Humboldt-Universität zu Berlin
Mathematisch-Naturwissenschaftliche Fakultät
Institut für Informatik

Fraunhofer FOKUS

Risk assessment in Machine Learning security - a framework for risk measurement

Masterthesis

for the attainment of the academic degree
Master of Science (M. Sc.)

submitted by: Jan Schröder
born on: 03.03.1996
born in: Lemgo

Surveyor: Martin Schneider
Prof. Dr. Holger Schlingloff

submitted on: ..... defended on: .....

Contents

Abstract

This thesis is Open Source and can be found on `https://github.com/EvilWatermelon/Risk-Measurement-Framework` together with the Risk-Measurement-Framework.

Acknowledgements

The following table explains and declares terms that are used in this thesis for standartization. The order of the table is organized by declaring a term before its relation to other terms.

Term	Description
International Organization for Standartization (ISO)	The ISO is an international statndard organization which declares international standards in all technical areas [3]. The ISO 27004 will be the basis for designing and implementing the Risk-Measurement-Framework.
Information Security Management System (ISMS)	The ISMS is a part of a management system that covers on the approach of a business risk approach the development, implementation, monitoring, review, maintenance, and improvement of information security [34]. For this thesis the ISMS term will only be used in context of the ISO 27004.
Model	A model in context of machine learning is a representation of a machine learning system that learned from the training sets [4].
Prediction	A predicition is an output of a machine learning model coming from an input e.g. data that the machine learning has never seen before [4].
Machine Learning	Machine learning is a research field and also describes a program or a system that trains from input data a predictive model. That predictive model makes predictions from never-before-seen data [4]. Machine learning models will be measured for security risks in this thesis.
Threat	A threat is a security violation when an event could cause harm [62]. Threats will be find in the threat models and the risk measurement.
Threat model	A threat model is a model to find security problems. This model should give a bigger picture away from the code [63]. A threat model will be used to declare different characeristics with their relation between attacks and an attacker.

Term	Description
Framework	A framework is a layered structure with a set of functions. It can specify programming interfaces, or offer programming tools [49]. In this thesis a framework will be designed, implemented and evaluated with a case study.
Vulnerability	A vulnerability is weakness of a program or system which could be exploited by a threat. [49]. The vulnerability term will be in this thesis used in context with the attacks and vulnerabilities in ML models.
Attacker	A person that exploits potential system vulnerabilities [49]. For this thesis an attacker stands in relation with its effort to attack an machine learning model.
Attacker's effort	The attacker's effort is a term that represent everything that an attacker do to attack the machine learning model. In this thesis the attacker's effort represent probability of occurrence, among other things.
Risk	Risk is the combination between the frequency of damage and the extent of damage. The damage is the difference between a planned and unplanned result [3]. The risk calculation will be used as the final result after the risk measurement.
Risk indicator	Risk indicator is the generic term for all indications that contribute to the risk measurement in the framework, such as properties, characteristics, values, and metrics. They will be used to measure risks and to represent the results as data, logs, or visual representations of the risk measurement.
Decision criteria	To describe the level of confidence in a given result, decision criteria pretend thresholds, targets, or patterns [2].
Measure	Variable which is assigned with a value that comes from a result of the measurement [2].
Analytical model	An algorithm that combines one or more derived measures with its associated decision criteria [2].

Term	Description
Measurement function	An algorithm to combine two or more measures [2].
Measurement method	Operations in a logical sequence [2].
Measurement	Gathering information about the IT security system by using a measurement method, function, analytical model and decision criteria [2].
Measurement result	One or more indicators with its interpretations which address an information need [2].
Information need	"Insight necessary to manage objectives, goals, risks and problems" [2].
Base measure	A measure that is defined by an attribute and the associate method for quantifying it [2].
Derived measure	"Measure defined as a function of two or more values of base measures" [2].
Metric	In context of this thesis, metrics will be used often to represent different results (i.e. accuracy) of the machine learning model.
High-level attributes	High-level attributes are subjective attributes that represent all characeristics of an attacker's effort [21]. This term will be used in context of a formal threat model.
Low-level attributes	Low-level attributes are objective attributes that represent all characeristics of the attack's data [21]. This term will be used in context of a formal threat model.

This thesis uses the terms decision criteria, measure, analytical model, measurement function, measurement method, measurement, information need, base measure, and derived measure in context with the ISO 27004 standard to design and implement the Risk-Measurement-Framework.

1. Introduction

Machine Learning (ML) is a constantly growing field and is essential for many innovative applications such as highly-automated and autonomous driving. Resulting from this, there is an increased need to maintain security. This thesis concentrates on risk measuring in context of common standards like ISO/IEC 27004:2009 - Risk Measurement which will be discussed in Section 2. Risk measurement is a part of risk assessment to analyze the system for vulnerabilities. This present thesis evaluates how to measure risks and what the extent of damage is by visualizing all results.

This thesis explains and discusses the design of a conceptual framework and its implementation to measure risks which is called Risk-Measurement-Framework (RMF). The RMF is designed by a conceptual framework based on risk indicators as a fundamental part upon approaches by Jakub Breier et al. [17] and Paul Schwerdtner et al. [58]. The core of the implementation of the RMF is the Adversarial-Robustness-Toolbox (ART) that is included as a Python library but also an open-source framework which will be explained in Section 2.

Sections 1 and 2 are intended to clarify the goals and expectations of this thesis, explain terms, show necessary prior knowledge so that it is well defined where this thesis should go. Section 3 is one of the main parts of the thesis. The section discusses and describes the conceptual framework and gives the basis for the technical framework explained in Section 4. Section 5 explains the case study that uses the framework and shows its potential and how to use it. In Section 6, a conclusion points out possible future work and summarizes the results.

1.1. Motivation

The classic IT security is a large field and essential for every software application. In ML, security is also essential and needs more tools to find vulnerabilites and measure risks for the subsequent defense implementation. This thesis evaluates a conceptual and technical framework in the context of IT security standards. The aim is to improve security in ML, which could help researchers and companies to optimize their work. Due to the research for this present thesis, there were a lot of scientific papers that evaluate IT security management in the context of ISO 27005 but less with ISO 27004. Therefore, there is a need to put more focus on ISO 27004. So ML in relation to ISO 27004 is another motivating factor to extend the research in the context of security for ML and ISO 27004. From the previously mentioned points, it should emerge that this thesis should show the possibility of using common standards for risk measurement in ML.

1.2. Research questions and hypotheses for this thesis

To understand the goal of this thesis the following hypotheses and research questions should show what this thesis is concentrating about.

Research questions

RQ1: How can the procedure and requirements from ISO 27004 be used for risk measurement at ML?

RQ2: Which requirements of ISO 27004 can be met by the RMF and which cannot?

RQ3: How can the training data be used to measure risks of poisoning attacks, especially backdoor attacks?

RQ4: What are risk indicators to measure poisoning attacks, especially backdoor attacks?

RQ5: What are risk indicators to measure the attacker's effort?

RQ6: How do the values of the risk indicators change before and after an attack on the ML model?

RQ7: What measurement methods need to be implemented in the RMF to measure and evaluate risks for backdoor attacks and the effort of an attack?

RQ8: Which attacks reflect an appropriate level of damage to mirror a real attack?

RQ9: Which risk indicators can be usefully evaluated in combination to obtain the best possible results from risk measurement?

Based on these questions, the goals of this thesis are defined. Research question RQ1 is about the extent to which an already known standard can be used to implement measurements in the field of ML security. Research question RQ2 follows from the first research question and is intended to clarify in more detail which requirements can be fulfilled by the RMF. The third research question RQ3 goes more towards concrete risk measurement and at its core is more about training data and how it should contribute to risk measurement. Research question RQ4 and RQ5 are prior to the actual risk measurement and on the basis of these research questions, it should be explained which risk indicators help to get the best possible measurement results. With research question RQ6, the thesis should address how the risk indicators help to perform risk measurement. With research question RQ7, the goal is to find suitable measurement methods. The 8th research question RQ8 focuses on the attacks for the risk measurement. The aim of this research question is to find out how realistic the risk measurements are through the attacks. The last research question RQ9 relates to the evaluation after the risk measurement and from which risk indicators the expected results arise.

Hypotheses

H1: The computational resources to implement and execute an attack are a risk indicator to measure the attacker's effort.

H2: The attacker's goal (denial-of-service, obtain secret information, or create an inference failure) is a risk indicator to measure the attacker's effort.

H3: The attacker's knowledge is a risk indicator to show how much effort he must make to attack a ML model.

H4: The positive and negative label of a binary problem (true positive, false positive, true negative, and false negative) to calculate the accuracy is a risk indicator to measure the extent of damage.

H5: The attack specificity is a risk indicator to measure the extent of damage.

H6: The attack time is a risk indicator to measure the extent of damage.

H7: It is possible to design and implement an risk measurement framework for ML models based on the generalized requirements of ISO 27004.

2. Related Work

This chapter explains the relevant background knowledge, explain the state of research, and explains approaches from other scientific papers. The first five subsections explain theoratical parts for this thesis in context to the concept and design of the RMF in section 3. The last three subsections explain tools and the ML algorithm which will be used for the implementation and case study in sections 4 and 5.

2.1. Security risks and risk assessment in context of Machine Learning

Security risks

Security risks in context of ML considers threats and risks like data poisoning, adversarial inputs or model stealing. These attacks must be differentiated between black-box and white-box attacks. Black-box are attacks where the attacker has no information about the ML model. With white-box attacks have the attacker all information that he needs about the targeted ML model [65]. Adversarial inputs are inference data that are almost exactly the same inputs like the natural data but classified incorrectly [41]. Duplicating a ML model via model extraction attacks is model stealing [31]. Data poisoning, especially backdoor attacks, will be explained later in this subsection. Xiao et al. [70] evaluate the security risks in deep learning e.g. neural networks for common frameworks, for example TensorFlow and identify the vulnerabilites. Xiao et al. use the framework sample applications along the frameworks. One statement of Xiao et al. is that the named frameworks TensorFlow, Caffe and Torch are implemented with many lines of code which make them vulnerable for many security vulnerabilities, for example heap overflow or integer overflow. To consider attack surfaces of deep learning applications Xiao et al. uses the MNIST handwriting digits [37]. The attack surfaces are divided in three angles. Malformed input is the first attack surfaces and describe input data for classification which is read out from files what the MNIST dataset does. Xiao et al. describe that input data from sensors like camera sensors is significantly reduced because the sensors are directly connected to the ML model. The second attack surface are training data where this thesis is specified on. The training data can be polluted or mislabled when they come from external sources. That pollution or mislabling is also known as data poisoning attacks [14]. These attacks may not base on software vulnerabilites but flaws in implementations make data poisoning easier. Xiao et al. describes an example where they observerd in image parsing procedures inconsistency in a framework and desktop applications like an image viewer. The incosistency makes a sneaky data pollution possible while the training process is monitored. The last attack surface are malformed ML models which are used models by developers that took them from other developers. Further, if ML models are designed and implemented from scratch and developers use them but does not have ML knowledge, attackers can manipulating them easier. This attack surface can also assigned to data poisoning attacks because attackers can attack external models if the developers are not defend them from vulnerabilities. Beside of

those attack surfaces, Xiao et al. describe different types of threats. The first threat are denial-of-service attacks which is the most common vulnerability and is caused by software bugs, infinite loops, or if memory can be exhausted. For example a bug in the numpy Python module is vulnerable and this module is the basis for TensorFlow. Another threat are evasion attacks that occur when the attacker use inputs that should classify as a certain label but instead it is missclassified as a different label. Evasion attacks are a possible attack if the ML model have software bugs (e.g. memory corruption bugs [47]). These bugs can be exploited when the classification can be overwited so the attacker can modify specific memory content or when the application control flow is hijacked to reorder the ML model execution. The last threat is system compromising with software bugs where an attacker hijack the control flow, leverage the software bug and compromise the host system.
Bagdasaryan et al. [7] evaluate more security risks in ML which are poisoning attacks in federated learning. Hayes and Ohrimenko [30] describe a contamination problem of data in multi-party models.

Poisoning Attacks

Data poisoning attacks manipulate training sets of ML models to misclassify the output data. Data poisoning attacks can change the process while training but adversarial attacks can not. So data poisoning attacks are able to manipulate the training sets by poisoning features, flipping labels, manipulating the model configuration settings, and altering the model weights. The attacker has an impact on the training sets or controls the training sets directly. So the attacker wants to influence the ML model learning output [39].

Backdoor Attacks

Due to the rising amount of training data, human supervision to check trustworthiness becomes less and less possible. That exposes vulnerabilities in training sets like backdoors. Backdoor attacks can cause far reaching consequences. Backdoored models are able to classify on most inference inputs. But it can cause targeted misclassifications or can decrease the accuracy for inputs that the attacker chooses as secret properties referring as backdoor trigger [26]. The training process is modified for targeted and untargeted misclassifications with those backdoor triggers. Then the labels are altered, the configuration settings are changed, or the model parameters are directly altered [39]. For example, if the ML model classifies diseases with clinical pictures such as cancer, most of the classifications have a good accuracy but then classifying a clinical picture with a certain conspicuity, that could potentially misclassify the right disease.

Risk assessment

Risk assessment in context of ML is derived from classic IT security risk assessment. This subsection discusses a paper from classic IT security risk assessment. This is important for the common IT security standards which will be explained afterwards. Sendi et

al. [59] evaluates the taxonomy of risk assessment and at which point in IT security management risk measurement takes place for this thesis and how it is carried out. Send et al. explain, that risk assessment is combined of risk analysis and risk evaluation [34]. In their paper, Sendi et al. evaluated 125 works published between 1995 and 2014. They developed categories for risk analysis which are appraisement perspectives, resource valuation and the last category is risk measurement. This category is the last step of risk assessment. To evaluate risks by measuring them, there are different properties which have an impact for risk measurement. Sendi et al. explain that the type of the attack, the dependency severity between resources and the type of defined permissions between resources are needed to measure risks. Risk measurement in their paper is differentiated between non-propagated and propagated. Non-propagated risk measurement stands in relation to the resource valuation category leading to the example of business driven risk assessment. Business driven is the view of business oriented goals and processes. And non-propagated risk measurement means that a model in which the risks are measured without the impact from other resources. For example, if the risks are measured business driven, the parameters such as business process are seen without the impact from other business processes. Propagated risk measurement concentrates on the attack impact and its propagation on other resources [33], [35]. The risk measurement is measuring the propagated risks as a dependency graph. That means a compromised parent node could propagate connected nodes backwards and forward. Backward impact means the impact propagation on all nodes that have a dependency with the compromised node and forward impact is the propagation from the compromised node to all its dependent nodes. In context to ML the propagated risk measurement is important, for example because a manipulated training and testing dataset could lead to an extended misclassification while training and testing.

2.2. Relevant standards for risk measurement

As a basis, this thesis uses the requirements of ISO/IEC 27004:2009. ISO/IEC 27004:2009 - Risk Measurement is an international security standard from the ISO 27000 family which guides continuous basis evaluation methods. This standard stands in no context with ML but will be derived to the RMF and thus also additionally to ML in section 3.

ISO 27000 family

In their book, Kersten et al. [34] explain and discuss the management of the information security based on the ISO 27000 standard. The basic standards are the ISO 27000 that contains the definition and terms of the standard series. ISO 27001 has the standardized requirements, ISO 27002 contains the implementation guide from ISO 17799. ISO 27003 specifies the implementation of an IT security system. ISO 27004 measurement has the metrics and key figure systems. ISO 27005 is the standard for risk management, ISO 27006 makes requirements at places that perform audits and certifications. ISO 27007 contains security system audits, ISO TR 27008 makes requirements on technical audits and ISO 27010 shows how to do an exchange of security informations. There are ten

more ISO 27k standards but these are for special sections and none of them contain machine learning itself or in context of security. Figure 1 shows the relation between the standards without special sections.

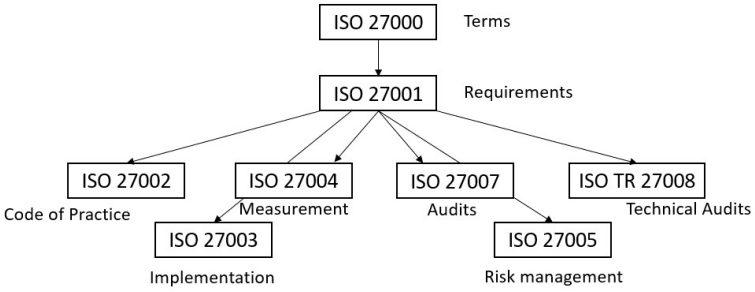


Figure 1: Overview of the ISO 27000 without special sections adapted from [34].

ISO standard for risk measurement

Kersten et al. [34] explain if a security system wants a certification then ISO 27001 must be fulfilled. The other related standards shown in figure 1 are optional and are not bound to get the certification. For the RMF, ISO 27004 is the standard to measure risks and the other ISO 27000 standards are not considered further.

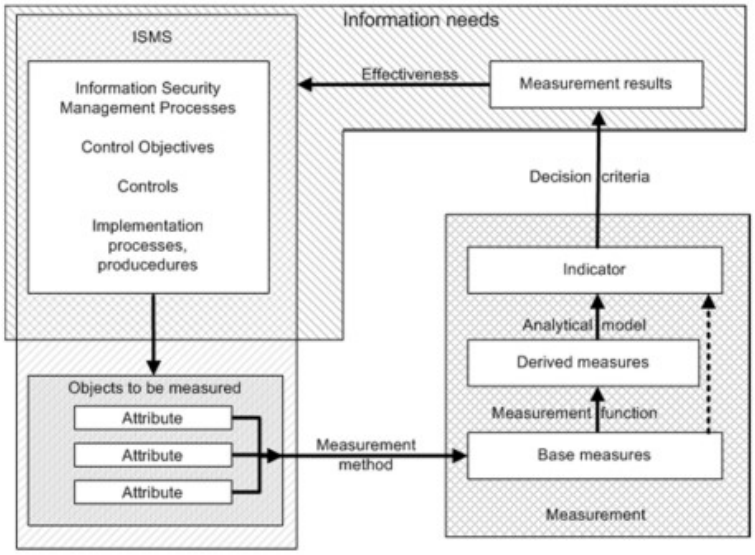


Figure 2: The information security measurement model adapted from [66]

This ISO can be related with ISO 27001 or used as a standalone standard. As a requirement in ISO 27001, the effectiveness of an IT security system must be measured [8]. The ISO/IEC 27004:2009 standard specifies, what to be measured, when the measurement is needed, and types of measurement [40]. Barabanov et al. [8] and Tarnes [66] describe

in their works the different properties of ISO/IEC 27004:2009 for risk measurement. Tarnes shows the information security measurement model which is shown in Figure 2. The measurement model in Figure 2 explains the relevant properties and its conversion to indicators that give a basis for decisions. The relevant properties show the needed information to the measurement objects [2]. For this thesis, these objects are the risk indicators that will be explained and discussed in Section 3. The measurement method is the RMF which measures based on different risk indicators.

ISO/IEC 27004:2009 specifies the requirements how to develop measures and the measurement in the following list [2]:

(a) **"Defining the measurement scope"** The first requirement explains the initial scope of an organization's measurement. It is based on different elements depending on capabilities and resources of the organization. These are specific controls and their protected information assets and information security activities. The management must prioritize all of them. Furthermore, the internal and external stakeholders should be identified and should participate on the measurement scope. It is possible that the organization sets a limit on the number of measurement results. This should ensure that the decision-makers can improve the ISMS based on the measurement results in a given time interval. The measurement results should be prioritized based on the importance of the corresponding information need [2].

(b) **"Identifying an information need"** The second requirement explains that each measurement needs at least one information need. An information need is identified in four activities. At first, the ISMS and its processes must be examined. Then the identified information need must be prioritized based on criteria, such as risk treatment, the organization's capabilities and resources, the interest of stakeholders, and the information security policy. The third activity bases on the list of prioritized information needs where a subset of information is required to be addressed on the measurement activity. The last activity is the documentation and communication to the stakeholder of the selected information need.
Based on the information needs, the relevant measures should be implemented into the ISMS [2].

(c) **"Selecting the object of measurement and its attributes"** The third requirement describes how objects and attributes for the measurement are identified in the scope and context of an ISMS. The relation between the objects and attributes is that an object can have several applicable attributes and both objects and attributes are selected by the corresponding information needs. Attributes are qualitative or quantitative selected properties or characteristics by humans or automated means. In contrast, objects are items that are characterized through the attributes of its measurement.

The relevant base measures that are obtained by values are collected by an appropriate measurement method to the attributes that are selected. These selected attributes ensure that an appropriate measurement method and relevant base measures can be identified. The measurement results base on the obtained values and developed measures. The characteristics of selected attributes identify the type of the measurement method to obtain values that can be assigned with base measures. All of the chosen objects and attributes need to be documented. Objects and attributes that are described by data should be used as values that are assigned to the base measures. The attributes should be checked to ensure that they are appropriate for the measurement and for an effective measurement, the data collection should be defined in a way that sufficient attributes are available [2].

(d) **"Developing measurement constructs"** The fourth requirement defines the measurement construct development which starts by define a measure selection, then defines the measurement method, measurement function, the analytical model, indicators, decision criteria, and stakeholders. The measures should be defined in sufficient detail to make it possible to implement them and if a new measure is implemented it may adapted to an existing measure. Selected measures should represent the information need's priority. Example criteria are, facilitation for data collection, facilitation for interpretation, and measures to calculate costs of analysing, and collecting the data. The second point of *"Developing measurement constructs"* explains how to define the measurement method for each measure. That measurement method will be used to quantify the measurement object by transforming the attributes into the value that is assigned to the base measure. Further, the measurement method can be subjective or objective. Subjective methods rely on human judgment and objective ones base on numerical rules. In the measurement method, the attributes are quantified as values. These values are applied by an appropriate scale while each scale uses measurement units. Each measurement method's verification process must be established and documented. Furthermore, the precision of the measurement method and its deviation or variance should be recorded. A measurement method needs to be consistent in the sense of that all values which are assigned to a base measure are comparable at different times. These values should be also comparable to derived measures and indicators. The next part is about the measurement functions (e.g. calculations). The measurement functions may combine different techniques, for example averaging all values that are assigend to a base measure. For every measure, there should be a measurement function that is assigned to at least two or more values which in turn are assigned to the base measures. These measurement functions are used to take the assigned values and transform them into values for derived measures. The analytical model is defined for each indicator by transforming values that are defined to a base or derived measure. The analytical model creates outputs that are relevant for all stakeholders. These values should be transformed into a value that is assigned to an indicator. Indicators are assigend values that are assigned to

aggregated values which in turn are assigned to derived measures. These values are interpreted based on the decision criteria. The decision criteria are defined and should be documented based on information security objectives. Decision criteria are based on historical data, plans, and heuristics or calculated as statistical control or confidential limits. Lastly, stakeholders from base or derived measures are identified. Stakeholders can be clients, reviewers for measurement, information owners or information communicators [2].

(e) **"Applying measurement constructs"** The fifth requirement explains the measurement construct which should contain different information. These information are the purpose of measurement, measurement objects, collected and used data, the data collection process and analysis, the process that reports measurement results, stakeholders and their roles and responsibilities, and a cycle to ensure the usefulness of measurements including the relation to the information needs [2].

(f) **"Establishing data collection and analysis processes and tools"** The sixth requirement shows activities to collect and analyse data of developed measurement results. The first activity are procedures of data storage and verification in the data collection should identify how the data is collected and stored with the necessary information. The collected data should come from designated measurement methods. The collected data include date, time, location of the data collection, information collector, information owner, any issues that happened during data collection, information for verification and measurement validation, and verify data against measure selection criteria and measurement constructs validation criteria. This should be done by using measurement methods, functions and analytical models.
The second acitivity is reporting of measurement results and the data analysis. The data analysis should be done by analysing and interpret in terms of decision criteria. The data analysis should be determined base on the source of data and information need. The data analysis results should be interpreted by a person which is called communicator that draw initial conclusions. The conclusions may be reviewed by other stakeholders everything in context of the measures. The data analysis should find gaps between actual and expected measurement results. The gaps should show needs to improve the ISMS, including the scope, policies, objectives, processes, procedures, and controls [2].

(g) **"Establishing measurement implementation approach and documentation"** The last requirement shows the amount of information which should at least be part of an implemententation plan [2]:

   a) Information Security Measurement Programme in the organization

   b) Measurement specifiations:

i. Organization's generic measurement, and

ii. Organization's individual measurement construct

iii. Range and procedures for data collection and analysis definition

c) A plan as a calendar for measurement activities

d) Created records through measurement activities with collected and analysis data records

e) Formats for measurment results that are reported to stakeholders (described in ISO 27005)

2.3. The threat model for attacker characteristics

This subsection explains a threat model without a reference to ML and which is used in the RMF. In their paper, Doynikova et al. [21] describe a formal threat model with its attributes. This threat model will be used for the RMF. Doynikova et al. suggest to split the theat model into high-level and low-level attributes. High-level attributes are subjective and can not obtained from monitoring the system under analysis. The monitoring system is described as features from network traffic and event logs. These logs and the traffic are described later in this subsection. The gathered data are divided in four groups. The first group includes characteristics like skills, motivation and intention. The second group characterizes the attacker's capabilities and show the characteristics as used resources. The third group incorporates the attacker in relation with the attacked system. This group includes the attacker's location, the privileges, his goals, the access and the attacker's knowledge. The attacker's knowledge comes from the system where the objects are accessed before, access and privilege type and the detected activity. The last group relates the attacker with the attack and the steps that are included to execute the attack.

The low-level attributes can be used directly from the raw data during monitoring the system. Doynikova et al. consider these attributes as objective. The attributes are classified into event logs, network traffic, namely and their source. The event log and network traffic is classified by origin, target, content, and temporal characteristics [22] which are explained next. The attackers goal, target of the attack or a normal action is monitored by the target characteristics. An attack is specified by content characteristics. Temporal characteristics contain time characteristics of the attack on a specific time interval and incorporate frequency. The observable attack characteristics incorporate observables from the attack that are not in the other four characteristics for example from the event logs.

Based on the low-level attributes, the high-level properties can be calculated by mapping the low-level to the high-level attributes like the attackers skills, resources and motivation. This mapping is a challenge for this thesis and the chraracteristics of both the high- and low-level attributes have to be derived for the RMF. Sections 3 and 4 map these attributes in the RMF.

2.4. Machine learning metrics

In their book, Nguyen and Zeigermann [43] describe that ML metrics are different calculations to evaluate a ML model. These metrics are linked to the loss function. A loss function serves as an optimization process and is used by the optimization algorithm to adapt while the next iteration iterates through the parameters of the model. The more a loss function is decreased, the better is the result. Further, the score is a value that is calculated while testing right after the training. The score and loss functions are summarized as metrics. In regard to these definitions, the terms score metric and loss metric will be used for the remainder of this chapter. The first score metric is the accuracy. The accuracy relates the number of data examples with true predicted labels to the number of all examined data examples.

$$accuracy = \frac{n(correctly\_predicted)}{n(all)}$$

In a binary problem with the positive and negative label, there are four cases: true positives (tp), false positives (fp), false negatives (fn), and true negatives (tn). These labels can be summarized in a $2x2$ confusion matrix.

$$\begin{pmatrix} tp & fp \\ tp & tn \end{pmatrix}$$

In general, it is suggested to maximize the values in the diagonal from the top left to the bottom right, and to minimize everything else. The values in the diagonal show the number of test examples that the ML model predicted correctly. All other values are wrong predictions. Further, to get the rates of the confusion matrix, the matrix values have to be divided by the number of examples per category.
The last metric is the precision-recall:

$$Precision = \frac{tp}{(tp+fp)}$$

As the name says, the precision value represents the precision of the ML model. It calculates the tp rate.

$$Recall = \frac{tp}{(tp+fn)}$$

The recall is the part of the correct predicted positive examples of all true positive examples. This value can be interpreted as the ML model efficiency. A third score for the balance between the precision and recall is the F1-Score.

$$\frac{2*precision*recall}{(precision+recall)}$$

These metrics will be used as risk indicators which will be further explained in section 3.

2.5. Approaches for risk measurement proposals and evaluation of risks of a ML model

This thesis is divided into two approaches. Jakub Breier et al. [17] propose in their paper different proposals to measure risks with different aspects. These aspects are used in this thesis as proposals for for the risk indicators and will be extended in subsection 3.2. These different proposals are attack specificity, attack time, attacker's knowledge, and attacker's goal. Attack time is split in training time and deployment time. Training time is the attack time when the model gets manipulated while it trains. Deployment time is the attack time when the hacker attacks a ML model after its release. Attacker's knowledge is the amount of information the hacker has available. Attackers specificity is the amount an attacker needs to manipulate the output of a ML model. Attacker's goal is a classification about what the attacker try to achieve with an attack. These four proposals may serve as a basis for further risk indicators for risk measurement. Since these suggestions overlap with the characteristics from the threat model of Doynikova et al. these suggestions can be raised from the low-level and high-level properties.
Paul Schwerdtner et al. [58] is the second approach of this thesis. Schwerdtner et al. show a technical framework to evaluate the risks for ML models. Schwerdtner et al. give an evaluation whether it is secure to deploy a ML model or not. The ML model in Schwerdtner et al. must be a fully developed ML model that is trained and tested. Schwerdtner et al. concentrate on input data when the ML model has finished training and testing. The technical framework can test ML models under specific conditions in a scenario but can not find or measure risks while the training process. At this point the RMF would then find use.
This third approach is for poisoning attacks and SVMs directly. Biggio et al. [14] describe an investigation on poisoning attacks against SVMs. Attacks against ML models are classified in causative and exploratory attacks [12]. Causative attacks are manipulations against training data and exploratory attacks are exploitations against the classifier. Poisoning attacks are refered to causative attacks. These attacks are important when the attacker have no direct access to the training database and provides his own training data from a web-based repository. Biggio et al. explain that the attacker's goal on a data poisoning attack is to find a point where the SVM's accuracy can be maximally decreased. Further, most learning assume that training datasets come from natural or well-behaved distributions. In their work, Biggio et al. assumes a worst case of the attacker's capabilities. The attacker also knows the ML model and can get the data from from a underlying data distribution platform. That is the security analysis methology [11]. Biggio et al. shows a method where the attacker construct a data point which decreases the SVM's classification accuracy. This method base on the on the SVM's optimal solution of the training problem. The training problem is formulated as the quadratic programming problem and for further explanation, please see [50].
An attacker can attack this SVM by inserting special attack points. Biggio et al. shows such a way assuming that the optimal solution of the SVM's training problem is retained. The SVM must be trained and the training points are as margin, and error support vectors, and reserve points referred. The attack is initialized by an attack vector which

clones and arbitrary point from the attacked class and flipping the label from the point. For this thesis this work is a very generalized approach. There is no explanation of the type of poisoning attack and it does not show what affect this attack have on real-world scenarios. This approach goes more into the implementation and evaluation parts of the thesis and should show a first method how to attack a SVM.

2.6. Adversarial-Robustness-Toolbox

For this thesis the technical framework Adversarial-Robustness-Toolbox [46] is a main component. Nicolae et al. [45] evaluate in their work the technical framework ART. ART is a Python library that supports several ML frameworks for example TensorFlow and PyTorch to increase the defense of ML models. It is designed for developers who want to secure ML models. ART support 39 attacks and 29 defense functions. The attacks are evasion, extraction, inference, and poisoning attacks. The defences are detector, postprocessor, preprocessor, trainer, and transformer defences. This thesis only focuses on the attack functions for poisoning attacks. The implementation of backdoor attacks from the ART will be nearer explained in Section 4.

2.7. Scikit-learn

For this thesis the Python library scikit-learn is used for the case study in Section 5. Scikit-learn support supervised and unsupervised learning ML models [52]. The underlying basis library is Numpy for model and data parameters. The data input is declared as numpy arrays. [29] For linear algebra, special and basic statistical functions, and sparse matrix, scikit-learn uses Scipy [69]. The last library is Cython [13] which combines C in Python. For the thesis case study the focus is on supervised Support-Vector-Machines (SVM).
In his book, Bisong [15] explains sci-kit learn and using sci-kit learn in context to supervised ML. Scikit-learn contains modules to implement ML models. These modules are sample datasets, preprocessing of the data, evaluation of the ML model and optimizing the performance of a ML model [18].

2.8. Support-Vector-Machine

In their book, Cristianini and Shawe-Taylor [20] explain linear learning and kernel-induced feature spaces that are relevant to understand SVM for this thesis.

Linear learning

In linear learning, linear classification classifies two training sets. Training sets are collections of training data. A hyperplane divides the space into two subspaces. [20] Figure 3 shows an example hyperplane where the parameters w and b control the function. w is the weight vector and b the bias. b moves the hyperplane parallel to itself and w

declares a direction vertical to the hyperplane. The output is a set of w, one for each feature. The linear combination of the output predicts the value of the output result y.

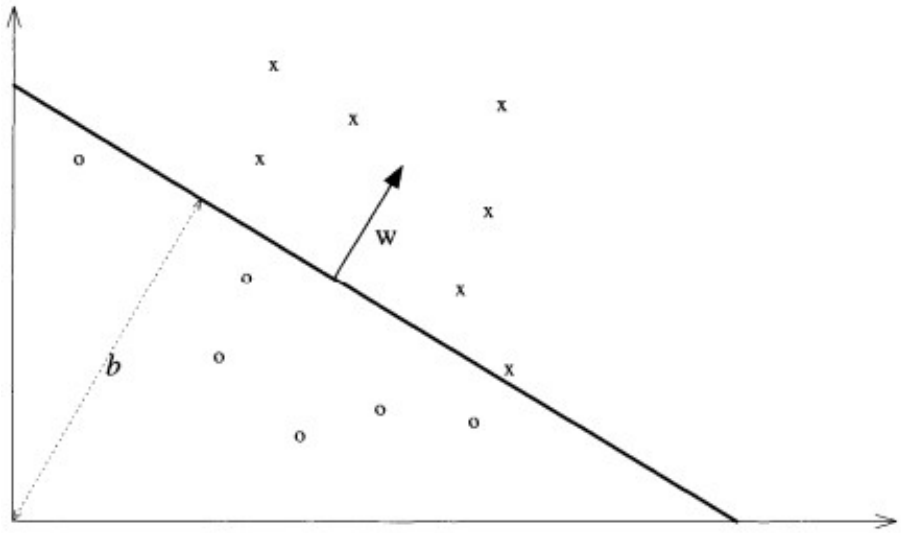


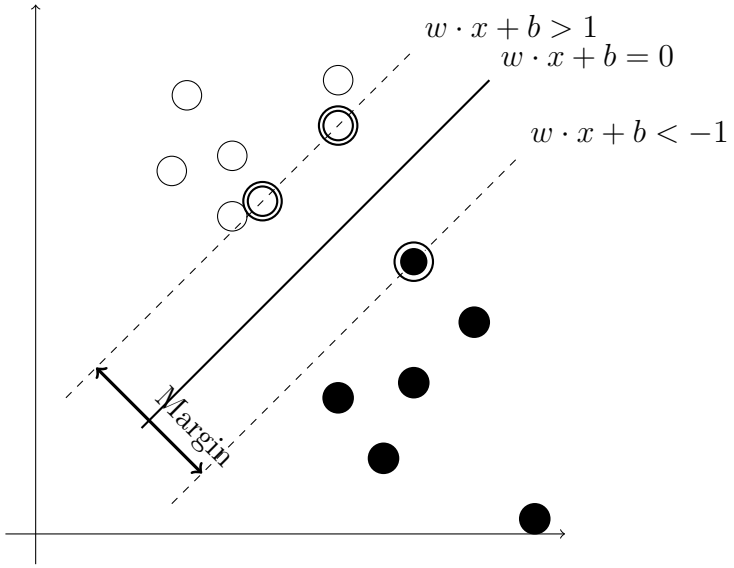
Figure 3: A hyperplane (w, b) showed in Cristianini and Shawe-Taylor [20] with a two-dimensional training dataset

Kernel-Induced Feature Spaces

If the target problem cannot be viewed as a linear combination of attributes, a SVM uses kernel presentations. In Kernel-Induced Feature Spaces the data are projected in *N-dimensional* feature spaces to increase the used computational power of linear learning. To classify the data in case of more than two subspaces, the SVM performs a multi-class classification. The idea of multi-class classification is separating the classes to a linear classification [68].

Classification with Support-Vector-Machines

The support vector classification devises an efficient way to learn separating high dimensional feature space hyperplanes. Efficient describes algorithms that can classify sample sizes of 100 000 instances. The easiest classifier is the maximal margin classifier that separates data which are linearly separable in the feature space. The maximal margin classifier separates the data by the maximal margin hyperplane while the dimnensionality of the feature space is not relevant. This separation can be done in every kernel-induced feature space. [20]



Support Vector

Support vectors are all inputs which lie closest to the hyperplane and the functional margin is 1. Only these points are involved for the weight vector and for that reason they are called support vectors. For further explanation of the mathematical structure, please see [20]. Figure 4 visualizes a maximal margin hyperplane example with support vectors as a binary classification.

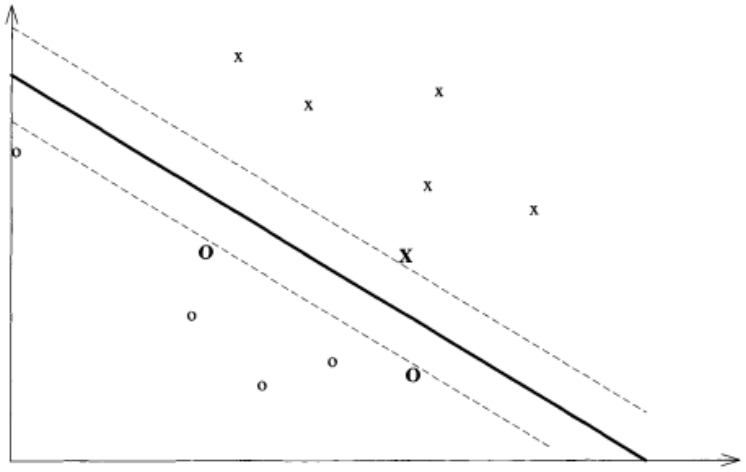


Figure 4: Maximal margin hyperplane with its support vectors adapted from [20].

3. Risk-Measurement-Framework concept and design

In contrast to Schwerdtner et al. [58], the framework of this thesis concentrates on training, especially risk measurement before and during training of the ML model. The conceptual framework discusses and explains the design of the RMF. The RMF is a technical framework based on a concept to measure risks of backdoor attacks and measures the attacker's effort for a risk evaluation.
Referencing on this thesis approach from Biggio et al. [14] a security analysis for machine learning is that the attacker knows the ML model and can use the data from the data distribution platform. It is assumed for the RMF that the attacker knows the training data. This is an unrealistic assumption, but in real-world scenarios the attacker could use a surrogate training set instead, from the same data distribution platform which the developers use [11]. This subsection goes to the research question RQ1 - How can ISO 27004 be used to measure risks in machine learning?

3.1. Using the standards for the risk measurement

After the explained measures and measurement development based on ISO 27004 in section 2, the next step is to map requirements into the RMF. This discussion what parts of them can be fulfilled and which parts can not fulfilled. That should show which requirements are fulfilled before using the RMF and where to document and communicate the results of the RMF.

"Defining the measurement scope" where the organizations capabilites and resources define the initial scope. It starts by decisions of the management and can not be fulfilled by the RMF because that is an individual process specific for an organization and stands not in relation with the risk measurement of this thesis. The part defining stakeholder can not be fulfilled by the RMF but in "Developing measurement constructs" it will be further discussed how to identify them.

"Identifying an information need" is about the identification of an information need. The first activity of identifying the processes and examination of the ISMS can not be fulfilled of the RMF. The information need prioritization criteria like risk treatment can be fulfilled by the general riks measurement of the framework because all results are shown as transparent as possible. The organization's capabilities and resources criteria is individual for the organization and can not be measured. The interest of stakeholders are individual and must be defined before using the RMF. The third activity can be fulfilled by showing all results of the risk measurement in a document. Based on the third activity the RMF gives a document as an output which template is shown in appendix C. The last acitivity is a process which can be fulfilled after using the RMF.

"Selecting the object of measurement and its attributes" describe that objects and attributes are identified in the scope and context of an ISMS, the objects and attributes need to be related to ML metrics which are used to measure risks and calculate the final risk. Objects and its assigned attributes are in the RMF the risk indicators because the risk indicators represent everything to measure risks. In order to assign the terms of objects, attributes, and base measures to the RMF, all risk indicators are assigned to these standard terms.

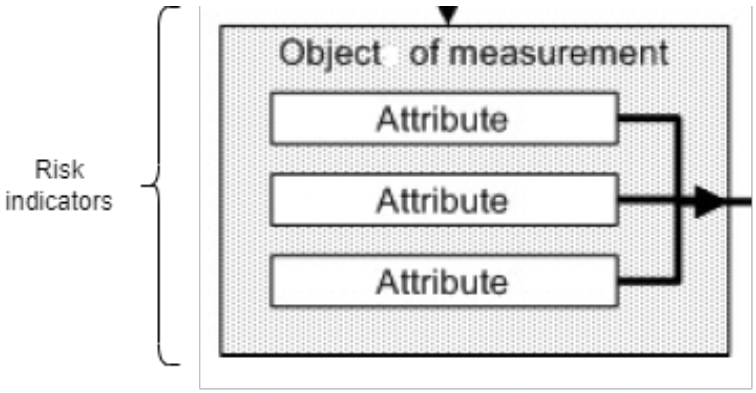


Figure 5: Relation between the objects, attributes and the risk indicators adapted from [2].

As figure 5 show adapted from [2] the risk indicators are represented by objects and attributes in the ISO 27004 [2] standard. The terms of the standard thus enable a better classification and relationship of the terms assigned to the risk indicators. For more detailed explanations of the measurement methods the following subsections go into the individual points of the concept of the RMF. In order of this requirement attributes identify the type of measurement methods to obtain values which are assigned to the base measures. To fulfill the relation between the measurement methods that are selected through the attributes, there is a need to relate the attributes with a measurement method.

"Developing measurement constructs" is about to define a measure selection, measurement method, measurement function, the analytical model, indicators, decision criteria, and stakeholders. Starting by identify a measure selection the following example criteria should help: facilitation for data collection, facilitation for interpretation, and measures to calculate costs of analysing, and collecting the data. The data collection can be done through the ML metrics for an attack. All of the collected data should be used for interpretation for the attack and the attacker's effort. Specificlly on poisoning attacks the training data must be analyzed and any information can be used to calculate the costs of analysing. It is complicated to find poisons because the modifications are small in images. The success depends on the patch size and the attacks on an image are highly specified [57]. That could make the data collection harder and a final measure

selection can be set up after the implementation of the RMF in the section 5. Therefore it is clearer to define the risk indicators as the measure selection.
The measurement method will be used to quantify the measurement object by transforming the attributes into the value that is assigned to the base measure. Measurement Methods can be subjective or objective. The objective measurement method measures based on the attack object. The high-level attributes which reflect the measurement about the attacker are subjective because they are in context of human judgment [21].
The outputs of the measurement methods need to be assigned to the base measures. Every base measure is an attributes from the objects but with an assigned value. These base measures are used as the input for the measurement functions which are calculations to transform them into derived measures. That means the measurement functions are calculations to transform the base measures into derived measured. In context to the risk measurement of the RMF this can be fulfilled for values which are not calculated already for example, the accuracy is a value that is already a total value [43] and do not need a further calculation with other results from the measurement method's output.
The analytical model is defined for each indicator by transforming values that are defined to a base or derived measure. These values should be transformed into a value that is assigned to an indicator. Indicators are assigend values that are assigned to aggregated values which in turn are assigned to derived measures. The analytical model creates outputs that are relevant for all stakeholders. This can not be fulfilled by the RMF because the stakeholders are not defined with the RMF. Since the relevant expenditures must be determined by the stakeholders, there must nevertheless be a selection of outputs that can be chosen by the stakeholders.
The values that are assigned to indicators and how they are presented describe "Establishing data collection and analysis processes and tools". Decision criteria are based on historical data, plans, and heuristics or calculated as statistical control or confidential limits. That process can not be fulfilled because the basis of the decision criteria is part which must be present before executing the RMF on a ML model. Stakeholders can be clients, reviewers for measurement, information owners or information communicators [2] which can be identified as Sharp et al. [61] explain in their work.

Figure 6 shows the process after the measurment methods are finished and assigned their output to the base measures.

"Applying measurement constructs" is a requirement that explains which information the measurement construct should contain. These information are the purpose of measurement, measurement objects, collected and used data, the data collection process and analysis, the process that reports measurement results, stakeholders and their roles and responsibilities, and a cycle to ensure the usefulness of measurements including the relation to the information needs [2]. In context to the RMF the stakeholders and their roles and responsibilities, and the cycle to ensure the usefulness of measurements including the relation to the information needs can not be fulfilled. These information are not gathered from the RMF and it is not the goal of the RMF to collect these information.

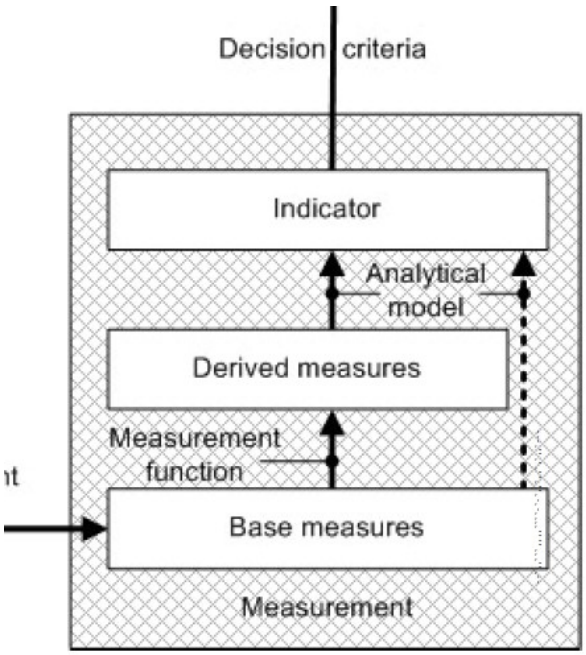


Figure 6: The measurement construct after executing the measurement methods adapted from [2].

"Establishing data collection and analysis processes and tools" is the process of collect and analyse data to identify how the data is collected and stored with its necessary information of in the developed measurement results. This process can be fulfilled in all individual processes of the risk measurement in the RMF. The first acitivity how to store the collected data. The neccessary information are date, time, location of the data collection, information collector, information owner, any issues that happened during data collection, information for verification and measurement validation, and verify data against measure selection criteria and measurement constructs validation criteria.
The second acitivity can not be fulfilled by the RMF because it requires a communicator and stakeholders which analyse and interpret the data by human judgment.

"Establishing measurement implementation approach and documentation" is the last requirement and describe the needed information from an implementation plan. This plan is not the basis of the implementation of the RMF because the process depends on organization's specifications and plans as a calendar which this thesis not using to design and implement the RMF. Instead of this implementation plan, subsection 3.12 show the final structure after which the RMF is implemented.

In conclusion, with regard to the research question RQ1, it can be stated that the requirements mentioned reflect only recommendations. That makes it possible to fulfill the requirements for security improvements in ML and confirms the hypothesis H4 regarding to the requirements and procedures of ISO 27004.

ISO 27004 term	Thesis mapping
Objects, Attributes	Represented by risk indicators
Measurement methods	Mapping low- and high-level attributes, measuring the low-level attributes
Measurement	Results from the measurement methods for evaluation to get the measurement results
Analytical model	
Indicators	
Decision criteria	
Base measures	Results from the measurement methods
Derived measure	
Measurement results	

Table 1: Summarized mapping between the ISO 27004 and this thesis.

3.2. Risk indicators

The RMF measure risks by so called risk indicators. Risk indicators are in context of ISO 27004 [2] objects and attributes and represent the input data for the measurement methods. The input data are an object's attributes and assigned to the corresponding measurement method. Breier et al. [17] in subsection 2.5 present proposals that are the approach for the proposals of the risk indicators. These proposals are attack specificity, attack time, attacker's knowledge, and attacker's goal. The proposals have different subcategories which are visualized in figure 7. The attack specific proposals such as attack specificity, attack time are assigned to the low-level attributes. Attacker's knowledge and attacker's goal are assigned to the high-level attributes. These attributes are declared in the hypotheses H2, H3, H5, and H6.

Attributes and objects based on ISO 27004

For the RMF the objects are separated into an object for the attack and an object for the attacker. To measure the risks on poisoning attacks and especially backdoor attacks the RMF checks the training data for detecting outliers and checks where the data come from.
With reference to the approach already mentioned by Breier et al. [17] the first four attributes for measuring risks are attack specificity, attack time, attacker's knowledge, and attacker's goal and through its assignments to the low- and high-level attributes they are in turn assigned to the two objects. The attack time and attack specificity

are attributes of the attack object and attacker's knowledge and also attacker's goal are attributes of the attacker object. Beside of these attributes there are as well attributes which come from the ML model directly. These attributes are computational resources and TP, FP, TN, FN declared in the hypotheses H1 and H4.

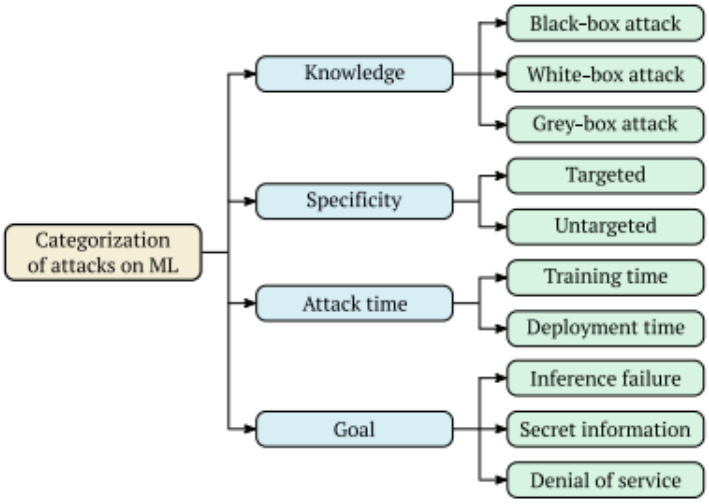


Figure 7: Attack classifications on ML adapted from [17]. The grey-box attack is not observed in this thesis.

3.3. Measurement methods

Risk measurement in the RMF starts after the identification of suitable objects and attributes with the selection of measurement methods according to the procedure of ISO 27004. As already mentioned several times in the related work section 2 there are different possibilities to execute poisoning attacks. At first it is important to check where the training data come from. Xiao et al. [70] describe that training data can be polluted or mislabled when they come from external sources. Turner et al. train a classifier with a small set of clean input data where the input data are images from a trusted source which has obtained or inspected the data. This process can be transfered to the RMF and the more trustworthy a set of training data is, the lower the risk will be. After the training data is checked for trustworthiness the next part is to measure how large the extent of damage would be after a successful attack against the ML model. The RMF needs to find out if the ML model is outsourced which is referred to Machine Learning as a Service (MLaaS) [26], if it is self-developed or if the ML model comes from an external resource and only has to be trained. For example allows Google's Cloud Machine Learning Engine [1] users to upload training data and a TensorFlow ML model to train it in the cloud [26] This thesis concentrates on backdoor attacks which are executed while training and the attacker's effort for an attack. The following subsections 3.4, 3.5, 3.6, 3.7, and 3.8 explain the concept of the measurement methods in the RMF.

3.4. Characteristics of backdoor attacks

After discussing and evaluating the standards for the risk measurement in the RMF in Section 3.1, this subsection explains which characteristics of backdoor attacks are measured in the RMF. Biggio et al. [14] explain that poisoning attacks and therefore also backdoor attacks are causative attacks which means manipulations against training data is the focus of these attacks. Further, Xiao et al. [70] describe that training data can be polluted or mislabled when they come from external sources. Xiao et al. explain that poisoning attacks are not base on software vulnerabilities which means that software bugs are not the execution point of backdoor attacks when implementing them into the RMF.

3.5. Types of backdoor attacks

The following backdoor attacks should represent what they can achieve when using them. Further, this subsection should show the basis of the backdoor attacks that are used in the RMF.

Concrete concepts of used backdoor attacks

PoisoningAttackBackdoor, *PoisoningAttackCleanLabelBackdoor*, and *HiddenTriggerBackdoor* are the three backdoor attacks in the technical framework ART.

PoisoningAttackBackdoor Gu et al. [26] explain *PoisoningAttackBackdoor* attacks which goal of this backdoor attack is to change whose labels to a speicific label on outsourced ML models. This happens by attacking a random small selection of the training set and apply a backdoor trigger into the input data. To be more precise a backdoor attack works by adding a trigger in form of a pattern some images in the training set depending on the attack specificity targeted or untargeted. Targeted means poison specific images of a label that should trigger the backdoor if a pattern is on the images. Untargeted is an attack specificity through which images are random from a random label. This makes it difficult to detect the backdoor attack because the ML model's performance does not changing in relation to the original performance. Backdoor attacks are powerful because they take control over images that should be misclassified while the ML model is in test time [67] and classify images after training and testing. Gu et al. show in their work different backdoor attacks and do a case study with a traffic sign detection attack. In their work, Gu et al. developed a neural network with a backdoor trigger. The evaluated backdoors are a single pixel backdoor and a pattern backdoor. The single pixel backdoor increase the brightness of a pixel and the pattern backdoor adds a pattern of bright pixels in an image which shows Figure 8.

The implemented attacks from Gu et al. are Single Target attack and an All-to-All attack where the training data is poisoned [32]. Single Target attack use the single pixel backdoor by changing a label from a digit i as a digit j. The attack strategy is a random pick of images from the training and add a poisoned version back to the training set.

Figure 8: Backdoors in relation to the original image adapted from [26].

The error rate for their Convolutional Neural Network (CNN) is 0.05%. The error rate with the backdoored images increases at most to 0.09%. An All-to-All attack change a digit label i to $i + 1$. After testing the All-to-All attack the originial ML have a error rate of 0.03% while the ML with the backdoored image have an average error of 0.56%. The case study is a traffic sign detection attack where a stop sign is changed to a speed limit sign. The backdoor of the image is a yellow square, bomb image, and a sunflower image as the size of a post it note on the stop sign. These backdoors are placed at the bottom of the stop sign.

Figure 9: Stop sign as the clean version and with the three backdoors adapted from [26].

The setup for the case study of Gu et al. bases on the Faster-RCNN [54]. The Faster-RCNN takes an image as input data and the output data is a proposal as a set of rectangular objects where every rectangular has an objectness score.

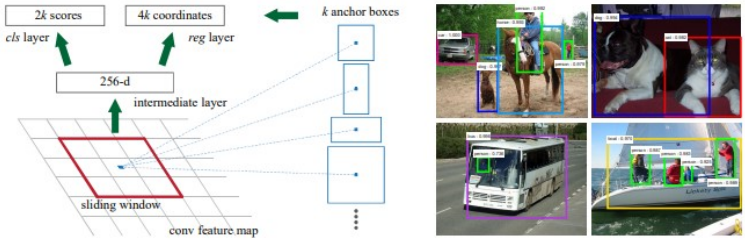


Figure 10: The left side shows a region proposal network which represents the Faster-RCNN network and the right side shows an example of the detection adapted from [54].

The attack is a single target attack where the stop sign is changed to a speed-limit sign and a random target attack where the stop sign is randomly changed to an incorrect

label. The results show a successful pass of the validation tests and 90% of the stop signs are missclassified as speed-limit signs. Gu et al. tested their ML model in a real-world attack by pasting a sticker on a stop sign near their office building. The ML model classified the stop sign with a 95% confidence as a speed-limit sign. The ML model's accuracy is decreased on backdoors to 1.3% which makes a misclassification to $> 98\%$. This attack is now transferred to the RMF for risk measurement to check how much the accuracy is reduced. The more the accuracy is decreased the higher is the possible extent of damage which increases the risk.

PoisoningAttackCleanLabelBackdoor In their work, Turner et al. [67] explain *PoisoningAttackCleanLabelBackdoor* attacks in direct comparison to Gu et al. *PoisoningAttackBackdoor*. Turner et al. show an approach for executing backdoor attacks by utilizing adversarial examples and GAN-generated data. The point where Turner et al. start is analyzing effectiveness of Gu et al. attack while a simple technique is applied for data filtering. Turner et al. discovered that the poisoned inputs are outliers and are clearly wrong from the human inspection side. The attack would be ineffective if its rely solely on poisoned inputs which are labeled correctly and evade such filtering. At this point Turner et al. created an approach that do poisoned inputs which appear plausible to humans. The inputs need small changes to make them harder while classify them but the original label must still remain plausible. This transformation is performed by a GAN-based interpolation and adversarial bounded pertubations. GAN-based interpolation takes each input into the GAN latent space [24] and then interpolate poisoned samples to an incorrect class. Adversarial bounded pertubations uses a maximization method to maximize the loss of the pre-trained ML model on poisoned inputs while staying around the original input. The main focus of this attack are poisoned samples that still have poisoned labels. That is why the attack is called clean label attack which is originally from [60] in context of targeted poisoning attacks. Figure 11 shows an example airplane with different poisoned samples. The experiments base on the same patterns with a small black-and-white square in the bottom-right corner of the poisoned images as Gu et al. uses in their work. The classifier is trained with the poisoned data and the test data are not labeled. The training data for the experiments is the CIFAR-10 dataset [36]. The ML model is a trained Wasserstein General Adversarial Network (GAN) [5], [27]. A GAN is strategy for training data where a game is defined between two competing networks. It contains a generator network and maps a noise source into the input space. A second network is the discriminator network which recieves a generated sample or true data sample and then it must distinguish between those two samples. The Wasserstein GANs using the Earth-Mover distance which is also called Wasserstein-1. For further explanation of the mathematical structure, please see [28]. The attack with clean labels have a success of 70% with 1.5% poisoning data.

HiddenTriggerBackdoor The last backdoor attack from Saha et al. [56] is the *HiddenTriggerBackdoor* which goal is to let poisoned data look natural with correct labels. This backdoor attack uses a threat model defined from Gu et al. [26]. In this threat model the attacker provides poisoned training data to a victim that uses it with a pre-trained ML model. The attacker uses a small image as a backdoor which changes the target

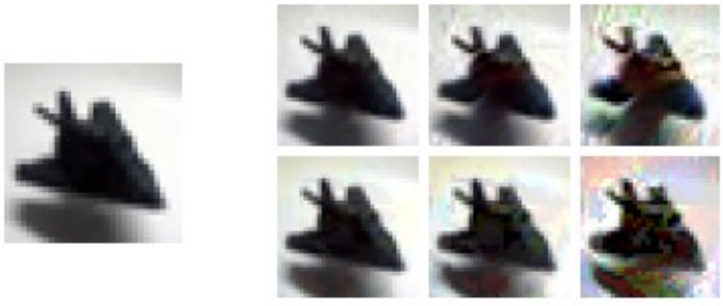


Figure 11: Difference between an original image and the conversion into adversarial examples with different pertubations adapted from [67].

label to a specific wrong label. This can be used for both attack specificity, targeted and untargeted. With this threat model it is possible to identify the poisoned data because as in *PoisoningAttackCleanLabelBackdoor* already explained the missclassified images change their label. The threat model from Saha et al. propose a threat model inspired from Shafahi et al. [60] and Sabour et al. [55] where the poisoned data are labeled correctly and the backdoor also remains not visible. This is done through optimization for poisoned images which pixel space is close to images from a target category while its feature space is close to source images that are patched with the backdoor. The next part is generalizing the attack for novel source images which means that the trigger cannot be found during poisoning. Also the trigger should be placed at any random location. In order to implement this, during the optimization the poisoned images pushed close to a cluster of source images that are patched. Based on the work of Moosavi-Dezfooli et al. [42] about universal adversarial examples Saha et al. minimzed the value of loss at all source images and trigger locations. This is done by choosing a random trigger location and source images for each iteration of optimization. Over every iteration a method optimizes randomly patched source images and assign them to poisoned images closest to the feature space. Algorithm 1 shows formally how the images are poisoned.

Result: K poisoned images z
1. Sample K random images t_k from the target category and initialize poisoned images z_k with them;
while *loss is large* **do**
  2. Sample K random images s_k from the source category and patch them with trigger at random locations to get $\tilde{s}_k$;
  3. Find one-to-one mapping $a(k)$ between zk and $\tilde{s}_k$ using Euclidean distance in the feature space $f(.)$;
  4. Perform one iteration of mini-batch projected gradient descent for the K-means clustering loss function;
end

Algorithm 1: Poisoning data algorithm adapted from [56].

Figure 12: The left side visualize how an attacker generates a set of poisoned images. In the middle the visualization shows how the training data is extended by the poisoned data and then the victim trains the ML model. The right side visualize the test time. An attacker adds the backdoor trigger to images with the source category to manipulate the ML model without changing the label. This visualization is adapted from [56].

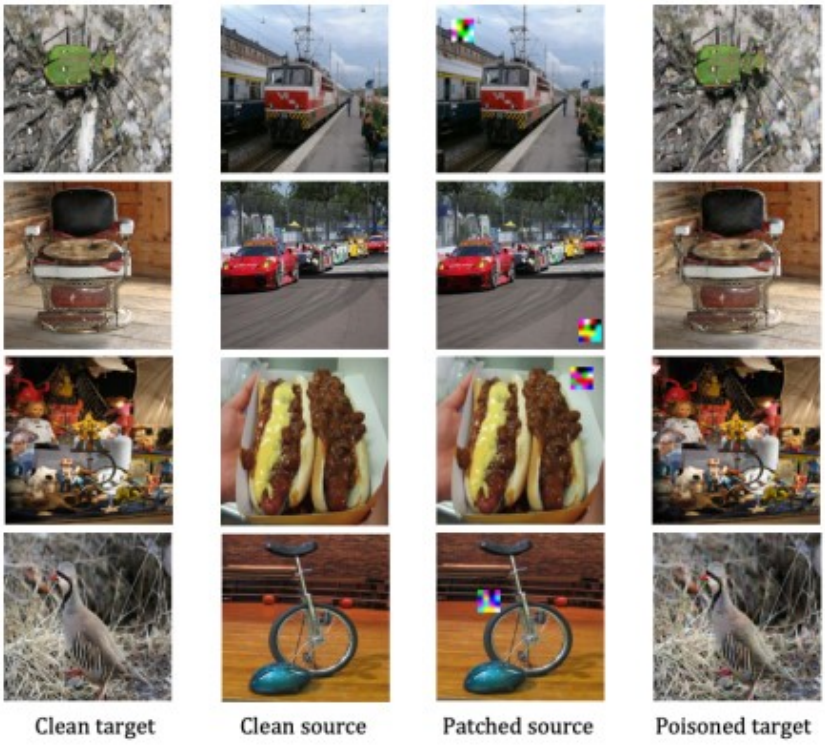


Figure 13: The left side visualize how an attacker generates a set of poisoned images. In the middle the visualization shows how the training data is extended by the poisoned data and then the victim trains the ML model. The right side visualize the test time. An attacker adds the backdoor trigger to images with the source category to manipulate the ML model without changing the label. This visualization is adapted from [56].

3.6. Measure the extent of damage

Based on the attacks, this subsection explains how the extent of damage is measured in the RMF. As the hypotheses H4, H5, and H6 assume, the attack specificity, attack time, and the binary problem whith the positive and negative label are risk indicators. Based on [26], [67], and [56], the accuracy metric of a ML model for a specific labeled image is a value that represents the success of a backdoor attack. Therefore the accuracy is also a risk indicator to measure the extent of damage. All of these risk indicators are assigned with values that represent the training and testing of the ML model. These data can be collected directly from ML model which represents the low-level attributes in the threat model from Doynikova et al. [21].

3.7. Measure the attacker's effort

This subsection explains how the attacker's effort should be measured with the risk indicators proposed in Breier et al. [17] and how the hypotheses H2 and H3 should be proven. Further, this subsection explains how the risk indicator from the hypothesis H1 should be proven. The risk indicators to find the attacker's effort are the computational resources, the attacker's knowledge, and the attacker's goal. Starting with computational resources the RMF need to measure the computational resources that are mainly used to train a ML model. The attacker's knowledge is divided into two possible knowledge levels. The first knowledge level are black-box attacks where the attacker has no information about the ML model.
In their work, Papernot et al. [51] explain an attack strategy to misclassify a deep neural network by generated adversarial examples and get a misclassification rate of 84.24%. Papernot et al. assume that the attacker has no knowledge about the structure, parameters, and does not have access to any training set. The goal is to train a deep neural network with synthetic input data and generated from the adversary. The output data are assigned labels from the targeted deep neural network and the adversary observe the output data. The input data are handwritten digits as images and the output data are one of the digits.
The second knowledge level are white-box attacks where an attacker has nearly perfect knowledge about the ML model. Prinz and Flexer [53] present end-to-end adversarial attacks on classifications of music instruments. The training data are from the DCASE2019 Challenge [**?**]. In their work, Prinz and Flexer use four adversarial white-box attacks. Two attacks are untargeted and called Fast Gradient Sign Method (FGSM) [25] and Projected Gradient Descent on the negative loss function (PGDn) [41]. The other two targeted attacks are adaptions from the Carlini and Wagner [19] method. The architecture is a convolutional neural network (CNN) as Figure 14 shows.

Prinz and Flexer [53] and Papernot et al. [51] show both ways to attack ML models and in both works they used specific attacks for specific ML models. Both attacks bases on white-box or black-box attacks which shows that it is possible to find out if an attack is a black- or white-box attack. And when that is found out it should be possible measure the knowledge by pre-determined steps to execute the attack [23]. In the RMF, this is

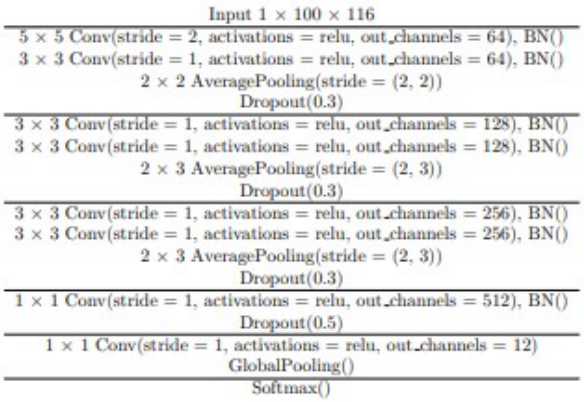


Figure 14: The neworks contains $5x5$ and $3x3$ convolutional layers with the ReLU activation, batch normalisation, and average-pooling layers. The CNN uses dropout for regularisation and the final layer is a $1x1$ convolutional layer adapted from [53].

how the knowledge of the attacker is measured.

3.8. Using the formal threat model

For the risk measurement the attacker's effort is important to evaluate how high or low the risk is for an ML model. In this subsection the research questions RQ5, RQ6 are addressed in more detail. In reference to the research question RQ8 this threat model is a possible method for the RMF to measure risks which will be proved in Section 5. As in subsection 2.3 explained the high- and low-level attributes have to be mapped to find the high-level attributes based on the low-level attributes.

The low-level attributes

To find the attacker's effort there is a need to collect data which can be measured from every attack on a ML model. These data is classified and explained in Subsection 2.3. Doynikova et al. explained which data is required to meausre the low-level attributes.

1. The first requirement is a dataset which contains information about the attack actions against a ML model. The information must be based on the skills, resources, intention, and motivation of the attacker.

2. The second requirment for the dataset is that everything is marked in such a way that the analysis shows which actions the attacker performed. But this requirement is more about having multiple attackers or the analysis accross multiple attackers.

The low-level attributes will also be used to measure the extent of damage based on the collected data.

The high-level attributes

The high-level attributes show the attacker's effort based on the risk indicators attacker's knowledge, attacker's goal, and the computational resources used for the ML model.

Mapping the low-level with the high-level attributes

For the measurment method it is important to measure the risks of an attack. That makes it possible to measure the risks of the attacker. Therefore the mapping must also lead the high- and low-level attributes to each other. This is designed in such a way that all risk indicators are measured while the ML model is trained and after it is attacked.

3.9. Define measurement functions to calculate derived measures

Not every derived measure need to be calculated such as the accuracy.

3.10. Define an analytical model for each indicator

The indicators are the final results from the measurement and provide the transition to the measurement results. This is the last step before the measurement results.

3.11. Develop measurement results by evaluating the risk measurement

The measurment results term in table 1 summarized how the results should be presented in the RMF. The implementation of the measurement results are possible through the decision criteria which are also defined in [2]. The RMF show the results as visualized Python plots and calculated results. Both bases on the risk indicators.

Analyze the dataset for vulnerabilites

In this subsection the concentration lays on the training data which are the attack point of poisoning and backdoor attacks [6]. The focus is on training data that come from an external source. Therefore it must be established that the sources are also trustworthy. A method to do this describe Turner et al. [67]. It must also be noted that external ML models do not poison images before training.
To check the trustworthiness of training data they can be compared with trusted training data. Another point is to train the model with direct input data that come from sources that are directly connected with the ML model [70]. This can be checked by asking questions before executing the measurement with the RMF.

Logging the execution of the attack

In the RMF every Python function send its process and output into a log-file except visualizations but it is logged on which data they are created.

Machine learning metrics for risk measurement

With regard to poisoning attacks, the goal is to decrease the accuracy [14], [26]. But the RMF should also use the precision-recall, the F1-score and shows learning curve of the training process. That should make it possible to identify everything of the attacks. Also with regard to the attacker's effort could be every collected information of the ML model and the training data a possible value.

Vizualising the risk measurement

To evaluate the risk measurement as good as possible all data should be visualized. This could show more possible insights from human judgment.

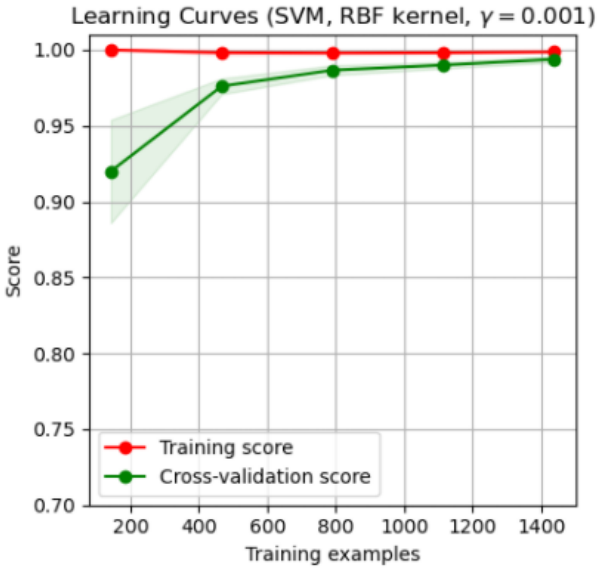


Figure 15: Learning curve example adapted from `https://scikit-learn.org/stable/auto_examples/model_selection/plot_learning_curve.html`.

Calculate the risks

The main calculation is $Risk = Extent\ of\ damage * Probability\ of\ occurence$. This calculation is intended to show how high the risk is for an ML model. Other calculations are to be displayed in detail as probabilities and stand in relation to the extent of damage or probability of occurance. For example, the composition of the extent of damage from the various risk indicators can be presented again in detail.

3.12. The final design to implement the RMF

The last point (g) - "Establishing measurement implementation approach and documentation" of 3.1 shows the needed information for an implementation plan. This subsection

shows the final concept as a complete structure. At first a classifier check the trustworthiness of the training data by comparing the training data with trusted training data. To measure the extent of damage there need of an implementation of the low-level attributes. To get the attacker's effort another measurement method should represent the measurement of the high-level attributes. These two classes need to be mapped.

Attack object	
Attributes	Description
Accuracy	The accuracy relates the number of data examples with true predicted labels to the number of all examined data examples [43].
TP, FP, TN, FN	
Attack specificity	The attack specificity can be targeted or untargeted
Attack time	The attack time differentiate between training and deployment time

Table 2: ISO 27004 Object (attack)

Attacker object	
Attributes	Description
Attacker's goal	The attacker's goal can be a denial-of-service, doing an inference failure, or obtaining secret information
Attacker's knowledge	The knowledge of an attacker can be categoraized between white-, black-, or grey-box
Computational resources	The CPU, memory, GPU are the three parts which represent the used effort from the computer to attack and train a ML model.

Table 3: ISO 27004 Object (attacker)

4. Implementation

The technical RMF uses Python 3.7 as the programming language and ART as the basis. Beside the attacks given by the ART, there is a function from the technical RMF to execute individual attacks. This technical RMF should be used a step ahead of using the framework of Schwerdtner et al.

4.1. Structure of the RMF

Directory tree

The RMF is structured as follows:

```
rmf/
├── attacks/
│   └── art/
│       └── backdoors.py
├── backdoors/
│   └── png-Files
├── measurement/
│   └── monitoring.py
├── metrics/
│   └── log.py
├── visualizations/
│   └── plot.py
├── log_file.log
└── case_study.py
```

4.2. Using ART as the basis for the technical framework

The ART implemented two backdoor attacks which will be explained in 4.3. Since art is an open-source technical framework, the two backdoor attacks can also be used as a basis for simplifying the implementation of other attacks.

4.3. Implementing backdoor attacks

The following three attacks are all based on the ART and represent white-box and black-box attacks and both targeted and untargeted attacks. These attacks are used to measure the extent of damage and the types of attack help to measure the attackers knowledge.

Backdoor attacks from the ART

All backdoor attacks use the *PoisoningAttackBackdoor* class which expects a pattern argument. The pattern is a picture which is for the poisoned images in the training

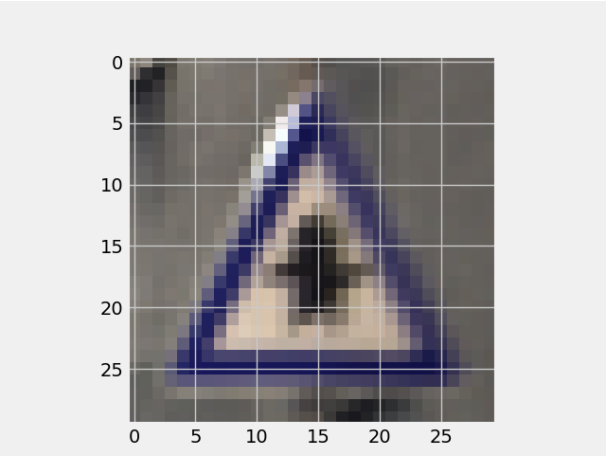


Figure 16: Street sign without a backdoor pattern with the label *Right-of-way at intersection*

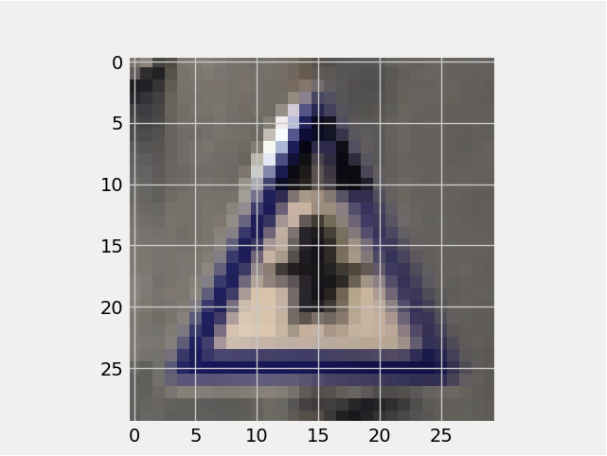


Figure 17: Street sign with a backdoor pattern but still with the original label *Right-of-way at intersection*

data. The pattern must be implemented before training and choose a random selection of images. This is implemented in the RMF as follows:

```
n_train = np.shape(x)[0]
num_selection = num_of_rand_images
random_selection = np.random.choice(n_train, num_selection)
x = x[random_selection]
y = y[random_selection]
```

Then the arguments x and y are passed to the poisoning function from the ART. x and y are parameters which the function expects when calling it. Appendix A describe the functions and parameters. Further it is important that the shape of the images from the training data are *N, H, W, C* or *N, C, H, W*. N is the number of images in the batch, H is the image height, W is the image width, and C is the channel number of an image such as grayscale or RGB. After adding a backdoor as a pattern to the random images, the poisoned images are replaced back to the training data. These poisoned images are saved in a different folder to check if the images are missclassified after or while testing the ML model.

The first attack uses the *PoisoningAttackBackdoor* class without any other backdoor classes from the ART. This attack which bases on Gu et al. [26] is a black-box attack which is untargeted. In the RMF it uses a pattern backdoor which Figure 16 and Figure 17 show as the difference between the original and the poisoned image. The goal of this attack is to change the original label to a random other label. This attack can be executed without any information because it is not important which training data the ML model use and what ML model is used for the training itself.

After poisoning the images these image need be copied back into the original training data. Before this can be done the poisoned data must replace the original training data

which contain no backdoor. When the RMF take the random original images, it save them into a temporary variable and then delete the images from the original training data. The next step is the poisoning while the poisoned data and the original training data need the same shape and dimension which make it possible to copy the poisoned images. As mentioned before the poisoning function takes only two specific shapes which make it easy to have the same shape in the original training data and poisoned data. The implementation of the attack additionally shows the effort an attacker have to implement this attack. Thus the steps can be used for the attacker's knowledge risk indicator.

The *PoisoningAttackCleanLabelBackdoor* poison training images to misclassify the test data. To use this attack the *PoisoningAttackBackdoor* must be used before and then the clean label attack can be executed after training.

The *HiddenTriggerBackdoor* need to be executed after training. To add the backdoor, the *PoisoningAttackBackdoor* must be used before. After training the poisoned data and a smaller number of clean training inputs are used to finetune the model. Finetuning means, taking a equal number of training inputs from each label. The following Python code shows the finetuning from the attack in the RMF.

```
dataset_size = size
num_labels = label_size
num_per_label = dataset_size/num_labels

poison_dataset_inds = []

for i in range(num_labels):
    label_inds = np.where(np.argmax(y_train, axis=1) == i)[0]
    num_select = int(num_per_label)
    if np.argmax(target) == i:
        num_select = int(num_select - min(num_per_label, len(
 poison_data)))
        poison_dataset_inds.append(poison_indices)

    if num_select != 0:
        poison_dataset_inds.append(np.random.choice(label_inds,
 num_select, replace=False))

poison_dataset_inds = np.concatenate(poison_dataset_inds)

poison_x = np.copy(x_train)
poison_x[poison_indices] = poison_data
poison_x = poison_x[poison_dataset_inds]

poison_y = np.copy(y_train)[poison_dataset_inds]
```

4.4. Implement the risk indicatiors

The risk indicators are the main part for the risk measurement. Therefore the risk indicators are used through the complete risk measurement. Every risk indicator is implemented as an own function in the RMF. This makes it possible to measure the risk

indicator values at every step during the ML model training. The goal is to use measure the risk indicator values with the original training data and the manipulated training data.

4.5. Implementation of the logging function

Show measured risks is able with logging from the Python logging module. The function waits for two parameters. A message string and the wanted logging level (i.e. INFO or DEBUG). The called log function in the RMF could look like this:

```
log(f"{variable_name}", 'INFO')
```

In order not to depend on the different ML libraries the rmf gets its own functions of the different metrics. That increases the support of different Python libraries for ML risk measurement.

4.6. Implementation of the visualization

For the visualization Python modules like sci-kit learn have implemented different plots that are signed as metrics.

5. Evaluation

A common example to show backdoor attacks is traffic sign detection ([44], [26], [48], [38]). That makes it easier to find datasets and already finished ML models to make a case study. The following case study uses a traffic sign dataset and show the risk measurement with the RMF.

5.1. Evaluation of the ISO 27004 standard in context to the RMF

After mapping the ISO 27004 to the RMF one result is that this standard should be mapped to a framework if the process stands in relation to a organization and an implemented ISMS.

5.2. Case Study: Developing a SVM for traffic sign detection

For the case study scikit-learn [52] and for preparation of the dataset in Python OpenCV2 have different function to load and resize images [16]. In their work, Stallkamp et al. [64] built a mulit-category classification dataset. The mulit-category classification dataset contains german traffic signs for image classification. That mulit-category classification dataset uses the german traffic signs from a approx. 10 hours daytime video from different roads. This case study is an example to show the functions and results of the RMF. After showing this case study there will be explain and discuss realistic case studies where backdoor attacks could have a more realistic impact for scores of ML models.

5.3. Preprocessing the original training data

The original dataset from Stallkamp et al. is splitted between a training and testing folder. The training folder separate 43 signs into subfolders. This subfolders make it easy to use specific traffic signs which decrease the training time. The information of the folders are written in an eponymous csv-file that are not needed further in this case study. In Figure 18 the shown traffic signs can be used for training the SVM and are all labeled in the data preprocessing like the subfolder name 0 - 42.

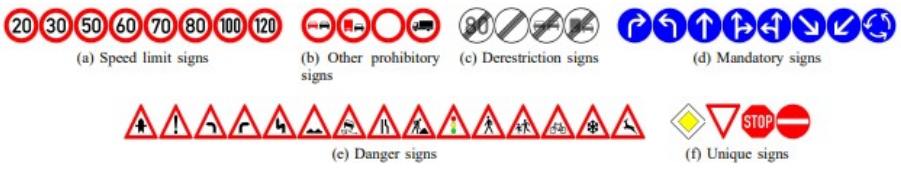


Figure 18: Labeled traffic signs adapted from [64]

All signs are resized to 30x30 pixel and are flattened for the SVM. The training sets are also scaled with the scikit-learn *StandardScaler()* to increase the performance of the training time. The training data are splitted into training and validation data. The test data are an own folder and read in after the training. All functions, the arguments and a description of them can be found in appendix B.

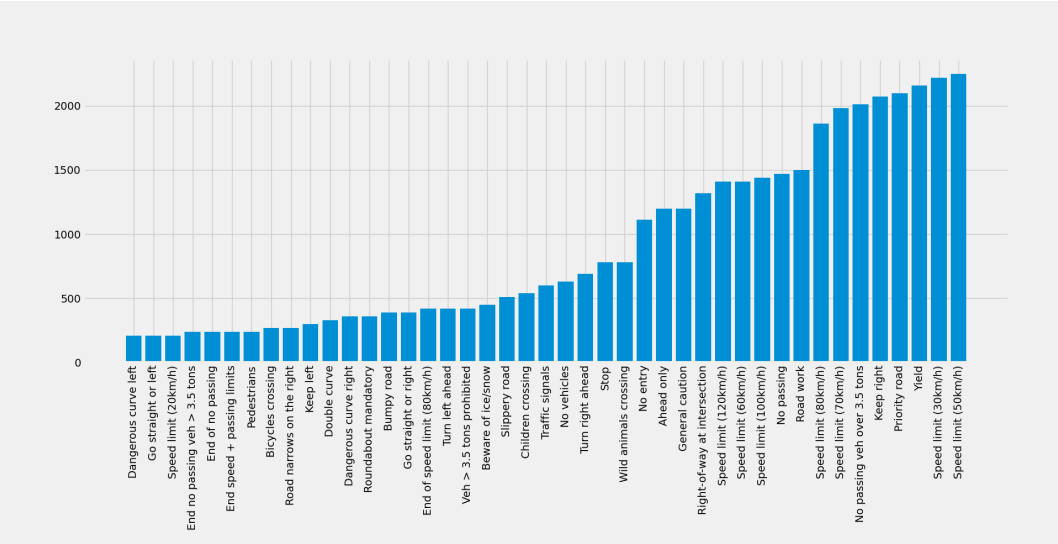


Figure 19: Number of images per labels

5.4. Differences between manipulated and original dataset

The Python plots from the case study show here based on different ML metrics the differences between the original and manipulated dataset.

5.5. Results from the risk measurement based on the risk indicators

5.6. Poisoning and backdoor attacks in real applications

Beside the exemplary application from the case study, the scientific papers in this subsection show real applications where the RMF can then help in a more real environment. An example for real-world poisoning attacks against ML models is Microsoft's chatbot Tay. This chatbot learned racist and offensive language from Twitter users [10], [9]. Microsoft removed the bot after 16 hours because the bot produced offensive tweets.

Label	precision	recall	f1-score
0	0.25	0.37	0.30
1	0.71	0.86	0.78
2	0.74	0.89	0.81
3	0.69	0.76	0.73
4	0.87	0.76	0.81
5	0.73	0.81	0.77
6	0.70	0.49	0.58
7	0.89	0.77	0.83
8	0.89	0.82	0.85
9	0.93	0.87	0.90
10	0.94	0.91	0.93
11	0.87	0.91	0.89
12	0.98	0.87	0.92
13	0.95	0.98	0.96
14	0.95	0.93	0.94
15	0.77	0.81	0.79
16	0.74	0.97	0.84
17	0.99	0.71	0.82
18	0.81	0.62	0.70
19	0.39	0.53	0.45
20	0.53	0.59	0.56
21	0.51	0.57	0.54
22	0.89	0.87	0.88
23	0.48	0.49	0.49
24	0.36	0.43	0.39
25	0.85	0.81	0.83
26	0.80	0.80	0.80
27	0.48	0.50	0.49
28	0.87	0.47	0.61
29	0.52	0.91	0.66
30	0.65	0.41	0.51
31	0.81	0.84	0.83
32	0.37	0.60	0.46
33	0.88	0.90	0.89
34	0.80	0.97	0.88
35	0.89	0.84	0.87
36	0.91	0.93	0.92
37	0.96	0.75	0.84
38	0.96	0.88	0.92
39	1.00	0.67	0.80
40	0.69	0.64	0.67
41	0.40	0.73	0.52
42	0.57	0.64	0.60

Table 4: Classification report of the case study

6. Conclusion

The ISO 27004 standard is very generalized. That makes it possible to design and implement frameworks which are not covered as a standard or intended to be.

6.1. Future work

The attack object should be splitted into different attack techniques because every attack technique has its own characteristics and different goals to achieve with it.

A. Framework functions

```
log(message, logging_levelname: str = 'INFO')
```

message output in the log

logging_levelname (Optional) string value to show the logging level

The following functions are the attacks in the RMF:

```
art_poison_backdoor_attack(x, y, num_of_rand_images)
```

x This argument takes the array of training images.

y This argument takes the array of labels that are assigned to the training images.

num_of_rand_images This argument takes the number of untargeted images that should get a trigger pattern.

```
clean_label(x, y)
```

x This argument...

y This argument...

```
art_hidden_trigger_backdoor(x, y, target, source)
```

x This argument...

y This argument...

target This argument...

source This argument...

The following functions visualize the ML model training process:

```
create_learning_curve(est, x_train, y_train, train_sz)
```

est This argument...

x_train This argument...

y_train This argument...

train_sz This argument...

```
make_meshgrid(x, y, h=0.02)
```

x Data to base x-axis meshgrid on

y Data to base y-axis meshgrid on

h (Optional) stepsize for meshgrid

```
plot_contours(ax, clf, xx, yy, **params)
```

ax Matplotlib axes object

clf Classifier

xx Meshgrid ndarray

yy Meshgrid ndarray

****params** (Optional) dictionary of params to pass to contourf

The following functions show the data results of the risk measurement:

```
probability_calculation()
```

```
list_probability()
```

The following functions represent the risk indicators in the RMF:
These three functions form the computational resources risk indicator:

```
ram_resources()
```

```
cpu_resources()
```

```
gpu_resources()
```

```
accuracy_log(true_values, predictions, normalize=False)
```

true_values

predictions

normalize=False (Optional) the accuracy can be normalized but the default value is *False*.

```
precision_log(true_values, predictions)
```

true_values

predictions

B. Case Study functions

class_num This argument gets the key value from the labels which is an integer.

train_number This argument gets the number of images from a labeled folder.

train_path This argument gets the path where the local training data is stored.

data_dir This argument gets the path where all local images are stored.

image_data This argument gets an array with all images from a label.

image_labels This argument gets the label which belongs to the corresponding images.

```
dataset_visualization(class_num, train_number)
```

With this function, the number of images are visualized and sorted from the lowest to the highest number of images per label.

```
read_training_data(train_path, data_dir)
```

This function reads in the training data, calls the *dataset_visualization()* function and resize the images to $30x30$ pixels. The function is called by the *preprocessing()* function.

```
preprocessing(train_path, data_dir, image_data, image_labels)
```

After calling the *read_training_data()* function, this function assign the **image_date** and **image_labels** arguments to shuffle the training data. Then the training data splits into training and validation data. The shape of the images must be reshaped for the SVM.

```
model_training(train_path, data_dir, image_data, image_labels)
```

After calling the *preprocessing()* function, this function calls a pipeline function with the *SVC()* class and then fits the classifier.

```
read_test_data(train_path, data_dir, image_data, image_labels)
```

After calling the *model_training()* function, this function reads in the test data, resizes the images to $30x30$ pixels and then reshape the images. The last step is the prediction with the test data.

C. Risk results template

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Selbständigkeitserklärung

Ich erkläre hiermit, dass ich die vorliegende Arbeit selbständig verfasst und noch nicht für andere Prüfungen eingereicht habe. Sämtliche Quellen einschließlich Internetquellen, die unverändert oder abgewandelt wiedergegeben werden, insbesondere Quellen für Texte, Grafiken, Tabellen und Bilder, sind als solche kenntlich gemacht. Mir ist bekannt, dass bei Verstößen gegen diese Grundsätze ein Verfahren wegen Täuschungsversuchs bzw. Täuschung eingeleitet wird.

Berlin, den April 26, 2022 .....