Open Problems in Engineering Machine Learning Systems and the Quality Model

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Abstract

Fatal accidents are a major issue hindering the wide acceptance of safety-critical systems that use machine learning and deep learning models, such as automated driving vehicles. To use machine learning in a safety-critical system, it is necessary to demonstrate the safety and security of the system to society through the engineering process. However, there have been no such total concepts or frameworks established for these systems that have been widely accepted, and needs or open problems are not organized in a way researchers can select a theme and work on. The key to using a machine learning model in a deductively engineered system, developed in a rigorous development lifecycle consisting of requirement, design, and verification, cf. V-Model [29], is decomposing the data-driven training of machine-learning models into requirement, design, and verification, especially for machine learning models used in safety-critical systems. In this study, we identify, classify, and explore the open problems in engineering (safety-critical) machine learning systems, i.e., requirement, design, and verification of machine learning models and systems, as well as related works and research directions, using automated driving vehicles as an example. We also discuss the introduction of machine-learning models into a conventional system quality model such as SQuARE to study the quality model for machine learning systems.

1 Introduction

Recent developments in machine learning techniques, such as deep neural networks, have led to the widespread application of systems that assign advanced environmental perception and decision-making to computer logics learned from big data, instead of manually built rule-based logics [10]. The availability of big data and affordable high performance computing, such as deep learning frameworks on off-the-shelf GPUs [34], have made highly complex machine learning techniques practical. Machine-learning models are becoming indispensable components, even in systems that require safety-critical environmental perception and decision-making, such as automated-driving systems [44]. For human society to accept such safety-critical machine learning systems, however, it is important to develop common engineering frameworks, such as quality measures and standard engineering processes, for managing the risks of using machine learning models and the systems that include such models [39]. Such frameworks, and ultimately the quality assurance based on them, have an impact on social receptivity because they can be one of the approaches used to deliver safety and security. In fact, recent accidents caused during the use of several experimental auto-
Mated vehicles have revealed the imperative need to address the upcoming social issue of (quality) assurance based on such frameworks [1].

In this study, we review the open engineering problems for safety-critical machine learning systems while showing related works and future directions. We also study the system quality of machine learning systems, which can be used for future requirements and evaluations.

2 Background

An automated driving vehicle is a vehicle that operates without human input. Automated driving is not built as a stand-alone system in a vehicle, but can be realized using a system consisting of clouds, roadside devices (fog or cloud edge), and automated driving vehicles (edge) [11], which create and update high-precision digital maps [50] while cooperating with peripheral vehicles. An in-vehicle automated driving system installed in a vehicle is composed of multiple subsystems for perception, planning, and control; it realizes automated driving operations in cooperation with clouds and roadside units [2]. For simplicity, we shall focus on these in-vehicle automated driving systems in this paper. Each perception, planning, and control subsystem may contain necessary machine learning models. Supervised learning models [40] and reinforcement learning models [45] can be used for perception and planning, while non-machine learning control algorithms can be used for control. To build a machine learning system, it is necessary to define its engineering processes and quality measures in advance, then follow and measure them strictly during development time. This work is related to preceding works [23, 54] which studied the applicability of ISO 26262 [31] and Automotive SPICE [62] to automotive software using machine learning and deep learning. Our work is assuming more general development process to show open problems, and we examined a quality model for machine learning systems, based on Systems and software Quality Requirements and Evaluation (SQuARE) [32], which was not in the previous works.

In this study, we identify open engineering problems at two levels (systems and machine learning models) and use an automated driving system as an example of a safety-critical machine learning system. We proceed to investigate the problems in terms of the three steps of the development process: requirement, design, and verification. The two levels and three steps are shown in Fig. 1. Notably, many of the problems considered in this paper do not occur only in automated driving systems, but in safety-critical systems generally.

3 Engineering Machine-Learning Models

A machine learning model is acquired by executing a training algorithm with a model structure and training data sets for inputs, while trained models are evaluated using testing datasets [47]. This is
a data-driven inductive method that differs from the deductive development used for conventional systems. In this paper, we call a machine learning model with undefined parameters as a model structure. To use machine learning models in a deductively engineered system, it is necessary to break down the data-driven training of a model structure into requirements, designs, and verifications, especially for models used in safety-critical systems.

We hypothesize the engineering process for machine learning models in Fig. 2. The dotted boxes shown in the figure illustrate the differences from the conventional training process. A requirement of machine learning models can be the specification of test data, although the current practice is to split the original data into training and test data sets [5, 58]. The design process then specifies or builds the training data to ensure the highest possible performance from the test data, and ultimately to satisfy the background requirements of the model. The explicit specification of training data addresses a lack of design specification. In the current practice, the verification of machine learning models is measured using performance metrics on the test data. However, we consider it important to check properties that cannot be measured using the test data, such as robustness and interpretability.

![Diagram](image.png)

Figure 2: Engineering of Machine-Learning Models

In the following subsections, we shall introduce our ideas for the requirements, designs, and verifications of machine learning models, as well as directions for solutions and related works.

### 3.1 Requirements of Machine Learning Models

Most current machine learning research assumes that test data is given and do not doubt it [27, 40]; however, it should be the main part of a models requirements. Test data should be carefully specified at the beginning of development by either the machine learning model developers or by contractors to their contractors. Thus, the main open engineering problem here is the deductive definition of the requirements for machine learning models and their testing data, so that the testing data connects with the deductive requirements and data-driven training. In machine learning, we should consider the roles of training data and testing data to be different. While training data is used to improve the performance of a machine learning model [33], we propose to consider the testing data to accurately reflect the environmental conditions in operation. However, in offline learning, [7] when all data obtained at the time of development are split, some are used as training data and the others become testing data [5, 58]. For simplicity, we shall ignore validation data for model selection. In this way, the training and testing data are approximately equally distributed. In spite of the ultimate goal of machine learning models to work well in operation, we test machine learning models on test data which originated from the same source of training data. Therefore, this practice implicitly assumes that testing and operational data sets are close [8], and machine learning models are trained using data-driven methods that lack requirements specification.

Particularly in a safety-critical machine learning system, it is necessary to specify the testing data distribution (considering the operational environment the system will actually be operated in) and to collect the testing data based on those specifications. By accepting an a priori viewpoint of the testing data distribution, we can define the assumed environment deductively and collect data inductively. Moreover, by assuming the distribution of the testing data, we can now discuss and define the operational domain (distribution) to specify the requirements. The deviation between testing data used during development and operation data can become larger as time elapses from
the completion of development, and phenomenon is referred to as covariance shift [8], distributional
shift [3], or concept drift [61]. Operational data tend to change with time, deteriorating model
performance in operation [61,63]. If the operational data trend changes from that of test data, then
machine learning models trained on the test data do not work on the changed operational data. It is
important to check the consistency between operational data and testing data (assuming the original
environment), and to either make the machine learning models follow the operational data in a
continuous maintenance process or to, at least, detect the deviation between testing and operation
data. Lack of requirements is a barrier to do it.

**Related Works and Research Directions of Machine Learning Model Requirements**

Although it does not incorporate specifying test data, an approach does detect change points using
neuron activation patterns [14]. Change is detected when the activation pattern at operation time
becomes detached from the neuron activation pattern at training time.

Even in the current development of in-vehicle automated driving systems, the testing data would
be collected assuming the operational environment to make the distribution at the time of operation
and to make the distribution of the testing data as consistent as possible. However, the methods of
describing the assumed environment of machine learning models are not organized. In particular,
methods are required to define the completeness of testing data. In the previous literature, CV-
HAZOP [66] defined test data coverage in computer vision problems, resolving the combination
explosion problem experienced in systematically testing machine learning models when achieving
coverage [12].

However, these previous works focused on combinatory environments, where the importance of
each environment may change. Testing data should have attributes, such as time and weather, and
their distributions that are based on the assumed environment. Furthermore, since the required
performance may change for each environment, it is necessary to express the association between the
assumed environment and the required performance. Each condition of the testing data distribution
can have a different confusion matrix (or other performance metrics) that machine learning models
will have as desired values (Table 1).

**Table 1: top - sample environment (data distribution), bottom - sample requirements (confusion
matrix)**

| time | day | night |
|------|-----|-------|
| weather | fine | 40% † | 30% ‡ |
|       | rain | 20% † | 10% ‡ |

| prediction | pedestrian | vehicle |
|------------|-------------|---------|
| actual pedestrian | 90% † | 10% |
|                 | 20% † | 80% |
| actual vehicle | 20% † | 80% |

| prediction | pedestrian | vehicle |
|------------|-------------|---------|
| actual pedestrian | 85% | 15% |
|                 | 15% | 85% |
| actual vehicle | 15% | 85% |

† e.g., when it is a fine day, there are many pedestrians; therefore, precision on pedestrians is prioritized.
‡ ‡ e.g., when it is a rainy night, there are many vehicles; therefore, precision on vehicle is prioritized.

### 3.2 Design of Machine Learning Models

A machine learning model is automatically obtained by training the parameters of a model structure
using the training data. Thus, specifications cannot be designed a priori (i.e., machine learning
models lack design specifications). This limitation is essential and unavoidable because high-
performance machine learning models are achieved by learning high-dimensional parameters from
data that engineers cannot manually specify. However, in the development of a safety-critical ma-
chine learning system, it is necessary to record the model structure, the training data, and the training
system (including hyper parameters, initial parameters, and random number seeds) to secure the re-
producibility of the training process.
Engineers cannot design the training; however, they can design the training data. Training data, as a large indirect part of the specification, coupled with training specifications (such as the learning rate and initialization) is carefully designed to achieve the requirements. In this way, the lack of design specification is remedied indirectly. Yet, there is no standard or widely accepted process of designing training data for machine learning models to the best of authors’ knowledge.

Related Works and Research Directions of Machine Learning Model Design

One of challenges with the lack of design specification is establishment of a training process for machine learning models by designing training data and models. Training data should be designed in the process by iteratively identifying the weak points of the model and then generating or collecting additional data for training. A previous suggestion [49] indicates that a criteria for growing training data is that the training error is low while the test error is high; however, the suggestion does not show what types of data are added. It is known that especially deep learning models easily fit a random labeling of the training data [67], and thus training data distribution is important.

3.3 Verification of Machine Learning Models

The verification of machine learning models is done mainly by running a model on test data; however, some properties of a machine learning model, such as robustness, cannot be evaluated with testing data. Therefore, we shall introduce property checking in the verification of machine learning models.

An increasing stability against disturbance, or a lack of robustness, is a key to the verification of machine learning models. It has been reported that image recognition models incorrectly recognize slight noise that cannot be recognized by humans with high confidence, creating what are called adversarial examples (AEs) [59]. An AE is known to have model-independent versatility and is an issue that can threaten the safety of automated driving systems, depending on image recognition. For example, when evaluating robustness against an AE as fault tolerance, it is necessary to artificially generate perturbations around data points. We can generate an AE near a data point specified in the requirements and quantify the robustness using the maximum radius in which the model can give correct answers.

The inference processes of advanced machine learning models, such as neural networks (NN), are considered black boxes, and machine learning models lack interpretability. In this context, a black box refers to a situation where, although feature activations can be observed physically, the actual phenomenon cannot be understood. That being said, safety-critical systems should exhibit interpretability and transparency. The interpretability of machine learning models has been well-researched recently, and there are several methods for addressing it. LIME [53] is one of the most well-known methods to improve interpretability. It derives a simple interpretable model to explain the behavior of an original model around a given data point. NN visualization also shows great promise to improve interpretability. One of NN visualization methods intentionally performs occlusion on input data and specifies the region where the inference result changes drastically as a region of interest [68]; another back-propagates activation values from the influencer nodes during the later feature extraction process to identify the region of interest [65] and generate heat maps for convolutional NNs. Interpretability is also useful for performance improvement, debugging during training, and validating of training results. Developers can understand the internal behavior of a trained NN to train higher performance models [41]. For example, a developer can visualize a NN’s focus points for an incorrect inference, and understand what was wrong, before additional training data is collected according to the analysis. If a machine learning model outputs an incorrect inference, but the visualized focus area is natural for humans, then an inaccurate ground truth label is suggested.

Research Directions of Machine Learning Model Verification

In the field of theoretical computer science, the automatic design verification based on formal verification technologies for some properties, such as safety and liveness [24], makes the verification of a machine learning model possible. Several automatic verification techniques exist for neural networks and we shall categorize them. The first categories are function and decision problems. The former quantify the degrees of properties, while the latter identify if properties are met in a
machine learning model. Related works for function problems address adversarial frequency and severity [6], and maximum perturbation bound [15], referring to the frequency of found adversarial examples, the expectation of the closest adversarial example, and the maximum absolute value of the perturbation of inputs which do not change the outputs, respectively. Decision problems are further subdivided into verification and falsification, which look for a complete proof, and counterexamples by best effort, respectively. Related works of verification are global safety [52], local safety [51], $(\epsilon, \delta)$-robustness [36], and $(x, \eta, \delta)$-safe [28]. Global safety is output bound, and local safety is the consistency of inference among close data points. A related works for falsification is the CNN Analyzer [21, 22]. It finds counterexamples against the signal temporal logic [20] properties of in-vehicle automated driving systems, and counterexamples of object (vehicle) detection by convolutional NNs. Reluplex [37] is a solver used to both verify and falsify first-order propositional logics [4] against NNs using Rectified Linear Unit (ReLU) [48] for activation functions. Reluplex is an SMT solver [19] to verify properties of deep neural networks or provide counter-examples against them, by utilizing simplex method [18] and the partial linearity of ReLU function. There is a related work proposing a set of dependability metrics (properties) for NNs [13].

4 Engineering Machine Learning Systems

In this section, we review the open engineering problems in terms of the system level of in-vehicle automated driving systems as an example of a safety-critical machine learning systems. Problems of machine learning systems originate from machine learning models and the open environments on which automated vehicles work. The former is low modularity of machine learning systems due to the characteristics of machine learning models (such as the “Change Anything Change Everything” (CACE) model [55]), the lack of design specifications. The latter include capturing physical operational environments and user behaviors of in-vehicle automated driving systems for requirements, and addressing the intractability of field operation testing (FOT) for verification. An open environment problem is not directly related to machine learning, although it is an important challenge for in-vehicle automated driving systems. In this paper, we consider open environments to be a common challenge for machine learning systems because machine learning models are employed to capture these complex environments.

4.1 Requirements of Machine Learning Systems

To develop high quality systems and products, comprehensive requirement specifications and the evaluation of machine learning systems is needed, requiring appropriate quality characteristics for the systems that can be used for requirements and evaluations. Quality characteristics of machine learning systems is more industrially important than the those of machine learning models, because machine learning models are not used in a stand-alone way, but they are always embedded in systems. System and software quality models have been developed for years, however to the best of authors’ knowledge, there is no standard quality model taking the characteristics of machine learning models, such as lack of requirement specifications, design specifications, interpretability, and robustness, into account. Thus, we study a gap analysis on the conventional quality model Systems and software Quality Requirements and Evaluation (SQuARE) [32] in [5].

Another important aspect of machine learning (or any other) systems is that they cannot operate in every environment and require limitations or warranty scopes. Thus, a machine learning system must be implemented for a predefined environment. There are various types of roads, traffic lights, and traffic participants, such as other vehicles (be they automated or manually driven) and pedestrians, therefore it is not easy to define the operational environment for in-vehicle automated driving systems. An open engineering problem in the requirement of machine learning systems is that there is no standard way to design and define such environments, i.e., requirements cannot be clearly defined. In the automobile industry, this is called the operational design domain [25, 60], and it can be defined by conditions including geographical areas, road types, traffic conditions, and maximum speed of the subject vehicle [16].

Related Works and Research Directions of Machine Learning System Requirements

The German PEGASUS project is a joint initiative of vehicle manufacturers, suppliers, tool vendors, certification organizations, and research institutes, which aims to define standard quality assurance
methods for automated-driving systems [43]. The purpose of this project is to clarify the expected performance level and evaluation criteria of automated driving systems through scenario-based verification. Scenarios are collected from test drives and the market to demonstrate that systems are equal to, or better than, human drivers. The PEGASUS project is an excellent example of the continuous requirements and verification for in-vehicle automated driving systems and their verification.

4.2 Design of Machine Learning Systems

One of the open engineering problems at the system level of machine learning systems is designing systems that include machine learning models by considering and applying the characteristics of CACE. CACE originates from the lack of design specification in machine learning models. Machine learning models are trained in a data-driven way, making the localizing of change difficult. If a small part is changed, then the entire machine learning changes once trained again. Subsequently, machine learning systems have to be changed for the newly trained machine learning models. To prevent reworking after training machine learning models, system architectures that can cope with additional requirements without modification of the model are required.

Related Works and Research Directions of Machine Learning System Design

To the best of authors’ knowledge, we do not find special techniques directly address designing machine learning systems. SOTIF [64], a safety standard/process concerning performance limits of functions, is focusing on securing functions with uncertainty. Uncertain functions shall include machine learning models. SOTIF has a process including identification of scenarios which can trigger unsafe actions (triggering events) for the system, and system modification to address them [17]. The process can be potentially applicable to machine learning system design in general. Researches directions include test stubs for machine learning models, the encapsulation of machine learning models by rule-based safeguarding, and the use of redundant and diverse architecture that mitigates and absorbs the low robustness of machine learning models.

4.3 Verification of Machine Learning Systems

The simplest approach to verify an in-vehicle automated driving system is through a verification against actual data. Accumulating a large number of safe automated driving trips, with long distances to match human drivers, will effectively demonstrate that in-vehicle automated driving systems are as safe as human drivers. To verify the system within a realistic time-frame, there are two options: reduce the required verification scenarios or accelerate the verification. High precision verification models must therefore be able to exclude unreal scenarios. It is necessary to accelerate simulation experimentation, reproducing corner-case scenarios on test courses with a short mileage (i.e., scenarios with an extremely low probability of occurrence and that are difficult to statistically obtain by FOT on an actual road).

Related Works and Research Directions of Machine Learning System Verification

Obtaining statistically significant results would require hundreds of thousands to hundreds of billions of miles FOT [35], which is based on a simple hypothesis testing, and the resulting required miles do not reflect optimized to actual situations.

5 Quality of Machine-Learning Systems

We reviewed the open engineering problems in machine learning systems, and recognized the characteristics of machine learning models are their lack of requirement specifications, design specifications, interpretability, and robustness. In this section, we study quality models for machine learning systems by discussing the combination of these machine learning model characteristics, and a conventional system quality model, SQuARE [32].

5.1 Conventional System Quality Model

We focus on SQuARE, ISO/IEC 25000 series [32], as the conventional system quality baseline. It is a widely acknowledged system quality standard and includes quality measures (QMs) and quality
measure elements (QMEs), as well as quality models, characteristics, and sub-characteristics. These components have a tree structure (one-to-many relationships), and the top-level quality models are product quality, data quality, service product quality, and quality in use, as shown in Fig. 3. Green circles represent quality characteristics in Fig. 3. Quality sub-characteristics are not defined for data quality.

![Quality models, quality characteristics, and quality sub-characteristics in SQuARE](image)

Each quality characteristic of data quality, or each quality sub-characteristic of product quality and quality in use, has multiple QMs which define how to quantify the quality. A QM $X$ is defined as a formula, such as $X = A/B$ and $X = 1 - A/B$, and the elements in the formula $A$ and $B$ are QMEs. QMs and QMEs are not defined for the service product quality. An example set of quality model, characteristic, sub-characteristic, QM, and QMEs are the system and software quality (quality model), reliability (characteristic), maturity (sub-characteristic), mean time between failure (QM), and the operation time with the number of system/software failures that actually occurred (QME). There are other QMs for the sub-characteristic maturity (such as failure rate, whose QMEs are the number of failures detected during the observation time and the duration of observation).

5.2 Gap Analysis

We performed a gap analysis between a conventional system quality and a system quality for machine learning systems, given the conventional system quality and characteristics of the machine learning models introduced in this paper. For the most fine and precise analysis, we checked each QME (such as the number of systems/software failures actually occurred) against each machine learning characteristic (such as lack of robustness) to see if the QME was affected by the machine learning characteristic. If a QME in machine learning systems became immeasurable, as is the case with conventional systems, then the parent quality (sub-)characteristic would have gaps. The service quality model was ignored in this gap analysis because it has no QME defined. Table 2 shows sample QMEs and characteristics of machine learning models. Req, Des, Rob, and Tra are abbreviations for lack of requirements specification, design specification, robustness, and transparency.

We examined 1,464 combinations of 366 QMEs and 4 characteristics of machine learning models to obtained the results. The number of combinations we identified as affected by machine learning models was 21. Tables 3, 4, and 5 are the summaries of the quality models affected by the characteristics of machine learning models, where the QM and QME levels are omitted in the tables. Each QME associated with a quality (sub-)characteristic was examined to determine if it was affected by any of machine learning model characteristics. The number of QMEs affected by characteristics of machine learning models are shown in these tables. We consider the ratios of QMEs affected by characteristics of machine learning models are the impacts to quality (sub-)characteristics. At the
Table 2: Sample impact analysis of machine-learning characteristics on functional suitability in product quality model

| QM                  | QME                                                                 | Req | Des | Rob | Tra |
|---------------------|---------------------------------------------------------------------|-----|-----|-----|-----|
| Func. coverage      | # of functions missing                                               |     |     |     |     |
|                     | # of func. specified                                                  |     |     |     |     |
| Func. correctness   | # of func. that are incorrect                                        | †   |     |     |     |
|                     | # of func. specified                                                  | ††  |     |     |     |
| Func. appropriateness of usage objective | # of func. missing or incorrect among those that are required for achieving a specific usage objective | † † † |     |     |     |
|                     | # of func. required for achieving a specific usage objective         | † † † |     |     |     |
| Func. appropriateness of system | Appropriateness score for usage objective ✿ |     |     |     |     |
|                     | # of usage objectives                                                |     |     |     |     |

† When the input changes slightly, the result can change drastically. We cannot measure the correctness of the function precisely. Perturbed trials can quantify the uncertainty.
† † Functions considered cannot be defined strictly. For example, there are many pedestrian variations of pedestrian detection for an auto emergency braking (AEB) function, and it can be multiple functions. We cannot define functions without ambiguity.
† † † When the input changes slightly, the result can change drastically. We cannot measure the correctness of the function precisely. Perturbed trials can quantify the uncertainty.
† † † † Functions considered cannot be defined strictly. For example, there are many pedestrian variations for pedestrian detection, and it can be multiple functions. We cannot define functions without ambiguity.

quality-model level, it is clear that the impact to product quality is the highest, while those of data quality and quality in use are low.

The characteristics of machine learning models which affected QMEs the most were a lack of requirements specification and a lack of robustness. First, we shall discuss the impact of a lack of requirements specification. Quality characteristics involving preconditions (such as operational contexts, the interval of values (domains), and operational environments) were affected by a lack of requirements specification. As discussed previously, machine learning models are trained using data-driven processes. Preconditions are encoded in training/test data and not explicitly described. QMEs not measurable due to lack of preconditions are

- Number of functions which were tested in different operational environments;
  (Product quality model/Portability/Adaptability/Operational environment adaptability)
- Total number of additional contexts in which the product might be used;
  (Quality in use model/Context coverage/Flexibility/Flexible context of use)
- Total number of required distinct contexts of use;
  (Quality in use model/Context coverage/Context completeness/Context completeness)
- Number of data items which can be defined as a required interval of values.
  (Data quality model/Accuracy/Data accuracy range)

Note that the quality model, characteristic, sub-characteristic, and QM are described in brackets.

The lack of requirements specifications in machine learning models are twofold: a lack of preconditions (introduced in the last paragraph) and a difficulty defining the desired behaviors of machine learning models due to the wide variety of input and output patterns. For example, there are many variations of pedestrians (such as young and old, one with bags and umbrella) for an AEB function and it is difficult to define the function precisely (what types of pedestrians are dealt in the system) without ambiguity. Being unable to define precise functions affects function suitability and appropriateness, as well as the portability of product quality. QMEs not measurable due to difficulty of defining behaviors are

- Number of functions that are incorrect;
  (Product quality model/Functional suitability/Functional correctness/Functional correctness)
- Number of functions missing or incorrect among those that are required for achieving a specific usage objective;
  (Product quality model/Functional suitability/Functional appropriateness/Functional appropriateness of usage objective)
- Number of functions which produce similar results as before;
  (Product quality model/Portability/Replaceability/Functional inclusiveness)
Table 3: Impact of machine-learning characteristics on system & software product quality

| Characteristic            | Sub-characteristic     | #QME |
|--------------------------|------------------------|------|
|                          |                        | all affected |
| Functional suitability   | Functional correctness | 2 (Rob,Req) |
|                          | Functional appropriateness | 4 (Rob,Req) |
|                          | Others                 | 2     |
| **Subtotals**            |                        | 8     |
| Performance Efficiency   | Others                 | 29    |
| **Subtotals**            |                        | 29    |
| Compatibility            | Others                 | 8     |
| **Subtotals**            |                        | 8     |
| Usability                | Operability            | 18 (Tra) |
|                          | Others                 | 25    |
| **Subtotals**            |                        | 43    |
| Reliability              | Maturity               | 8 (Rob × 2) |
|                          | Fault tolerance        | 7 (Rob,Des) |
|                          | Others                 | 8     |
| **Subtotals**            |                        | 23    |
| Security                 | Integrity              | 22    |
| **Subtotals**            |                        | 22    |
| Maintainability          | Modularity             | 4 (Tra,Des) |
|                          | Analysability          | 6 (Tra) |
|                          | Modifiability          | 7 (Des) |
|                          | Testability            | 6 (Rob) |
|                          | Others                 | 4     |
| **Subtotals**            |                        | 27    |
| Portability              | Adaptability           | 6 (Req) |
|                          | Replaceability         | 8 (Rob,Req) |
|                          | Others                 | 5     |
| **Subtotals**            |                        | 19    |
| **Total**                |                        | 179 17 |

- Number of data values that are outliers.
  (Data quality model/Accuracy/Risk of data set inaccuracy)

Next, we shall discuss the impact of a lack of robustness. QMEs that observe machine learning system behavior are affected by the lack of robustness. When the inputs of machine learning models change slightly, the results can change drastically. Therefore, observing the behavior of such systems becomes uncertain. We noticed that the QMEs affected by low robustness were similar to those affected by the lack of requirements specification. The QMs using these QMEs are ratios, with the numerator being a QME counting correct behavior, and the denominator being a QME counting preconditions. For example, a quality measure of functional correctness is \( X = 1 - \frac{A}{B} \), \( A = \) Number of functions that are incorrect, \( B = \) Number of functions considered, and we cannot measure either \( A \) or \( B \) due to the two characteristics of machine learning models (i.e., a lack of robustness and a lack of requirements specification). QMEs not precisely measurable due to a lack of robustness are

- Number of functions that are incorrect;
  (Product quality model/Functional suitability/Functional correctness/Functional correctness)

- Number of functions missing or incorrect among those that are required for achieving a specific usage objective;
Table 4: Impact of machine-learning characteristics on data quality

| Characteristic | Sub-characteristic | all affected |
|---------------|-------------------|--------------|
| Accuracy      | -                 | 14 (Req,Rob&Req) |
| Completeness  | -                 | 16 0         |
| Consistency   | -                 | 12 0         |
| Credibility   | -                 | 8 0          |
| Currentness   | -                 | 6 0          |
| Accessibility | -                 | 6 0          |
| Compliance    | -                 | 4 0          |
| Confidentiality | -             | 4 0          |
| Efficiency    | -                 | 14 0         |
| Precision     | -                 | 4 0          |
| Traceability  | -                 | 6 0          |
| Understandability | -            | 14 0         |
| Availability  | -                 | 6 0          |
| Portability   | -                 | 6 0          |
| Recoverability| -                 | 6 0          |
| **Total**     |                   | **126 2**    |

Table 5: Impact of machine-learning characteristics on quality in use.

| Characteristic | Sub-characteristic | all affected |
|---------------|-------------------|--------------|
| Effectiveness | -                 | 8 0          |
| **Subtotals** |                   | **8 0**      |
| Efficiency    | -                 | 11 0         |
| **Subtotals** |                   | **11 0**     |
| Satisfaction  | Others            | 13 0         |
| **Subtotals** |                   | **13 0**     |
| Freedom from risk | Others | 21 0         |
| **Subtotals** |                   | **21 0**     |
| Context coverage | Context completeness | 2 1 (Req)  |
| Flexibility   |                   | 6 1 (Req)    |
| **Subtotals** |                   | **8 2**      |
| **Total**     |                   | **61 2**     |

(Product quality model/Functional suitability/Functional appropriateness/Functional appropriateness of usage objective)

- Number of avoided critical and serious failure occurrences based on test cases.

(Product quality model/Reliability/Fault tolerance/Failure avoidance)

QMEs related to negative events affected the difficulty of capturing rare cases of machine learning models, another type of a lack of robustness. Outliers and failures should include rare cases, but rare cases may not appear in a limited time frame or the extremely low probability of occurrence can be neglected. As mentioned previously, a long FOT is required to capture rare events. QMEs underestimated due to the difficulty of overlooking rare cases are

- Number of data values that are outliers;
  (Data quality model/Accuracy/Risk of data set inaccuracy)

- Number of test functions required;
  (Product quality model/Maintainability/Testability/Test function completeness)
• Number of system/software failures that actually occurred;
  (Product quality model/Reliability/Maturity/Mean time between failure, MTBF)
• Number of failures detected during observation time.
  (Product quality model/Reliability/Maturity/Failure rate)

There is a small impact on machine learning systems by the lack of design specification and lack of transparency characteristics. If there are no design specifications, we cannot estimate the effort of a system modification nor the impact of a local modification to the overall system. We do not know the strengths and weaknesses of machine learning models (i.e., the redundancy of components without design specification). Models with similar weaknesses do not work as redundancies, and redundant installation does not make sense. QMEs unmeasurable due to a lack of design specifications and a lack of transparency are

• Expected time for making a specific type of modification;
  (Product quality model/Maintainability/Modifiability/Modification efficiency)
• Number of components which are implemented with no impact on others;
  (Product quality model/Maintainability/Modularity/Coupling of components)
• Number of system components installed redundantly.
  (Product quality model/Reliability/Fault tolerance/Redundancy of components)

As there is no established method of diagnostic and monitoring functionalities for machine learning models, the following QMEs are not measurable for machine learning systems.

• Number of diagnostic functions useful for causal analysis;
  (Product quality model/Maintainability/Analyzability/Diagnosis function effectiveness)
• Number of functions having state monitoring capability.
  (Product quality model/Usability/Operability/Monitoring capability)

We discussed the combination of the machine learning model characteristics with the conventional system quality model, SQuARE. The typical gaps for the quality model of machine learning systems were the precondition specification, the level of detail for function specification, the uncertainty of observation, and the extremely low probability rare cases. To address these gaps, system quality models can be modified and/or extended. We will introduce the direction to address these gaps in 5.3.

5.3 Toward Machine Learning System Quality Model

The first set of challenges exist in quality measures for preconditions and function for machine learning systems, i.e., requirements specification. We assume that precondition and function specification are defined by input range and pairs of input/output, respectively. If input and/or output data are high dimensional, both defining precondition and detailed function specification are difficult. As machine learning models are trained in a data-driven way, we inevitably conclude that data is involved. One natural idea is that first to manually engineer the deductive specifications as detailed as possible, and second to prepare data which includes example instances for requirements specifications. Requirements specification of machine learning systems cannot fully define the preconditions and functions, however, the remaining uncertainty of specifications is covered by examples. QM for requirements specification shall be the sum of the quality of deductive requirements specification and the quality of sample data. The quality of requirement specifications for machine learning systems, i.e., the level of requirement specifications detail, is not straightforward to measure. Although not quantitative, a proxy of requirements specification quality is recording the argument to derive it. An earlier study [30] used structured argument such as goal structure notation [38] to address uncertain requirements and environments. Quality measures of requirement specification such as “Number of functions having preconditions specified with structured argument” divided by ”Number of functions that could benefit from specifying preconditions,” and ”Number of functions having detailed function specification with structured argument” divided by ”Number of functions that could benefit from detailed function specification” can be added for machine learning systems. Quality of sample data, i.e. test data should be defined as the coverage of requirement specifications. If the structured argument is in a tree structure, the ratio of leaf nodes which have corresponding sample data can be a quality measure of sample data. Quality of test data will be revisited later in this section.
Handling the uncertainty of observation of machine learning systems in quality model is also important. The current quality measures are deterministic. Introducing number of trials and variance to quality measures will improve expression power for machine learning systems. Another aspect in the lack of robustness is the extremely low probability rare cases. It is not possible to find all of rare cases by definition. We cannot evaluate the result of rare case discovery, however, we can see the quality of the process. Quality measures of rare case discovery process would be the effort of rare case discovery and the number of rare cases discovered in a unit time.

A point of view not in the current quality model is development data, although it has data quality. Data quality of SQuARE is about the data included in the system, such as customer database. For machine learning systems, development data, i.e. testing and training data, is quite important, and the quality models for machine learning systems should include the corresponding quality. There are two qualities related to development data, testing data quality and training data quality.

6 Conclusion

With the rapid development of technology in recent years, machine learning has been used in various systems. To use machine learning in a safety-critical system, such as an automated driving system, it is necessary to demonstrate the safety and security of the system to society through the engineering process. In this paper, taking automated driving as an example, we presented open engineering problems with corresponding related works and research directions from the viewpoints of requirements, designs, and verifications for machine learning models and systems.

At the machine learning model level, we hypothesized an ideal training process connecting deductive requirements and data-driven training, considering test data as a requirements specification and training data as a design specification. We recognized that the characteristics of machine learning models are a lack of requirements specification, a lack of design specification, a lack of interpretability, and a lack of robustness. The key points at the machine learning system level were the requirement specifications and verifications for open environments, as well as a system quality model.

We also discussed the combination of a conventional system quality model, SQuARE, and the aforementioned characteristics of machine learning models to study the quality model for machine learning systems. It turned out that a lack of requirements specifications (the precondition specification and the level of detail for function specification) and a lack of robustness (the uncertainty of observation and the extremely low probability rare cases) have the most impact on the system quality model. We discussed the direction of future quality model for machine learning systems, however, most of it is in the future works.

Future works include the development of element technologies for engineering machine learning models and systems, such as requirements specification techniques to cover test data distribution or open environments. However, an engineering process for safety-critical machine learning systems cannot be established, even if each company carries out its own engineering based on its own concepts. It is because the private engineering works cannot be widely accepted by human society. As we saw in this paper, there are many open engineering problems and possible directions to address them. One approach is to develop a standard quality model for machine learning systems. We discussed the quality model based on SQuARE this paper. Future works include discussing quality characteristics outside of SQuARE, defining specific QM and QME, and quality characteristics and sub-characteristics if necessary. Attempts to research element technologies along with guidelines for requirements, designs, and verifications would be also practically helpful. For example, a guideline for multiple verification tiers (real data testing for normal conditions, simulated data testing for the corner cases, automatic verification for highest integrity levels only, falsification is middle integrity levels, etc.) would encourage the practical use of verification techniques and help an industry suffering from a lack of machine learning systems quality assurance.

Conflict of Interest: The authors declare that they have no conflict of interest.

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