, we identified several challenges. Understanding the problem, identifying the problem from data, maintaining effective communication, aligning technical and domain knowledge to manage technological feasibility challenges also identified in other works [5]. As a doctoral proposal, we seek to investigate how much an ER process for innovation projects based on ML helps to develop this type of system.

This paper proposes an RE process for ML-enabled systems in innovation projects that would guide requirements analysts in understanding the data and identifying characteristics and their distribution, which is essential to achieve a high-quality ML model [27]. An RE process would also help in understanding the context and domain [15], stakeholder collaboration [16], concerns about model degradation [26], perception regarding quality, non-functional requirements (NFR), and trade-offs [2, 22, 10].

This paper is organized as follows: Section 2 presents background on RE for ML; Section 3 discusses related work; Section 4 details our proposal; Section 5 presents our evaluation method; Section 6 outlines the current state of our research; and Section 7 brings our concluding remarks.

2 Background

2.1 RE for ML-enabled systems

Given the difficulties in addressing requirements for the context of developing ML-enabled systems, some works present RE challenges for such systems [24, 2]. Most research on the intersection between RE and ML uses the latter to support the former's activities [24]. Among the RE research that underpins the development of data-based systems, we highlight elicitation and conception. Therefore, part of the requirements process is neglected, which is the case with vanity and management, which can affect the quality of these systems.

2.2 ISO/IEC 12207:2017

The ISO/IEC 12207:2017 [1] establishes a common framework for the software lifecycle process. It is made up of processes, activities, and tasks that may be applicable during the acquisition, supply, development, operation, maintenance, or decommissioning of software systems, products, and services. The objective is to facilitate communication and establish business environments with methods, procedures, techniques, tools, and trained personnel.

Besides, ISO groups activities that can be performed during the software system life cycle into four process groups: agreement processes, project-enabling organizational processes, technical management processes, and technical processes. We have processes corresponding to the RE phase in the technical processes group. These are the business analysis processes, the definition of stakeholder needs and requirements, and the definition of system or software requirements.

These processes allow the identification of the problem and solution domain, stakeholders, the context of use, constraints, needs, prioritization, critical performance measures, and the description of the system, interfaces, functions, definition of requirements, analysis of requirements, and development of traceability. We also have the system analysis process, which helps make decisions throughout development.

However, when we analyze ISO processes to support reuse activities in development based on ML, we come across a broad but robust structure that does not contemplate the iterative and agile development related to this type of system.

2.3 Design Thinking

We direct our research towards a more agile and incremental process. In this context, some works highlight the use of Design Thinking and RE [11, 4, 13, 19, 12]. Design Thinking is a structured approach to problem-solving and has been used to develop innovative products [13]. It is a method that explores needs and integrates an agile and flexible environment to solve complex and ill-defined problems. It relies on non-technical prototyping and iterative reformulation of the issues with an interdisciplinary team. It provides a plan to promote creativity during development and allows the improvement of engineering approaches and requirements [12].Design thinking can be divided into three major phases: understanding, exploring, and materializing.

Various charts, graphs, and structures have been generated to accurately categorize and simplify the steps taken throughout a design brief [9]. The Double Diamond design process is a suitable example of a standardized method. This version easily applies to most projects as it follows a standard means of working through a project. However, when applied to a project with specific characteristics, Double Diamond process can take on a customized form [9].

The approach is usually described through the illustration of the double diamond. For each phase, we have an expansion or narrowing option. In the *empathizing* phase, there is an expansion of the exploration of problems, which is followed by the *definition* phase, where there is a bottleneck that characterizes the analysis of the feasibility of treating problems until, at the end of the first diamond, the problem to be treated is defined. The second diamond begins again with the expansion phase supporting the *ideation* activity, where solutions are studied for a specific issue, followed by the funneling phase, when the *prototype* is defined, developed and tested until the solution that meets the customer's expectations is achieved.

After examining the two approaches, we identified that ISO/IEC 12207 and Design Thinking can complement each other in proposing an RE process to support the development of systems based on ML. This proposed process (see Section 4) helps in the execution of RE activities for systems based on ML, aiming to improve the quality of the RE process and, consequently, of the delivered system.

3 Related Work

This section presents works with similar solution proposals. We identify requirements for ML-enabled systems, RE processes, and the use of DT to support RE activities. However, we did not identify an RE process proposal that helps handle requirements for ML-enabled systems based on ISO/IEC 12207 and DT.

PerSpecML [25] is a perspective-based approach to specifying ML-enabled systems encompassing concerns related to typical tasks of practitioners involved in defining and structuring these systems. Concerns are grouped into five perspectives: system goals, user experience, infrastructure, model, and data. These perspectives align activities between business owners, domain experts, designers, software engineers and data scientists, the main stakeholders involved in the development of ML systems. The authors described 28 tasks that group concerns associated with development. The specification model consists of a set of questions that guide the exploration and evaluation of concerns. We extend this approach by thinking about how to guide the process from problem identification to product development.

Silva et al. [21] developed an RE process for developing *Internet of Things* (IoT) systems based on the ISO/IEC 12207:2017 standard. RE can help create these systems, aiming to improve customer and user satisfaction. As with ML-enabled systems, IoT systems development presents new challenges for software engineering and, therefore, RE. Several related issues still do not have a correct answer, such as how to capture and describe hardware and software elements and how to manage and describe the interactions between hardware and software elements. ISO/IEC 12207:2017 establishes some criteria for defining processes that are not clear in the work, such as determining the purpose of the process and explaining the expected results. This approach, however, may not be suitable for data-driven development.

Ahmed et al. [3] combine strengths of CRISP-DM, DT, and Lean. As a result, the authors proposed a three-step approach: business, data, and product. To reiterate, LDTM works by combining Design Thinking (to understand the customer/user and discover the business need) with Lean Startup (to evolve the model/solution) and CRISP-DM (to develop the algorithmic/technical elements of the model/solution). This approach does not address specific aspects of requirements or define how each phase will be created. Besides, practitioners do not know which methods or tools can support development, and this knowledge is not explicit in the literature [18, 24].

We believe that our process and artifacts can help establish an agile and adaptive RE process for software systems based on ML, assisting in identifying and satisfying needs, driving development without overlooking process components, and improving delivery quality, thus helping with challenges pointed out by the practice of developing ML systems [5, 18].

4 Materials and Methods

We studied the RE-related ISO technical processes. We listed the activities and tasks of each process and highlighted what we considered essential for executing the RE phase so that they could not be suppressed. We also defined activities with experience in requirements engineering and with the support of a data scientist. The activities were discussed iteratively over four weeks.

Regarding the *business analysis* process, we included the following activities: (i) define the scope of the problem and analyze complaints, (ii) characterize the solution space and identify alternative solutions, (iii) evaluate alternative solutions, and (iv) maintain traceability. For the *stakeholders' needs definition* process, we defined the following activities: (i) identify stakeholders; (ii) define needs, context of use, and scenarios; (iii) classify and prioritize needs; (iv) identify restrictions and relationships with non-functional requirements; (v) analyze the set of requirements and define performance measures; (vi) discuss and give feedback; and (vii) obtain agreement and maintain traceability.

Concerning the *system requirements definition* process, we chose the activities as follows: (i) define the functional boundary; (ii) identify modes of operation, implementation restrictions, and risks, and define requirements; (iii) analyze requirements; and (iv) obtain agreement and maintain traceability. Finally, we defined the following activities for the *system analysis* process: (i) identify contexts and assumptions, analyze the results, establish conclusions and recommendations, record results, and (ii) maintain traceability.

As ISO is flexible and allows a partial implementation of its processes, we believe that a simplified guide process can aid experimental and iterative ML-enabled systems development. Therefore, it is not clear how ISO can be applied in this context.

After defining the essential activities, we seek to fit these activities into the Design Thinking double diamond approach according to Figure 4. So, in the *empathize* phase, we group the activities related to the *business analysis* process. In the *define* phase, we map activities related to the *stakeholders' needs definition* process. In the *ideate* phase, we list activities of the *system requirements definition* process. We model the *system analysis* process covering these three cited phases. In the *prototype* phase, we envisage the development of an ML-enabled system through prototyping, testing or evaluation, and refinement until it becomes a product that satisfies stakeholders. Therefore, the requirements elicitation and specification activities are carried out iteratively; the requirements analysis is carried out at all phases of the process, ensuring the involvement and understanding of stakeholders, followed by the requirements validation activity, where agreement and management are obtained to ensure the maintenance of traceability.

After designing the process, we identify the stakeholders involved in each phase. The process must be led by a requirements engineer. In the needs discovery phase, we list the stakeholders: business owner (BO), project manager (PM), and data scientist (DS). In the problem definition phase, we add the domain expert (DE). In the ideation or requirements definition phase, we add stakeholders responsible for infrastructure (SE) and user experience (UX).

As ISO predicts expected results for the application of each process, we also identify what is expected from each phase of the proposed method. The empathize phase is expected to discover the needs of customers and users. The expected result of the definition phase is the definition of challenges, problems, possible solutions, and evaluation references. Finally, the ideate phase foresees greater knowledge of the proposed solution based on the multiple views of the stakeholders.

For each phase, we are delimiting artifacts and subprocesses suitable for the development of data-based systems. Based on the process implemented in this work, we developed questions to identify a problem, analyze solutions, and raise other important questions based on available data involving the different stakeholders important for the development of this type of system.

5 Method for Evaluation

To evaluate the effects of technology and build a body of evidence to guide its adoption in specific contexts, we based ourselves on the Model for Technology Transfer (MTT) method [8, 20]. MTT allows research results validation in natural environments and collaboration between researchers and professionals to improve current development processes applicable in the context of this research applied to the RDI scenario [8]. According to the MTT method, the proposal evaluation phase includes laboratory, static, and dynamic validation.

The method begins with identifying an industry problem supported by formulating an academic problem from which a candidate solution is created that is iteratively validated and improved until a viable technology is delivered [8]. MTT has been widely applied in software engineering and RE research [8, 25, 20].

For validation in the laboratory, we will seek to use the proposal in an academic environment and evaluate it with undergraduate students enrolled in RE disciplines. After applying the approach, we will apply a *survey* to collect the perception of usability and ease of use with questions guided by the *Technology Acceptance Model* (TAM) and collect suggestions for improving the approach.

For static validation, we will seek to use the proposal with retroactive instantiating of projects from the Embrapii unit in some projects. This assessment must involve project coordinators to apply the approach retroactively, that is, to projects that have already been completed. After applying the strategy, we will apply a *survey* to collect the perception of usability and ease of use with questions guided by the TAM and collect suggestions for improving the approach.

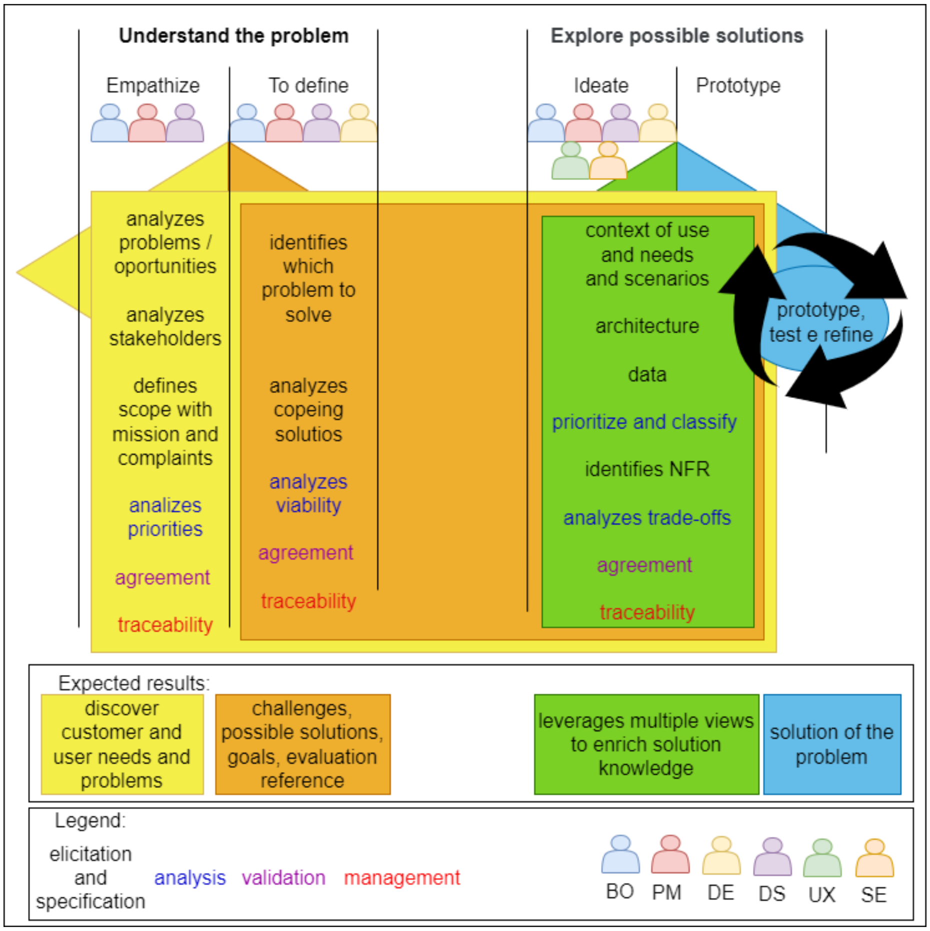

Fig. 1. An RE process for ML-enabled systems.

For dynamic validation, we will seek to use the proposal with instantiating in the Embrapii unit. The assessment must involve the different project stakeholders, including requirements engineers. After applying the approach, we will carry out a *survey* with everyone involved to collect the perception of usability and ease of use with questions guided by the TAM and collect suggestions for improving the approach [6].

To answer the research question, we sought to evaluate our work according to the three validation stages provided for in the MTT. As an outline of the method, we define the **population** of stakeholders involved in developing ML systems. We consider BO, DS, and PM crucial validation representatives. In laboratory validation, we seek to carry out with students; in static validation, we seek to identify the profiles mentioned above to carry out the process of a retroactive project; and in dynamic validation, we aim to apply the method to projects that are starting. As **sampling**, we will investigate the use of our approach in an innovation scenario in an Artificial Intelligence Unit of the Brazilian Industrial Research and Innovation Company (Embrapii). As a **recruitment** strategy, we will select different projects from the unit with varying maturity levels and domains. In laboratory validation, we will apply the study to Software Engineering and Requirements Engineering subjects and invite students to participate in the evaluation. In static and dynamic validation, we will send email invitations to project coordinators. As an evaluation **procedure**, we will explain the approach, apply the Free and Informed Consent Form, apply the process to each of the projects, and finally, we will apply a questionnaire to obtain the perception of ease of use and usefulness [6] of the approach. As a **data collection** procedure, we will use and question the artifacts generated during the process. For **data analysis**, we will check suggestions for improvement and aspects in which participants had difficulty.

6 State of Research

The RE process for developing ML-based systems is in the development phase. We seek to define the artifacts that can be used in each phase. With a partial version of the process, we strive to apply the evaluation methods presented (see Section 5) and improve the process. It is planned to finalize the process modeling after the qualification exam that will take place by 4th July 2024. The evaluation phase should take place throughout 2024 and 2025. This doctoral research is expected to be defended on 1st April 2026.

7 Concluding Remarks

This paper presented a doctoral work proposal involving an RE process for ML-based systems based on ISO/IEC 12207:2017 and Design Thinking. The work is in its second year of development, in the qualification phase, and defining the scope of the proposal.

The research contributions are a process for requirements engineering for developing machine learning-enabled systems, artifacts that are part of the process, and a checklist for verification of process application. These contributions will help identify an ML problem based on available data, address requirements throughout the process, and manage customer expectations and challenges highlighted in innovation scenario [18].

In future work, we will delimit artifacts with essential questions for each of the proposed process's phases to help obtain the expected results and complete the development of quality ML systems. Later, we will evaluate the process in three stages with students in retroactive and ongoing projects to verify how much it helps develop ML systems in innovation scenarios.

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