Towards a Robust and Trustworthy Machine Learning System Development

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Machine Learning (ML) technologies have been widely adopted in many mission critical fields, such as cyber security, autonomous vehicle control, healthcare, etc. to support intelligent decision-making. While ML has demonstrated impressive performance over conventional methods in these applications, concerns arose with respect to system resilience against ML-specific security attacks and privacy breaches as well as the trust that users have in these systems. In this article, firstly we present our recent systematic and comprehensive survey on the state-of-the-art ML robustness and trustworthiness technologies from a security engineering perspective, which covers all aspects of secure ML system development including threat modeling, common offensive and defensive technologies, privacy-preserving machine learning, user trust in the context of machine learning, and empirical evaluation for ML model robustness. Secondly, we then push our studies forward above and beyond a survey by describing a metamodel we created that represents the body of knowledge in a standard and visualized way for ML practitioners. We further illustrate how to leverage the metamodel to guide a systematic threat analysis and security design process in a context of generic ML system development, which extends and scales up the classic process. Thirdly, we propose future research directions motivated by our findings to advance the development of robust and trustworthy ML system development. Our work differs from existing surveys in this area in that, to the best of our knowledge, it is the first of its kind of engineering effort to (i) explore the fundamental principles and best practices to support robust and trustworthy ML system development; and (ii) study the interplay of robustness and user trust in the context of ML systems.

CCS Concepts: • Computing methodologies → Machine learning; • Security and privacy → Software and application security; Software security engineering; • Human-centered computing → HCI design and evaluation methods.

Additional Key Words and Phrases: threat modeling; adversarial sampling; privacy-preserving machine learning; empirical assessment; secure software development

1 INTRODUCTION

In the recent years, boosted by the much more powerful computing capabilities and much larger datasets available for model training, Machine Learning (ML) technologies, especially the Artificial Neural Networks and Deep Learning (DL) architectures, have made significant progress [79]. Machine Learning has many application areas such as spam and malware detection in cyber security, image classification and object recognition in autonomous vehicle control and medical diagnosis, and speech recognition and machine translation [11, 30, 63].

With the impressive success of applying ML in increasing areas, security weaknesses inherent in ML technologies, e.g., learning algorithms or generated models, have been revealed by a large number of researchers [11, 79]. Due to these weaknesses, an ML system is vulnerable to various types of adversarial exploitations that can compromise the entire system. In fact, a typical ML pipeline, which consists of data collection, feature extraction, model training, prediction, and model re-training, is vulnerable to malicious attacks at every phase [132]. The attacks against ML systems have negative impacts on the systems that may result in performance decrease, system misbehavior, and/or privacy breach [4, 30]. Machine learning and cyber security researchers are greatly

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motivated to uncover these ML inherent weaknesses, exploitable vulnerabilities and applicable attacks, and have been working hard to develop effective defense mechanisms.

The development of robust and trustworthy ML systems is a multi-disciplinary endeavour spanning machine learning, cyber security, human-computer interaction, and domain-specific knowledge. The robustness of an ML system can be defined as its resilience to malicious attacks to protect itself from the compromise of the system’s integrity, availability, and confidentiality. A robust ML system can inspire user trust in the system’s security compliance, while users’ trust in an ML system can contribute to achieve system’s security objectives by helping users to take appropriate responses to malicious attacks and to avoid incidental actions.

The ML/AI community recognizes that all-hands efforts at various levels are needed to support and ensure the development of robust and trustworthy ML systems. The policymakers around the world have made a number of ongoing efforts on regulation enactment to support and normalize AI practitioners’ behaviors [126]. For instance, the Government of Canada is developing the Algorithmic Impact Assessment (AIA) [93] under the Directive on Automated Decision-Making [92]. AIA is an online questionnaire tool designed to help identify the impact level of an automated decision system. Over 80 organizations in both public and private sectors have taken the step to develop AI ethic principles to guide responsible AI development, deployment, and governance [85]. A recent report, "Toward Trustworthy AI Development: Mechanisms for Supporting Verifiable Claims" [15], represents a joint effort of academia and industry to move beyond the ethic principles by proposing a set of mechanisms as a toolbox that AI practitioners can adopt to make and verify claims about AI systems. These verifiable claims, as evidence for demonstrating responsible behavior, can be used to enforce the compliance of the regulations and norms mandated in the high-level AI ethical principles.

1.1 Our Contributions and Related Work

This work presents our contributions from a security engineering perspective to the development of robust and trustworthy ML systems. We conducted a systematic and comprehensive survey on the state-of-the-art robustness and trustworthiness technologies for ML systems, focusing on the progress made in the past five years. We then pushed our effort forward above and beyond a survey by developing a metamodel specified in Unified Modeling Language (UML)\(^1\), which captures and represents the body of knowledge in a standard and visualized way for ML practitioners to leverage. We further studied how the metamodel can be used to guide a systematic process to perform threat analysis and security design in the ML system development. Figure 1 depicts the all-hands efforts at various levels needed for robust and trustworthy ML system development and the focuses of our effort. To the best of our knowledge, our work is the first of its kind of engineering effort to address the gap of knowledge in ML system development.

Our work differentiates itself from existing survey papers in the area in two important aspects: (i) we explore the fundamental principles and best practices to support robust and trustworthy ML system development; and (ii) we study the interplay of robustness and user trust in the context of ML systems. The existing surveys, including [3, 8, 11, 29, 41, 51, 53, 70, 81, 94, 98, 103, 105, 106, 114, 132, 139, 141, 144], primarily focused only on ML defensive and offensive technologies: in [8, 11, 70, 98, 132, 139], the authors presented a comprehensive robust ML defensive and offensive technologies including threat modeling and evaluation methods; in [3, 51, 53, 81, 94, 105, 106, 114, 141, 144], the authors focused their investigation on the attack and defense methods against DL/DNNs, with (i) a survey dedicated on deep learning in computer vision [3], (ii) a survey focused particularly on defenses mechanisms [81], and (iii) the analysis of the NIPS 2017 Adversarial Learning Competition results [94]; in [103], Pitropakis et al. dedicated their efforts on the taxonomy and analysis of attack vectors against plenty varieties of ML algorithms in a broad range of ML applications; in [41], Gardiner and Nagaraja investigated attacks against

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various supervised and unsupervised learning algorithms used in malware C&C detection; in [29], Dasgupta et al. conducted a detailed survey on the robust ML techniques by using the computational framework of game theory.

1.2 Organization of the Article

The paper is organized as follows. Section 2 sets up the context of ML technologies discussed in this article. Section 3 to 7 summarize our findings in the literature on the key technologies in supporting robust and trustworthy ML system development, including threat modeling, attack vectors, defense mechanisms, privacy-preserving ML, user trust, and system robustness assessment. Section 8 describes a metamodel we created that represents the body of knowledge we learned from the survey, and illustrates a systematic approach to performing threat analysis and security design for ML systems guided by the metamodel. Section 9 concludes our work and proposes future research directions to advance the development of robust and trustworthy ML systems.

2 SECURE MACHINE LEARNING: AN OVERVIEW

Machine learning encompasses a variety of approaches that facilitate problem solving through experience, typically by enabling the discovery of important patterns or regularities in large datasets [83, 84]. Machine Learning approaches can broadly be classified into three major paradigms: supervised learning, unsupervised learning and reinforcement learning. Each of these paradigms exhibit their own vulnerabilities. In this section, an overview is provided for each paradigm with introductions to the relevant techniques and models they include, followed by an introduction of some of the potential vulnerabilities as well as a brief review of possible exploitations as documented in the literature.

With supervised learning techniques, the objective is to develop a function that can map input instances to labels, using a set of examples referred to as the training set. The idea here is thus that, given the assumption that the sample used for training is representative of the population, a function that can be derived to perform well at correctly labeling the training data should perform well at labeling new data.

To illustrate, consider the left-hand graphic in Figure 2. This could possibly represent data on the number of class absences (in the x-axis) by a number of students, and the scores they ultimately received on an exam (in the y-axis), as an example. Here, a linear regression model can be trained on this example training data, to develop a function that maps hours studied to exam scores. Least-squared error techniques are typically employed to
determine a function (represented by the line in the graphic) that minimizes the differences between the scores that the model would predict for each case and the true scores. Regularization can be used in the modeling process to prevent overfitting to outliers that could possibly degrade the predictive performance of the model. The resulting function can then be used to predict exam scores for new students. The right-hand graphic in Figure 2 could alternatively represent a categorical classification model. Here, each student might be plotted according to the number of classes that they attended (x-axis) and the number of hours studied (y-axis), and is categorically labeled blue if they passed the final exam, and red if they failed. So-called discriminative modeling approaches, such as logistic regression and support-vector machines can then be used to predict the likelihood of whether a new student will pass or fail, depending on their personal input values. This is done by determining a direct mapping from feature values to labels, for example by determining a boundary in the data separating the two (or more) classes. Conversely, generative modeling approaches such as Naïve Bayes Classification consider the probabilities of the feature values that make up an example instance to compute the likelihood of each class. Artificial neural network-based approaches, such as deep learning, can also be used in a supervised manner to learn high-level features, such as those required for image processing, but can also be utilized in a semi-supervised or unsupervised manner.

Rather than relying on a sufficient set of examples upon which to train a classifier, unsupervised machine learning approaches instead look for other similarities in the data that can be exploited in such a way as to make possible inferences or assumptions during learning and prediction. Clustering methods focus on identifying certain commonalities among the data, which can then be used to make assertions about certain data depending on the level of fit. Anomaly detection, for example, can be used to deem particular instances as abnormal, providing evidence that they may be particular interest. Malicious network behaviour, as an example, might be identified using unsupervised anomaly detection approaches that can identify patterns that are inconsistent with typical observed activity.

Reinforcement learning is alternate paradigm where learning conducted in an exploratory manner, often modeled by a Markov Decision Process. The objective is to learn a solution to a problem, where proposed solutions can be evaluated via a reward function. Learning thus modifies solutions while seeking to maximize rewards. The ubiquitous nature of machine learning techniques, and their subsequent rapid adoption, has resulted in increased vulnerability and attractiveness for potential attacks [104]. Potential network attackers may want to influence a machine learning-based intrusion detection system to increase false negatives, allowing the attackers to enter undetected, or increase false positives to the point that so much legitimate traffic is flagged that alerts become too frequent. In such a case, either they are ignored, or operation is disrupted altogether via denial of service [8]. Advertisers may similarly seek to influence spam detectors to increase the likelihood of their messages penetrating email filters [72]. Training data for image recognition may be perturbed in such a way to allow unauthorized access or cause harm in other domains, such as connected and automated vehicles, as an example [125].
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To illustrate a general model of security for supervised machine learning, Barreno et al. [8] offered a taxonomy that divides the aspects of vulnerabilities and attacks along three different dimensions. Their discussion is framed in the context of a machine learning system that is designed to identify and defend towards potential attackers, but is generalizable to supervised ML systems. The three dimensions are as follows:

- **Influence: Causative vs Explorative.** This indicates whether the training data is compromised (causative), resulting in a faulty prediction or classification model being produced, or the classification of new data itself is compromised (explorative) in real time. Pitropakis et al. [104] refer to this as poisoning vs evasion.
- **Security Violation: Integrity vs Availability.** This dictates whether the exploitation focusses on compromise via the generation of false negatives (integrity), or via overload of false positives (availability).
- **Specificity: Targeted vs Indiscriminate.** This aspect pertains to whether a particular instance is the focus (targeted) or a wider class (indiscriminate).

There is a significant body of work that has explored various vulnerabilities of machine learning systems and how they might be exploited. Barreno et al. [8] center their discussion within the context of attacks on intrusion detectors, but also offer a detailed illustration on how attacks on a spam filter could fit within each possible outcome for the aforementioned taxonomy. Yuan et al. [142] explored attack mechanisms on deep learning systems, specifically at the classification/validation stage, as opposed to the training stage, positioning such attacks as explorative/evasion in the Barreno taxonomy. Su et al. [122] described a similar deep neural network vulnerability, and illustrate how image classification can be drastically modified via the perturbation of just a single pixel, facilitating attacks that would fall into the indiscriminate class of the taxonomy. Pitropakis et al. [104] further provided an extensive survey of ML system vulnerabilities and associated potential attack strategies.

3 THREAT MODELING

Threat Modeling is an engineering technique to support systematic security requirement analysis in the context of a concrete application scenario. It has been widely adopted by cyber security researchers and professionals to identify potential system threats, set feasible security objectives, identify relevant vulnerabilities and attack vectors, and design appropriate defense mechanisms. A well-defined threat model serves as a backbone of the secure development process to reduce the risk of security issues arising during the application development and shape the application security design to meet the security objectives.

In the context of ML security, the researchers focused on the following aspects of threat modeling [11, 41, 98, 100, 132]:

- **Attack Surface.**

  In Machine Learning, the workflow of the complete ML tasks is modelled as a Pipeline. An ML pipeline consists of several phases, including data collection, data pre-processing, feature extraction, model training and testing, prediction, and optionally model re-training. Tremendous sensitive and confidential data, from raw data to trained models, flows along the pipeline. A number of attack surface and various attack vectors have been identified in the pipeline as summarized below:

  - Stealthy Channel attack during raw data collection phase;
  - Mimicry and Poisoning attack against training and testing dataset;
  - Polymorphic/Metamorphic attack against feature extraction;
  - Gradient Descent attack against learning algorithm;
  - Evasion attack during prediction phase;
  - Model Stealing against trained model; and
  - Poisoning Attack during model re-training phase.
The majority of the research is focused on Poisoning Attack, Gradient Descent Attack, Evasion Attack, and Model Stealing.

**Attacker’s Goal.**
Attacker’s adversarial goals can be categorized from perspectives of Security Violation, Attack Specificity, and Error Specificity:

- **Security Violation.** With the classical CIA model (confidentiality, integrity, availability), an attacker may aim to undermine an ML system’s functionality (integrity and availability), or to deduce sensitive information about the ML system (confidentiality, or privacy): (i) *integrity violation* via false negative, e.g., evade a spam email detection system without compromising the normal system operation; (ii) *availability violation* via overload of false positives, e.g., significantly degrade the accuracy of a spam email detection system so that its functionalities are not available to legitimate users; or (iii) *privacy violation* by stealing sensitive or confidential information from an ML system, e.g., obtaining an ML model parameters or data used to train the model by an unauthorized approach.
- **Attack Specificity.** An attacker may launch targeted attacks against a specific ML algorithm or architecture or launch indiscriminate attacks against any ML system.
- **Error Specificity.** In the context of ML classifier systems, an attacker may aim to fool the system to misclassify an input sample to a specific class (error-specific attacks) or to any of the classes different from the right class (error-generic attacks).

An adversarial attack may present a goal of the combination of these different characters. For example, an adversary is motivated to launch attacks to evade a given spam email detection system by crafting malicious emails based on the algorithms specifically optimized against the detection system.

**Attacker’s Knowledge.**
The data and information related to an ML system, including training data, feature set, learning algorithms and architecture, hyperparameters, objective function, and trained model parameters (weights), are considered sensitive or confidential. Depending on the level of access to these data and information, an attacker can launch different types of attacks, that is, black-box based attack, gray-box based attack, and white-box based attack.

- **Perfect-knowledge (PK), white-box attacks:** An attacker knows everything about a targeted ML system including training dataset, ML architecture, learning algorithms, trained model parameters, etc. This setting is the worst-case attacking scenario.
- **Limited-knowledge (LK), gray-box attacks:** An attacker has a portion of the knowledge about a targeted ML system. Typically, the attacker is assumed to know the feature set, the model architecture and the learning algorithms, but not the training data and the trained parameters. The attacker may be able to collect a surrogate dataset from a similar source and get feedback/output from the ML system to acquire labels for the data, and then use the information to launch attacks further.
- **Zero-knowledge (ZK), black-box attacks:** An attacker is assumed to not know any “exact” information about a targeted ML system. However, this setting implies that inevitably the attacker is able to acquire partial but inaccurate information about the targeted system. For example, the attacker may not know the exact training data or feature representation used for training an object-detection model in autonomous vehicle control, the kind of data - images of traffic road signs, and the features - image pixels, are known to everyone including the attacker. While the black-box setting does increase the threshold of exploitability, an ML system is still vulnerable to various attacks.

**Attacker’s Capability.**
Attacker’s Capability refers to which extent an attacker can access and manipulate training data or input samples, or observe the corresponding output of a trained model. The level of attacker’s access and manipulation of the
data includes read, inject, modify, or logically corrupt training data or input samples, in the order of the capacity from weak to strong.

**Attacking Influence.**
The attacker’s influence can be categorized as Causative if the attacker can manipulate both training data and input samples during ML training (offline or online) and prediction phases, or Exploratory if the attacker can only manipulate input samples during ML prediction phase. Causative attack attempts to influence or corrupt the model under training. The goal of causative attack can be integrity violation that causes the model produce adversary desired outputs (error-specific attack) as the adversary supplies the model with the crafted input samples, or availability violation due to the logically corrupted model. Exploratory attack does not tamper with the targeted model. The goal of exploratory attack can be integrity violation that causes the model produce incorrect outputs, or privacy violation that deduces sensitive or confidential information about the model and training data.

**Attacking Strategy.**
Attacker’s Strategy refers to the systematic approach that an attacker is to take to optimize the attacking effort. For example, depending on how much knowledge about an ML system and how much capability of accessing and manipulating training data or input samples that an attacker may have, the attacker uses different objective function to measure attacking efficiency and optimize attacking methods and algorithms.

**Attacker’s Role.**
In the context of Privacy Preserving ML (PPML), there are three different roles involved in the ML pipeline [4]: (i) Input Party who is the owner or contributor of training data; (ii) Computation Party who performs model training; and (iii) Results Party who submits input samples to a trained model and receives results. It is common that the computation party and the results party are the same entity, while the input party is a different entity. For example, the input party can be individuals around the world, while the computation party and the results party is a company which collects the data, trains an ML model, and leverages the trained model to run its business.

### 4 COMMON MACHINE LEARNING OFFENSIVE AND DEFENSIVE TECHNOLOGIES

In this section, we study commonly used ML offensive and defensive technologies. We mainly focus on the literature published in the past five years. The prevailing publications during the period of time primarily addressed the adversarial sampling problems at the ML training and prediction phases in the context of DNN/DL based supervised learning algorithms and the application areas of image classification and anomaly detection. The content in this and the next section reflects this research trend. This section summarizes our findings on the technologies related to the security violation of system availability and integrity, followed by a case study illustrating how the offensive(defensive technologies have been adopted in the application of ML-based Intrusion Detection Systems (IDS). Next section will present the technologies related to the privacy aspect of machine learning.

#### 4.1 Attack Vectors

More than a decade ago, researchers started to gain awareness of ML security problems and relevant adversarial attacks against traditional, non-deep learning algorithms, such as linear classifier used in spam filtering and Support Vector Machine (SVM) based binary classifier used in malicious PDF detection [11, 70]. With the advances in the study of deep neural networks and deep learning architecture as well as the increasing application in various areas such as computer vision and cyber security, researchers continue to uncover vulnerabilities existing in the ML/DL algorithms and architectures.
While research is mainly focused on supervised ML methods, some unsupervised ML methods (e.g. clustering) are also vulnerable to adversarial attacks [11, 70, 132].

Adversarial attacks against an ML system exist at every phase of the ML pipeline, but attacks against the model training phase and the prediction phase, including poisoning attacks, evasion attacks, and privacy attacks, received the most interest. The way to launch these attacks can be categorized as input manipulation, input extraction, training data manipulation, training data extraction, model manipulation, and model extraction [79]. In the rest of this section, these attack vectors will be discussed with respect to Threat Modeling discussed in section 3, in particular, in terms of attacker’s goal, attacker’s knowledge and capability, and attacker’s role.

4.1.1 Root Cause of Adversarial Sampling.
One of the main research areas in ML security is adversarial sampling based attacks. Adversarial sampling, also known as adversarial input perturbation, intentionally perturbs a small portion of training/test/input data as an attempt to compromise the integrity, availability, or confidentiality of an ML system.

Typically, in the course of an ML system development, the test dataset is drawn from the same distribution as the training dataset. Large sets of the data domain remains unexplored by model learners [27]. In addition, due to some linear model behavior [117, 144], the decision boundary is extrapolated to vast regions of high-dimensional subspace that are unpopulated and untrained [55, 96]. This practice of ML development does not guarantee model generalization to a different distribution of input data space [79], and does not account for adversarial samples which often falls outside of the expected input distribution [78]. In fact, adversarial samples are intentionally created by perturbing training/test data or input data into these empty hyper-volumes to compromise model training or mislead the prediction of trained model. Basically, there are three approaches for adversarial sample generation: perturbation on valid samples, transferring adversarial samples across different learner models, and generative adversarial networks (GANs) [30].

The design of an ML system should take care of the entire input space. Various technologies to address these security threats by enhancing model robustness or detecting anomaly input are discussed in section 4.2.

4.1.2 Poisoning Attack.
Machine Learning is vulnerable to attacks at the model training phase (and re-training phase). This type of attack is called Poisoning Attack, which attempts to inject a small fraction of “poisoned” samples into training/test dataset in order to modify the statistical characteristics of the dataset, so that the compromised ML model will suffer increased rate of misclassified samples at the prediction phase [11, 132]. Poisoning attack is considered a causative attack that aims to compromise both the integrity and availability of an ML system. An attacker may launch error-generic poisoning attacks that aims to cause an ML system yield as many false outputs as possible so that the ML system becomes unusable to end users (compromise of availability), or the attacker may launch error-specific poisoning attacks that aims to cause an ML system yield specific outputs as what the attacker desired (compromise of integrity), e.g. output an specific incorrect classification.

Typically, an ML training dataset is considered confidential and is well protected from unauthorized access during model training. However, in some cases such as a malware detection system or a spam email filter, in order to adapt to the changing application scenes an ML system might need to re-train its model occasionally by taking samples out of the inputs from untrusted sources during its daily operation. A few feasible scenarios of model retraining, including adaptive facial recognition system, malware classification, and spam detection, were discussed in [70]. This brings in an attack surface to adversaries to poison the data for re-training by feeding the operational ML system with adversarial inputs. Therefore, poisoning attack can be launched as a white-box attack during the initial ML model training phase but it is limited to the attacker’s capacity to access and manipulate the training dataset, while it can also be launched as a black-box attack during the model re-training phase that the attacker has a viable attack surface but lacks the essential knowledge about the trained model to facilitate the attacks.
Adversarial Sampling Algorithms.
There are mainly two types of poisoning attack algorithms against supervised ML models in terms of the way adversarial samples are generated: Label-flipping attack and Gradient Descent attack [41, 70, 132]. In addition, we will discuss a number of attacks reported against unsupervised ML algorithms.

- **Label-flipping Attack**
  Label-flipping Attack is to introduce label noise into training data by flipping the labels, e.g. reverse the label of an amount of legitimate email samples in the training data as spam, and vice versa. Label-flipping Attack can compromise integrity or availability of an ML system, and is a type of causative attack. Several flipping algorithms are used to generate adversarial samples [10, 132, 136], including random label flipping (RLF), nearest-prior label flipping (NPLF), farthest-prior label flipping (FPLF), farthest-rotation label flipping (FRLF), and adversarial label flipping (ALF).

- **Gradient Descent Attack**
  Gradient descent-based poisoning attack is a type of causative, availability-compromised attacks that inserts adversarial samples in to training dataset to maximize the impact on an ML system performance, e.g. by reducing the performance to the level that the ML system is unusable. Gradient descent attack is commonly used with label-flipping attack by first flipping the label of a benign training data and then moving it to maximize learner’s objective function by leveraging the gradient descent function. Gradient descent-based attack is computationally demanding. In [11], the researchers reported an optimized algorithm called back-gradient poisoning that has much better performance, in terms of reducing the classification accuracy, than random label flipping methods.

Backdoor and Trojaning Attack.
With the increasing application of deep neural networks and transfer learning, a specific type of poisoning attacks arises called Backdoor and Trojaning attack [11, 60, 71]. Backdoor and Trojaning attack is launched by creating pre-trained network models that include “backdoors” inside. The manipulated models are then released publicly. In the case the models are adopted by innocent users to integrate in their ML system, the attacker can activate the backdoors using specific inputs to mislead the ML system to yield their desired outputs. Backdoor and Trojaning attack is considered a causative, integrity-compromising attack.

Attacks against Unsupervised Learning.
We have found very few work that analyze the effect of adversarial attacks against unsupervised machine learning algorithms. Nonetheless, unsupervised learning models are also vulnerable to adversarial attacks. In [109], the authors devised a technique called “Boiling Frog” to slowly poison PCA-based unsupervised anomaly detectors. Since online anomaly detectors retrain the models periodically to capture the current pattern of data, the authors showed that it is possible to boost the false negative rate by slowly adding useless data. In [61], the authors showed that online centroid anomaly detectors are not secure when an attacker controls 5-15% of all network traffic. In [22], the authors proposed a black-box adversarial attack against four popular clustering algorithms. They also carried out a study of cross-technique adversarial attack transferability.

4.1.3 Evasion Attack.
The adversarial attack against an ML system during the prediction phase is called Evasion Attack. The attack is a type of exploratory, integrity-compromising attack that aims to evade the trained ML model by elaborately manipulating input samples. Evasion attack can be error-generic or error-specific [11].

Adversarial Sampling Algorithms.
Gradient-based attacks apply a gradient descent function to find a state for adversarial samples that mislead an ML model to yield incorrect result. Gradient-based algorithms are widely used to attack differentiable learning
algorithms such as DNNs and the SVMs with differentiable kernels. For non-differentiable learning algorithms, such as decision trees and random forests, they are still vulnerable to gradient-based attacks as an attacker can leverage a differentiable surrogate learner [11]. The following adversarial sampling algorithms, designed specifically against DNNs used in the area of computer vision/image classification, are summarized in [132]:

- L-BFGS (Limited-memory Broyden–Fletcher–Goldfarb–Shanno) algorithm. L-BFGS is an optimization algorithm that uses a limited amount of computer memory to approximate BFGS algorithm to find imperceptible perturbations to images that can mislead trained DL models to yield misclassifications [124].
- FGSM (Fast Gradient Sign Method) algorithm. FGSM is an efficient adversarial sample generation method that creates samples by appending noise to the original image along the gradient directions [127].
- UAP (Universal Attack Approach) algorithm. Both L-BFGS and FGSM generate adversarial samples for one single image at a time. The adversarial perturbations cannot be transferred from one image to another. UAP algorithm was developed to generate “universal” adversarial perturbations applicable to the images with the same distribution as the images used to generate the perturbations [87]. UAP has been validated on ResNet but it was claimed to be effective on various neural networks.
- UPSET and ANGR algorithms. Both UPSET (Universal Perturbations for Steering to Exact Targets) and ANGR (Antagonistic Network for Generating Rogue) algorithms [112] are black-box attack methods. They have been reported to achieve favorable performance against DL models trained on CIFAR-10 and MNIST datasets.
- C&W algorithm. C&W attack, introduced by Carlini and Wagner, is a powerful adversarial sample generation algorithm that achieves better performance in terms of computation speed [18]. It has been reported to achieve impressive results on distilled and undistilled DNN models.
- DeepFool algorithm. DeepFool [88] algorithm finds the closest distance from original input to the decision boundary of adversarial samples based on an iterative linearization of the classifier. DeepFool algorithm provides an efficient and accurate way to evaluate the robustness of classifiers and to enhance their performance by proper fine-tuning.
- JSMA algorithm. The Jacobian-based Saliency Map (JSMA) algorithm was designed by Papernot et al. [97] to efficiently generate adversarial samples based on computing forward derivatives. JSMA computes the Jacobian matrix of a given sample \( x \) to identify input features of \( x \) that made the most significant changes to the output classification. While JSMA adds smaller perturbations in a smaller portion of features than FGSM, it is much slower due to its significant computational cost.

Transferable Adversarial Samples. Researchers observed that the adversarial samples generated for a trained model by some algorithms, such as C&W, can be transferred (being effective) against another trained model [11, 70, 130, 132]. This enables an attacker who does not have perfect knowledge of an ML system to be able to conduct black-box attack against the ML system. The attacker can develop a surrogate model by training it using surrogate training data, generate and test adversarial samples against the surrogate model, and then apply the adversarial samples against the victim ML system.
**Mimicry Attack.**
Mimicry attack is a type of evasion attack that was used to attack traditional ML models. With the emergence of DNN/DL, mimicry attack is used together with the gradient-based methods to attack neural networks [41, 131]. Mimicry attack attempts to modify the features of adversarial samples such that the adversarial samples mislead a trained model to classify them as benign inputs. For example, mimicry attack has been used to bypass an ML-based IDS by hiding the traces of system calls that actually carried out malicious activity. Mimicry attack can also be used to attack against unsupervised ML algorithms, e.g. attack clustering algorithms by effectively reducing the distance between the adversarial samples and benign inputs.

| Attack Vector | Citation | Attacking Method | Adversarial Algorithm | ML Pipeline | Attacker’s Influence | Security Violation | Attacker’s Knowledge |
|---------------|----------|------------------|-----------------------|-------------|----------------------|-------------------|---------------------|
| Poisoning Attack | [10, 132, 136] | Label-flipping | RLF, NPLF, FPLF | Model (re-) training | Causative | Integrity & Availability | White-box |
|                | [11, 41] | Gradient Descent | Back-gradient descent |    |                      |                  | Availability |
|                | [11, 60, 71] | Backdoor & Trojaning | — |    |                      |                  | Integrity |
|                | [61, 109] | — | Boiling frog, Greedy optimal attack |    |                      |                  | Integrity & Availability |
| Evasion Attack | [18, 87, 88, 97, 112, 124, 127, 132] | Gradient descent | L-BFGS, FGSM, UAP, C&W, JSMA, DeepFool | Prediction | Exploratory | Integrity | White-box |
|                | [11, 70, 130, 132] | Transferable samples | C&W |    |                      |                  | Black-box |
|                | [41, 131] | Mimicry | — |    |                      |                  | Black-box |

### 4.2 Defense Mechanisms
People often assume ML models are trained, tested and deployed in a benign setting. This assumption actually is not always valid. An ML system should be designed with the consideration of adversarial settings in mind in which capable adversaries can access and elaborately manipulate the training/test data and/or input data to compromise the integrity, availability, or privacy of the ML system. These risks should be analyzed and addressed when an ML system is designed [79]. In section 4.1, various attack vectors were discussed. In this section, the corresponding countermeasures against the attacks at the model training phase and the prediction phase will be discussed.

**4.2.1 Model Enhancement.**
Model Enhancement mechanism attempts to improve the robustness of the trained models during the model training phase by leveraging various methods including adversarial training, data compression, foveation-based method, gradient masking, defensive distillation, and deepcloak method [132].
Adversarial Training.
Adversarial training is essentially a robust generalization method [46, 116]. It adds and mixes adversarial samples into the original training dataset to enhance the model robustness against the attacks using these adversarial samples. This method is not adaptive to different types of adversarial sampling attacks [132], which means the model has to be trained on relevant adversarial samples in order to resist a particular type of adversarial attacks.

Adversarial training is a heuristic approach that has no formal guarantees on convergence and robustness properties [11, 30]. Some researchers leveraged the game theory computational framework to enhance model robustness through adversarial training [30], in which both a Learner (such as a classifier) and an Adversary can be utilized to learn a prediction mechanism from each of the other party. From the Learner’s perspective, the adversarial training techniques can be used as a defense method at the model training phase to make the trained model more robust against adversarial attacks. GAN-based methods have been used to construct robust DL models against FGSM-based attacks [64, 131, 132]. The authors reported that the trained models can successfully classify original and contaminated images, and even rectify perturbed images.

A more efficient adversarial training method called robust optimization which formulates adversarial training as a MiniMax problem [11]: the inner problem maximizes the training loss by manipulating training data under bounded, worst-case perturbation, while the outer problem trains the learner to minimize the corresponding worst-case training loss. The robust optimization aims to smooth out the decision boundary to make it less sensitive to worst-case input manipulation.

Data Compression.
Researchers found out that various data compression methods can counter adversarial sampling attacks against image classifiers [132]. For example, JPG compression and JPEG compression can mitigate FGSM-based adversarial sampling attacks by removing high frequency signal components, inside square blocks of an image [28, 35, 49]. These compression defending methods, however, may lead to the decrease in the classifier’s accuracy when the compression rate is set high.

Foveation-based method.
The foveation mechanism, which selects a region of the image to apply a Convolutional Neural Network (CNN) while discarding information from the other regions, can be used to mitigate adversarial attacks against image classifiers [73, 132]. Researchers observed that the CNN model which has been enforced by the foveation mechanism is robust to scale and transformation changes over the images. This method has not yet been validated against more powerful attacks.

Gradient Masking.
The gradient masking method enhances ML model robustness by modifying the gradients of input data, loss or activation function [132]. The method can defend against L-BFGS and FGSM based adversarial attacks by penalizing the gradient of loss function of neural networks [74] or minimizing loss function of neural networks over adversarial samples [116] when model parameters are updated. The method can also defend against C&W attacks by adding noise to a neural network’s logit output against the low distortion attacks [90]. Researchers also found that gradient regularization is helpful to improve model robustness as it penalizes the variation degree of training data during model training [11, 108, 132].

Defensive Distillation.
Distillation is a technique originally used to reduce DNN dimensionality. Papernot et al. devised a variant of the method, called defensive distillation, to enhance the model generalizability and robustness that can significantly reduce the effectiveness of adversarial perturbations against DNNs [99, 132]. Defensive distillation extracts the knowledge from a trained DNN model and then uses the knowledge to re-train the model to enhance the resistance to adversarial attacks.
DeepCloak.
The DeepCloak method identifies and then removes unnecessary features in a DNN model, which can enhance the robustness of the model as the method limits attackers’ capacity to generate adversarial samples [40, 132]. By applying DeepCloak, a masking layer is inserted between the convolutional layer(s) and the fully connected layer(s) of a DNN model. The deepcloak layer is then trained using original and adversarial image pairs. Since the most prominent features have the dominant weights, the prominent features can be removed by masking the dominant weights for the deepcloak layer.

4.2.2 External Defense Layer.
The External Defense Layer mechanism adds an extra layer in front of the trained model and attempts to pre-process input data before they are sent to the trained models during the prediction phase. The defense mechanisms that fall into the category of External Defense Layer include Input Monitoring and Input Transformation. Input Monitoring tries to detect and filter adversarial input samples e.g. using an anomaly detection system, while Input Transformation tries to sanitize suspicious input samples e.g. those are sufficiently far from the training data in feature space [11, 27, 79].

Input Monitoring.
Input monitoring against anomaly input data is a defense mechanism that can be applied at both the model training phase and model prediction phase [79].

A Feature Squeezing is an input monitoring method that is used to test input images. The method used two feature squeezing methods: reducing the color bit depth of each pixel and spatial smoothing [138]. It then compares the model classification accuracy on the original images and the squeezed images [132]. If there exists substantial difference between the accuracy, the input images are considered as adversarial samples.

In [27], Darvish Rouani et al. presented their ML defense mechanism - Adaptive ML model assurance. The researchers developed an external module called modular robust redundancy (MRR) to thwart potential adversarial attacks and keep the trained ML model intact so that the performance of the ML system is not impacted.

Carrara et al. [19] proposed a scoring approach to detecting adversarial samples for kNN (k-nearest neighbors) learning algorithm used for image classification. The method defines an authenticity confidence score based on kNN similarity searching among the training images, and analyzes the activations of the neurons in hidden layers (deep features) to detect adversarial inputs. The deep features are assumed to be more robust to adversarial samples as (i) the adversarial sample generation algorithms are meant to fool final classification but not deep features; and (ii) generated adversarial samples look similar to authentic ones for humans, and deep features have shown impressive performance in visual similarity/differentiation related tasks. It was reported that the method can filter out many adversarial samples while retaining most of the correctly classified authentic images.

Input Transformation.
Machine Learning models may include extraneous information in its learned, hidden representations which are not relevant to the ML learning tasks [79]. An attacker can conduct attacks against the ML system by taking advantage of these extraneous information. Input transformation mechanism can be used to defend against this type of attacks by attenuating or discarding these extraneous variation.

Perturbation Rectifying Network (PRN) is a universal perturbation defense framework to effectively defend DNNs against UAP attacks [2, 132]. A PRN is learned from real and synthetic image-agnostic perturbations. A separate perturbation detector is trained on the Discrete Cosine Transform of the input-output difference of the PRN. If a perturbation is detected, the output of the PRN is used for label prediction instead of the actual input. Therefore, the PRN can process input images and detect possible perturbations, and then rectify the images before sending them to the classifier.
4.2.3 Defense against Attacks During Training Phase.

During the model training phase, ML is vulnerable to Poisoning Attack that attempts to insert adversarial samples into the training dataset or modify the statistical characteristics of existing dataset to compromise the trained model. To defeat these attacks, there are two common countermeasures: Data Sanitization and Robust Learning [11, 70, 132]:

Data Sanitization.

Data Sanitization is a defense technique that tests and identifies abnormal input samples and then removes them from the training dataset. To be able to have impact on ML learner in a negative way, adversarial samples have to exhibit different statistical characteristics. Therefore, data sanitization technologies, which are able to detect anomaly training data by analyzing discrepancies in the statistical characteristics, can be used to filter out potentially adversarial samples. Cretu et al. proposed a sanitization scheme that is reported to significantly improve the quality of unlabeled training data by marking it as “attack-free” and “regular” [24]. Nelson et al. proposed a Reject On Negative Impact (RONI) defense method that has been used to protect several ML-based spam filters [70, 89]. RONI tests the impact of each email on training and discards the messages that have a large negative impact.

Robust Learning.

Robust learning is a defense technique that optimizes learning algorithms so that models are learned based on robust statistics that are intrinsically less sensitive to outlying training samples [11]. Robust learning hardens ML learners by improving the generalization capability. In [44], the author introduced a new algorithm for avoiding single feature over-weighting so that the trained classifiers are optimally resilient to deletion of features. The method was illustrated in the application scenarios of spam filtering and handwritten digit recognition.

4.3 An Intrusion Detection System Case Study

Intrusion Detection Systems (IDSs) are one of the key components to secure today’s computer networks. They monitor different properties of the hardware and software running in the network and detect possible intrusions and/or anomalies. Due to the huge volume of data in modern networks comprising of a multitude of devices, IDSs are still struggling to detect unknown attacks and reduce false positives. Machine learning techniques are a big part of IDSs as they can automatically detect anomalies and/or find attack signatures. However, as discussed in this section, machine learning techniques are vulnerable to intelligent adversaries that understand how these techniques work. As a result, adversaries can launch attacks that can fool an IDS. In this subsection, as a case study, we discuss how researchers use various offensive and defensive techniques to attack and protect machine learning-based intrusion detection systems.

Intrusion detection systems are defined as systems that monitor and analyze host or network communication properties and generate alerts when suspicious events are detected. There are two main types of intrusion detection systems: host-based IDS (HIDS) and network-based IDS (NIDS). NIDSs are placed strategically at different points of the network. HIDSs operate within a computer and monitor OS events in addition to network communications. There are also hybrid IDSs that combine various systems. The techniques that IDSs use to detect malicious behavior can be categorized as signature-based, rule-based, and anomaly-based. Due to the volume of today’s data and the need for autonomy, there has been an explosion of research happening to apply different machine learning algorithms in intrusion detection systems. There are many kinds of machine learning algorithms. In [69], the authors presented a taxonomy of machine learning algorithms used in IDSs. In addition to supervised and unsupervised algorithms, they divided the algorithms based on the number of layers used. The authors called them deep learning models and shallow models. In Figure 3, we present the taxonomy.
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Table 2. Defense Mechanisms

| Defense Mechanism       | Citation                        | Defense Method          | Algorithm or Framework         | ML Pipeline | Notes                                                                 |
|------------------------|--------------------------------|-------------------------|--------------------------------|-------------|----------------------------------------------------------------------|
| Model Enhancement       | [11, 30, 46, 64, 116, 131, 132] | Adversarial Training    | Game theory, GAN, Robust Optimization | Prediction  | Mitigate FGSM-based attacks against image classifiers                |
|                        | [28, 35, 49, 132]              | Data Compression        | JPG, JPEG                      |             | Mitigate scale and transformation perturbations against DNN image classifier |
|                        | [73, 132]                      | Foveation-based         | Object Crop MP, Saliency Crop MP, 10 Crop MP, 3 Crop MP |             | Mitigate L-BFGS, FGSM, or C&W-based adversarial attacks against neural network-based image classifiers |
|                        | [11, 74, 90, 108, 116, 132]   | Gradient Masking       | --                             |             | Decrease the dimensionality of trained DNN models                    |
|                        | [99, 132]                      | Defense Distillation    | --                             |             | Remove prominent features of convolutional neural network-based image classifiers |
|                        | [40, 132]                      | DeepCloak               | DeepCloak                      |             |                                                                      |
| External Defense Layer  | [19, 27, 79, 132, 138]         | Input Monitoring        | Feature Squeezing; MRR          | Prediction  | Defend image classifiers                                              |
|                        | [2, 79, 132]                   | Input Transformation    | Perturbation Rectifying Network |             | Defend image classifiers                                              |
| Secure Training Data    | [11, 24, 70, 89, 132]          | Data Sanitization       | RONI                           | Model Training | Leverage data sanitization technologies                             |
|                        | [11, 44]                       | Robust Learning         | Feature Deletion                |             | Improve the generalization capability of the learning algorithms    |

Although machine learning techniques are successful in solving many of today’s research problems, according to [129], machine learning-based intrusion detection systems are not frequently adopted by the industry in production environments. Some of the key factors are:

- A large number of false positives which is very costly in production environments.
- An anomaly can be benign. It is difficult to distinguish between malicious and benign anomaly.
- Lack of proper evaluation methods. Good datasets representing real-life attacks are not publicly available. As a result, researchers mostly work with synthesized or anonymized data that are not as effective.
- They are prone to adversarial attacks.

4.3.1 Adversarial attacks on intrusion detection systems.

An experienced adversary can attack ML-based techniques during the training phase (poisoning attacks) or the prediction phase (evasion attacks). Below, we will discuss these offensive techniques in the context of an IDS.

Poisoning techniques.

Rubinstein et al. [109] investigated the vulnerabilities of the PCA-subspace method for detecting anomalies in backbone networks. They designed an effective poisoning scheme called the “Boiling Frog” to slowly poison the detector over time. As network anomaly detectors are periodically retrained to capture evolving trends in the
underlying data, their scheme was able to boost the false negative rate with far less “chaff” (useless data), albeit over a long period of time. This makes sure that the poisoning itself is not detected. They showed that attackers can evade detection successfully by only adding moderate amounts of poisoned data. They poisoned a classifier to make it miss an upcoming DoS attack. In general, the authors were able to achieve a high level of evasion for the DoS attack (28% with as little as 10% chaff inserted). They also looked at the impact of the level of adversary’s knowledge and their timing strategy on the success of the attack.

Kloft et al. [61] attempted a poisoning attack on an online centroid anomaly detection with a finite sliding window of training data. They found that in order to stage a successful poisoning attack the attacker needs to control 35% of the training pool (when the attacker has full control over the training data) or 5-15% of all traffic (when they’re restricted to only a certain number of samples). Their results indicate that online centroid anomaly detectors with a finite sliding window size are not secure unless we can control the attacker’s access to data and that a poisoning attack cannot succeed unless an attacker controls more than the critical traffic ratio.

Evasion techniques.

In [134], the authors designed a neural network-based intrusion detection system and showed that the system can be fooled using adversarial examples. Many machine learning models used in intrusion detection systems create high dimensional features. This fact creates an opportunity for attackers to insert adversarial inputs and mislead the classifiers. The authors used a modified KDDcup99 dataset with a total of 24 attack types. The neural network-based IDS has 3 hidden layers of 100 neurons and the Grid Search algorithm is used to tune the number of neurons.

The authors used L1 norm to generate the adversarial examples which was originally proposed by Grosse et al. [48]. Interestingly, the authors were able to misclassify all the attacks in the test dataset which shows that
adversarial examples are a real threat to IDSs. Authors in [133, 140] also showed similar observations. Algorithms used to generate adversarial examples are Fast Gradient Sign Method (FGSM), Jacobian-based Saliency Map Attack (JSMA), Deepfool, and C&W attack.

Huang et al. [54] launched attacks against three deep learning-based IDSs (CNN, LSTM, and MLP) and showed that the most serious damage was done by FGSM. Because of the attack, the accuracy of the LSTM algorithm was reduced to 42% from 98%.

Black-box attacks are not as powerful as the white-box attacks since the attacker now has a lot less information about the underlying algorithm. Nonetheless, Rigaki et al. [107] showed that it is possible to avoid detection by using a Generative Adversarial Network (GAN). They modified the source code of a malware so that it receives parameters from the GAN and adapt its behavior accordingly to avoid detection. The GAN was trained to mimic Facebook chat traffic. After only 400 epochs, they were able to reduce the traffic blocking percentage to zero. Similarly, in [119], the authors used a GAN with active learning to generate successful adversarial traffic with minimal training labels.

4.3.2 Designing IDSs in adversarial settings.

Since adversarial machine learning is a real threat to today’s IDSs, we need to design anomaly detectors that perform well even in the presence of an adversary. In [129], the authors proposed an approach to reliably perform real-time anomaly detection in streaming data in adversarial settings. The proposal relies on a class-specific stream outlier detector to automatically and reliably update the intrusion detection engine over time and rejects potentially evasion attempts or non-reliable decisions.

To thwart exploratory attacks, the authors used the immutable behavior of the outlier detection algorithm. It is a restriction that does not allow an outlier to become an inlier over time. The authors consider that in anomaly-based intrusion detection, an event that is initially classified as outlier should not become an inlier at any moment in time. For example, an attack that was classified as an outlier (attack) by the normal outlier detection algorithm, must not be classified as a normal event afterward, even if its occurrence increases in the sliding window over time.

To prevent causative attacks, in addition to the immutable property of the detectors, a reliable initial population is necessary. One way to ensure that is the use of a predominant number of copies of the same inlier events during the initial training phase. Through a set of comprehensive experiments, the authors showed that their methods are resistant to both causative and exploratory attacks.

Rubinstein et al. [109] designed a robust defense mechanism against poisoning attacks on PCA-based anomaly detectors. The authors adapted PCA-GRID for anomaly detection by combining the method with a new robust cutoff threshold. Instead of modeling the squared prediction error as Gaussian (as in the original PCA method), they modeled the error using a Laplace distribution. They showed that their method provides robustness for nearly all the ingress POP to egress POP flows in a backbone network, rejects much of the contaminated data, and continues to operate as a DoS defense even in the face of poisoning.

Khamis et al. [59] used the min-max technique as a defense mechanism for IDSs in an adversarial setting. To increase the robustness of the machine learning models against adversarial attacks, the authors used the adversarial learning defender strategy that incorporates adversarial samples in the training phase. They used the max approach for generating adversarial samples that achieves maximum loss and attack deep neural networks used in the IDS and utilized the min approach to optimize intrusion detection systems to minimize the loss of the incorporated adversarial samples. The authors conducted experiments using the UNSW-NB 15 dataset and showed that DNN with min-max formulation increases the robustness of the experimental IDS. Moreover, they demonstrated that carrying out dimensionality reduction using PCA on the dataset helped in decreasing evasion rates.
4.3.3 Discussion.
Intrusion Detection Systems (IDS) are increasingly adopting machine learning techniques due to their ability to automatically learn underlying threat patterns/features from the network data packets. ML-based techniques are also capable of detecting zero-day attacks. Moreover, the fast-developing software-defined networks with programmable controllers have provided a convenient platform to implement ML-based IDSs [123]. Because of that, IDSs will be a prime target of adversarial attacks since they are one of the main tools to protect corporate networks. As a result, the need for developing a methodological way to build robust and trustworthy ML systems is more than ever.

5 PRIVACY-PRESERVING MACHINE LEARNING

Table 3. ML privacy & Countermeasure

| Citation       | Privacy Breaches                  | Countermeasures                  | ML Pipeline stage |
|----------------|-----------------------------------|----------------------------------|------------------|
| [118]          | Membership Inference               | Regularization techniques       | Prediction Phase |
| [38]           | Model Inversion                    | Differential privacy             | Training Phase   |
| [39]           | Model Extraction Path finding      | Differential privacy             | Training Phase   |
| [128]          | Model Inversion                    | Differential privacy             | Training Phase   |
| [14, 16, 21, 43, 47, 77] | Privacy-Preserving Training/Prediction | FHE & polynomial approximation | Training Phase   |
| [13, 75]       |                                   | MPC                              | Prediction phase  |
| [26]           |                                   | Secret sharing & additive HE     | Distributed training |
| [82, 91, 115, 145] |                               | FHE + MPC                        | Prediction phase  |
| [76, 111]      |                                   | Functional encryption            |                  |

In the previous section, we have presented various attacks that compromise the integrity and availability of ML systems, and corresponding multi-stage defense mechanisms. We now turn our attention to the various ways in which confidentiality or privacy may be compromised in an ML pipeline and some protection measures.

5.1 Types of Privacy Breaches
Statistical disclosure control states that the model should reveal no more about the input to which it is applied than would have been known about this input without applying the model. A related notion of privacy appears in [39]: a privacy breach occurs if an adversary can use the model’s output to infer the values of sensitive attributes used as input to the model. However, it is not always possible to prevent this kind of privacy breach if the model is based on statistical facts about the population. For example, the model may breach privacy not of the people whose data was used to create the model, but also of other people from the same population, even those whose data was not used and whose identities may not even be known. Valid models generalize accurate predictions on inputs that were not part of their training datasets. That is, the creator of a generalizable model cannot do anything for the privacy protection because the correlations on which the model is based or the inferences that these correlations enable exist for the entire population, regardless of the training sample or the model creation.

Machine Learning training data usually contains a large amount of private and confidential information. Meantime, trained models including model hyperparameters are also considered sensitive information since
adversaries can take advantage of the knowledge of these information to launch more powerful, white-box or gray-box based attacks. There are four common types of attacks during the ML training and prediction phases to steal these private and sensitive information [4, 128], including Reconstruction Attack, Model Inversion Attack, Membership Inference Attack, and Model Extraction.

5.1.1 Reconstruction Attack.
Reconstruction attacks reconstruct raw, private training data by using the knowledge of model feature vectors [4]. Reconstruction attacks are white-box attacks which require access to an ML model’s parameters such as model feature vectors. In the cases where the feature vectors are not removed from the trained model when the model is deployed in production, or for some learning algorithms such as SVM or kNNs (k-nearest neighbors), where those feature vectors are stored with the model, reconstruction attack is possible. Examples of this type of attacks include fingerprint reconstruction and mobile device touch gesture reconstruction. To resist reconstruction attack, researchers advised against using ML models e.g. SVM that store explicit feature vectors.

5.1.2 Model Inversion Attack.
Model inversion attacks [4, 38] utilize the responses for inputs sent to a trained ML model in an attempt to create feature vectors that resemble those used in model training. If the responses include confidence information of model prediction, the attack can produce an average of confidence that represents a certain class. Typically, the model inversion attack does not infer whether a sample was in the training dataset or not. However, in cases where a certain class represents an individual, e.g. in the application scenario of face recognition, the individual’s privacy might be breached.

Model inversion attack can be launched together with reconstruction attack to further breach ML privacy. To resist this type of attacks, researchers advised to limit the information included in the responses from model prediction. For example, in the case of classifier models, classification algorithms should only report rounded confidence values or even just the predicted class labels.

5.1.3 Membership Inference Attack.
Membership inference attacks attempt to determine if a sample was a member of the training dataset [4]. Shokri et al. [118] quantitatively explore how machine learning models leak information about the individual data records. Given a data record and black-box access to a model, they determine if the record was in the model’s training dataset. To perform membership inference against a target model, they train their own model to recognize differences in the target model’s predictions on the inputs that it trained on versus the inputs that it did not.

Overfitting is an important reason why machine learning models leak information about their training datasets. Regularization techniques such as dropout can help defeat overfitting and also strengthen privacy guarantees in neural networks. Regularization is also used for objective perturbation in differentially private machine learning.

5.1.4 Model Extraction.
In model extraction attacks described in [128], an adversary with black-box access and no prior knowledge of an ML model’s parameters or training data, can query an ML model to obtain predictions on input feature vectors. The adversary’s goal is to extract an equivalent or near-equivalent ML model and duplicate the functionality of the model. Unlike in classical learning theory settings, ML-as-a-Service offerings may accept partial feature vectors as inputs and include confidence values with predictions. Given these practices, the authors show simple, efficient equation-solving model extraction attacks that use non-adaptive, random queries to extract target ML models with near-perfect fidelity for popular model classes including logistic regression, neural networks, and decision trees. They demonstrate these attacks against the online services of BigML and Amazon Machine Learning and show that the natural countermeasure of omitting confidence values from model outputs still admits potentially harmful model extraction attacks.
5.1.5 Classic Privacy Considerations.
Training deep learning models is a computationally and data intensive task. As it was discussed in section 3, typically the computation party (cloud computing servers, machine learning as a service providers, etc.) is a different entity from the input party (who is the owner or contributor of the training data). In this case the model training task is delegated to the computation party. How to prevent privacy breach of the training data during the stages of data collection, data transition and data storage becomes a classic privacy-preserving problem. Furthermore, in the setting of Machine Learning as a Service (MLaaS), trained models are only available through a cloud service to end users. From the user’s perspective, there are privacy concerns when they supply samples to the service for prediction. These concerns on data privacy are primarily addressed by using various cryptographic mechanisms which will be discussed in detail in the next subsection.

5.2 Privacy-Preserving Measures
Privacy-Preserving ML (PPML) technologies protect against some of the privacy breaches described above and enable collaborative learning, in which the input party and the computation party are distinct entities. There are two main techniques to protect ML privacy [4, 70, 132]: Perturbation Mechanisms including differential privacy methods and dimensionality reduction methods, and Cryptographic Mechanisms including fully homomorphic encryption, secure multiparty computation, functional encryption, and crypto-oriented model architectures.

5.2.1 Differential Privacy.
Differential Privacy (DP) [33, 34] is a method to quantify and control the risk to one’s privacy by participating in a database. To achieve differentially private models, methods follow the paradigm of security-by-obscurity [11], which obscure training data by adding noise at various points to protect privacy. Examples of this technique include input perturbation (noised added to input data), algorithm perturbation (noise added to intermediate values in iterative learning algorithms), output perturbation (noise added to generated models), and objective perturbation (noise added to objective function for learning algorithms). Differentially private models are resistant to membership inference attacks.

Other specific model architectures and training regiments are used to satisfy DP. Randomized Aggregative Privacy-Preserving Ordinal Response (RAPPOR) proposed by Erlingsson et al. [36] is a method that employs randomized response mechanisms to achieve differential privacy in the context of crowdsourced datasets. Private Aggregation of Teacher Ensembles (PATE) proposed by Papernot et al. [101] protects the privacy of trained models by constructing a Teacher-Student model that prevents adversaries from having direct access to trained Teacher model, as a way to protect the training data and the Teacher model parameters.

Li et al. [65] proposed a differentially private scheme called privacy-preserving machine learning under multiple keys (PMLM) which supports multiple data providers to securely share encrypted datasets with a cloud server for model training. The PMLM scheme uses public-key encryption with a double decryption algorithm (DD-PKE) to transform the encrypted data into a randomized dataset without information leakage.

5.2.2 Dimensionality Reduction.
Dimensionality Reduction (DR) methods project training data to a lower dimensional hyperplane to prevent adversaries from reconstructing original data or inferring sensitive information. They offer resistance against reconstruction attacks.

Hamm et al. [50] proposed a DR-based defense method applied at the model training phase. The method uses a MiniMax filter to transform continuous and high-dimensional raw features to dimensionality-reduced representations of the data. This preserves the information on target tasks, but sensitive attributes of information are removed which makes it difficult for an adversary to accurately infer such sensitive attributes from the filtered
output. The MiniMax filter is designed to achieve an optimal utility-privacy trade-off in terms of prediction accuracy and expected privacy risks.

5.2.3 Homomorphic Encryption.
Homomorphic encryption (HE) [42] are cryptographic encryption algorithms that allow computations to be performed on the underlying plaintext by acting solely on the encrypted ciphertext. More formally, Enc is a Fully\(^2\) Homomorphic Encryption (FHE) if it is equipped with operations “⊕” and “⊗” such that \(\text{Enc}(a) \oplus \text{Enc}(b) = \text{Enc}(a + b)\) and \(\text{Enc}(a) \otimes \text{Enc}(b) = \text{Enc}(a \times b)\). Several challenges arise when applying FHE to machine learning:

- FHE algorithms are defined for polynomials over finite rings (e.g. the integers modulo \(n\) with addition and multiplication forms a ring) whereas machine learning operates over floating point numbers.
- It adds significant computing overhead to any operation. For most of the existing FHE schemes, the time complexity of each elementary operation (+ and ×) grows with the multiplicative depth of the total circuit to evaluate. This depth must be known in advance in order to select the appropriate parameters for the encryption scheme.
- It is restricted to computing polynomial functions. While polynomials can in theory compute any function as they can emulate boolean circuits, the multiplicative depth of the resulting function would make such implementations impractical. Hence a common approach in the works referenced in this section is to use polynomial approximation of more complex functions.

Homomorphic encryption has evident application to privacy-preserving prediction and training where the input party’s data is hidden from the computation party: the input party encrypts its input and the computation party performs operations homomorphically on the encrypted ciphertext.

Prediction Phase.
Since HE performs much better with polynomial functions that have low multiplicative depth, [47] proposed to build a system for training and classification composed exclusively of ML algorithms that are polynomials of low degree. This is a severe restriction in the context of machine learning; many common operations such as the comparison and division of two numbers, and the logarithmic and exponential functions cannot be expressed as bounded degree polynomials. Accuracy of the resulting ML model is thus severely impacted by these restrictions. Furthermore, the high computational costs and data representations associated with HE restrict the application of these techniques to binary classification (where model parameters are expressed as bits) on small datasets.

The first application of HE to more complex statistical models (i.e. neural networks) is in [43]. They focus on the task of classification (not learning) on encrypted data using HE. Their main contribution can be summarized as a new encoding of real numbers into polynomial rings and the use of low-degree polynomial approximation of non-linear functions used in machine learning. For example, activation functions such as the rectified linear unit \(z \mapsto \max(0, z)\) are replaced with the square function \(z \mapsto z^2\) and pooling layers such as max pooling \(z_1 \ldots z_n \mapsto \max(z_1, \ldots, z_n)\) are replaced with scaled mean pooling layers \(z_1 \ldots z_n \mapsto \frac{1}{n} \sum_i z_i\). This means that the classification function can be expressed as a bounded degree polynomial. They demonstrate the feasibility of this approach by benchmarking secure classification on the MNIST dataset of handwritten digits.

Chabanne et al. [21] use the observation that polynomial approximations of activation functions (e.g. ReLU) are more accurate on small values centered around 0. They exploit this insight by introducing batch normalization to the FHE prediction framework of [43] which allows them to run private prediction on a deeper neural network and achieve better accuracy.

By changing the way the input vectors are represented and by using a more advanced HE scheme which implements certain types of rotations homomorphically, the authors of [16] manage to drastically reduce the latency and memory usage of the framework presented in [43]. They also propose a solution for evaluating

\(^2\)“Fully” because it can compute any boolean circuit homomorphically.
deeper neural networks homomorphically using transfer learning. The approach involves additional computation on the client side by having it first computing a “deep representation”, then the representation is encrypted and sent to the server. This allows the learner to handle deeper networks while still preserving privacy and efficiency, with the tradeoff of offloading some of the computation on the client.

Training and Feature Selection.
The limitations of HE are evident in early attempts to apply it to privacy-preserving training of even a simple machine learning model. In [91], the authors construct a system to perform ridge regression (a simple model with application for recommender systems) while preserving the privacy of the underlying data. Their system uses homomorphic encryption to protect the training data and employs a trusted third party (TTP) tasked with performing multiparty cryptography with the evaluator who holds the encrypted data (the TTP must not collude with the evaluator, else privacy is no longer guaranteed). Homomorphic encryption is used for the linear parts of the computation and the MPC (Secure Multiparty Computation, see Section 5.2.4) interaction with the TTP is used for non-linearities (i.e. the parts that make HE inefficient).

While completely delegated training of a deep neural network on an encrypted dataset is still beyond reach using existing techniques, [145] offers a protocol that adds rounds of interaction between the client and server to achieve it. In their scheme, the parameters of the model itself are also in encrypted form. Between each step of the backpropagation algorithm, the server sends back to the client the (encrypted) result of the backpropagation step, the client decrypts it, updates the model parameters and sends back the encryption of the updated parameters.

Other components of a machine learning pipeline besides training and prediction are receiving attention. The authors of [77] use homomorphic encryption to the feature selection and prediction phases of a machine learning pipeline. Their techniques are similar to those of other works cited in this section, i.e. the use of a fully or levelled homomorphic encryption scheme and low-degree polynomial approximations of common machine learning functions.

End-to-end training of large models on encrypted data is something that is still out of reach with the current state of the art due to the overhead of FHE on already computationally intensive operations. Another challenge is that the whole training pipeline has to be automated as it is not possible for data scientists to inspect the training data. One of the challenges facing broader adoption of privacy-preserving prediction is that the state of the art techniques in terms of efficiency require special model architectures that need to be planned in advance of training and retraining large models can be expensive.

5.2.4 Secure Multiparty Computation.
Existing technology in homomorphic encryption is very computationally expensive, especially if evaluating complex functions homomorphically. Another solution researchers have turned to is secure multiparty computation (MPC) [67]. In MPC, two or more distrustful parties want to compute a joint function of their private inputs without revealing anything more about their inputs than the function output.

In MPC, adversaries are modelled as a set of corrupted participants. When this set is fixed at the onset of the protocol, we say that the adversary is static. Otherwise, if the set of corrupted participants can evolve, then it is adaptive. Additionally, if corrupted participants merely follow the protocol while trying to gain as much information as possible, they are passive (also known as honest-but-curious or semi-honest behaviour). In the case where they can deviate arbitrarily from the protocol, they are actively corrupted. Unless specified otherwise, the results presented here are in the passive and static security setting.

One of the most basic techniques in MPC is called secret sharing. Secret sharing consists of dividing a secret $s$ into $n$ shares such that at least $t$ shares are required to reconstruct the secret and no $t - 1$ shares reveal anything about the secret.

A natural setting where MPC can be used is in distributed modes of learning where many participants train a joint neural network from their respective datasets. The goal of distributed learning is both to preserve privacy of
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the respective datasets and to reduce communication costs. MPC is also used in conjunction with HE for example by adding interaction to help computing non-linear layers of a network, as done in [91] discussed in the previous section.

A basic operation in any distributed learning protocol is gradient aggregation, the step during which participants globally combine the results of their local training steps. Most often, gradient aggregation consists of the (weighted) sum of the local gradients obtained through gradient descent. Danner et al. [26] deal with distributed machine learning protocol called gossip learning where many parties contribute to the training of a joint model without using a centralized entity or broadcast communications. The author’s contribution is an efficient MPC solution to gradient aggregation by trading accuracy for efficiency and robustness. They propose the use of secret sharing with additively HE to compute an approximate sum of the gradients. Their solution is secure in the semi-honest model with static corruptions.

The work of [13] is in the setting where a server holding a private model and a client holding a private input (feature vector) want to produce a prediction on the client’s input while preserving privacy of both the model and feature vector. This is the general setting which was considered extensively in the last section, but for which MPC solutions are more efficient if one is willing to add rounds of interactions. The authors conceive new MPC protocols optimized for a core set of operations performed during classification tasks such as comparison, argmax and dot product. They apply these protocols to simple classification algorithms such as hyperplane decision-based classifiers, Naïve Bayes classifiers and decision trees.

Another popular form of distributed learning is federated learning [80] where gradient aggregation is performed at a centralized server that sends back the updated model after each aggregation step. Bonawitz et al. [12] apply an MPC layer over the federated learning framework to ensure data privacy by a secure gradient aggregation procedure where the server only learns the aggregated gradients, but not the individual gradients. Their techniques are based on a public key infrastructure with each party incorporating the other parties’ keys into its encrypted message to the server in a way that the encryptions cancel out. Secret sharing is used to handle dropped users by making it possible to reconstruct their keys from the shares. All communications are done through the server and their protocol provides active security.

The work of Makri et al. [75] considers again the setting of classification tasks with a client having a private input (in this case, an image) and the server providing a confidential model. However, unlike the above cited works, their framework involves multiple intermediate parties (called MPC servers) of which at least one must be honest to ensure privacy. Their framework uses transfer learning techniques to extract high-level features at the client with the image classification done using a simple SVM classifier on the encrypted features for improved efficiency. The “encryption” itself is an additively homomorphic secret sharing of the features distributed between the MPC servers. Non-linear operations are done using MPC protocols between the MPC servers.

Most of the papers cited in this section provide a weak notion of security where the adversary is assumed to act semi-honestly – it tries to gain information while following the protocol. In general, adversaries may act maliciously – arbitrarily deviating from the protocol – to gain more information. An important research question is to strengthen the security guarantees provided by the schemes cited here.

5.2.5 Functional Encryption.

Functional encryption (FE) is a primitive akin to homomorphic encryption with the key distinction that the holder of an encryption of $x$ may learn the value $f(x)$ through the use of a decryption key associated with $f$, while leaking only the value $f(x)$ and nothing more about $x$. Functional encryption can be used when the client of a service wants the service to act upon the value $f(x)$ for example in spam classification.

Sans et al. [111] argue that functional encryption is better suited to some delegated machine learning tasks. When the server is tasked with taking an action depending on the result of classification on encrypted data, FE lets the server learn the result without an additional round of exchange with the client. For example, spam
classification could in theory block incoming spam even in encrypted emails. The authors of [111] show that while the above use case is beyond existing FE technologies, some applications of FE to privacy-preserving classification are currently feasible. They demonstrate a classifier for MNIST digits based on a one hidden layer NN with quadratic activation functions where a decryption key allows the server to learn the classification outcome. Their private classification framework is based on their own FE scheme for quadratic functions which improves efficiency compared to previous results.

The idea of using FE for delegated machine learning purposes was pushed further by [76] who apply it to multiple privacy-preserving machine learning tasks. They also provide an open-source functional encryption library with implementation of common FE primitives used in machine learning such as inner product, the square function and attribute-based encryption.

5.2.6 Crypto-Oriented Model Architectures.

It should now be clear that special care needs to be taken when running machine learning alongside homomorphic encryption or secure multiparty computation, otherwise the time and communication complexity can spiral out of control. Beyond polynomial approximations of non-linearities in neural networks, recent results approach the problem of privacy-preserving prediction or training as a neural network design challenge.

Bourse et al. [14] propose looking at the problem as a whole and conceive a framework where changes are simultaneously made to the FHE scheme and the machine learning algorithms so they work in tandem. Their solution is based on discretized neural networks where model weights are integers and the chosen activation function is the sign function \( z \mapsto \text{sign}(z) \). They show that pre-trained conventional neural networks can be converted into discretized neural networks with sign activations. The main innovation of their techniques is that they achieve scale invariance in the complexity of FHE-related operations. This is done by doing a bootstrapping procedure at every neuron of the network, keeping noise at a tolerable level throughout the network evaluation.

Mishra et al. [82] propose an hybrid FHE + MPC approach to privately evaluate neural network architectures that use both ReLUs (executed using interactive MPC) and quadratic approximations (executed non-interactively using FHE). The original contribution of this work is a planning procedure that uses techniques similar to hyperparameter search to find which activations of a neural architecture to replace with quadratic approximations and which to keep as ReLUs.

Shafran et al. [115] propose a new kind of neural network architecture based on partial activation layers where activation functions (e.g. ReLU) are only applied to a fraction of the neurons in that layer, the rest acting only as linear operations. Through experiments, they demonstrate that partial activation layers can achieve a good tradeoff between accuracy and efficiency in the context of private prediction – where the model is privately evaluated using FHE or MPC and non-linearities are very expensive.

6 USER TRUST

While there is a lot of focus on the technical aspects of cyber secure systems, less attention is paid to the interactions between the users and the systems, including research into how end users deal with cyber security attacks. Jajali et al. [56] conducted a systematic review on cyber security of health care information systems and found out that the majority of articles were technology-focused, indicating that nontechnological variables including user interaction are understudied. There is an increasing demand for studies on user trust in machine learning systems. Our literature review investigated the issues surrounding user behaviours and trust of machine learning based systems, how user trust plays an important role in user acceptance of the ML systems, the security implication as users react to cyber security attacks, and the factors that have impacts on user trust. We further studied the design principles and best practices to increase user trust.

Our focus is an investigation on human factors of ML systems in health care and autonomous vehicles. The level of cyber security awareness and need for trust on the part of the user varies according to the type of task;
for example, there is a different level of trust required for trust in ML algorithm for Netflix compared to trust in ML algorithm for a medical diagnosis. This is why we are focusing on the literature concerned with healthcare and autonomous vehicles rather than social media and entertainment recommendations; the latter of which could be considered relatively low risk and requires a lower level of trust and speculation on the part of the user in to privacy and security concerns.

6.1 User trust and adoption of machine learning based systems

A common theme of articles on user acceptance and machine learning healthcare systems is that of trust; researchers identified trust as an important factor in user attitudes towards IoT based healthcare [5, 6, 52, 143]. In a review of articles on barriers to older people’s adoption of assistive technologies, researchers found that the top concern when adopting assistive technologies is related to privacy, followed by issues of trust [143]. Likewise Jaschinski & Allouch found that privacy and intrusiveness were the most important barriers to acceptance – both in the interviews and evaluation phases of their study [57]. In healthcare it is important to ensure that users do not feel like they are under surveillance, as it decreases the user’s willingness to accept such technologies; is easier for user to accept technologies if they feel in control. As a result, there is a need to design to keep user engaged [52]. Systems perceived as intrusive can lead to lower levels of user acceptance – a fact that many researchers overlooked [20].

Autonomous vehicles is an emerging market where research and commercialization is growing steadily. The rise of artificial intelligence (AI) based automated decision systems brings the need/right/obligation (due to regulations) for user explanations of outcomes to increase trust of the system’s decision. Beyond that, the lack of trust in automation as a result of ML tools results in an issue with user adoption [95]. Challenges in the adoption of autonomous vehicles includes issues of trust and ethical implications, both which pose serious threats to user acceptance of the technology [1]. Privacy and cyber security risks of autonomous vehicles are critical to building consumer trust. Informational privacy, which includes the protection of data against misuse, building consumer trust and safeguarding against surveillance [66], is needed to receive the benefits of personal data while controlling the risks.

6.2 User reaction to security attack

While partial automation in vehicles has been in use for decades, high and fully autonomous vehicles represents a relatively new level of technology. Assets in level 4 (high autonomous) and 5 (full automation) vehicles [37] are numerous, likewise potential threats to autonomous vehicles are vast. There is a large body of research on the potential for cyber security attacks on this technology, but not a lot of research on how users react to such attacks. While there has not been any example of real world cyber-attacks on autonomous vehicles, there have been plenty of experimental white hat attacks such as the remote attacks on autonomous vehicles to enable, disable or manipulate the systems; the attacks against various in-vehicle sensors e.g. GPS spoofing; and physical attacks such as drawing white lines/circle around the vehicle to trap it [37].

There is yet to be any studies on user trust in autonomous vehicles to help users react appropriately and timely to cyber security attacks, which is problematic for the average user especially when using new technology and experiencing cognitive overload [68]. This could lead to issues related to the security of the system if a user ignores or overrides any warnings or alerts generated by the system. Parkinson et al., in 2017 identified 14 cyber threats facing autonomous and connected vehicles. Amongst the list they identified several knowledge gaps related to reactions to errors at run-time. In particular they noted a lack of research on how the vehicle and the driver would react to detection of a cyber-attack – how would the vehicle behave during a suspected attacks and how information could be given to the user in order to make any necessary decisions [102]. Likewise, Linkiov et al. state that there is a current need to study how people might behave during a cyber-attack on their autonomous
vehicle. They note that cyber-attacks generally cause increased stress on the user. However, there is no current research on how users react during an attack on a vehicle they are riding in – there needs to be research on how cyber security issues can be communicated to the user in order to elicit appropriate reactions [68].

6.3 User trust: design principles and best practices
The aforementioned research on the interplay of user trust with system adoption and cyber security leads researchers to propose to conduct further studies on user-centered-design principles and best practices.

6.3.1 Increase user visibility.
User visibility has an effect on user trust – there is a need for greater efforts if the product has a higher level of visibility, and therefore there is a need for proactive communication [52]. One key issue with data sharing and privacy of health care data is that of control. In their study on IoT based healthcare, Alraja et al. noticed that there was an increase in user trust when they believed they had control over what data people could access on the system. Their trust levels also increased when providers ensured them that their personal data would be protected [6].

There is a need to understand not just the technological tools needed to ensure cyber secure healthcare systems but also what the end user wants these systems to look like, how much control they require over such systems (while still receiving the benefits of the system) and how they interact with such systems in real work conditions. Trust and trade-offs are linked in ML healthcare systems, whereby users will not consider trade-offs between giving up personal information for usability without trusting that their personal information is safe.

6.3.2 Safety protocol design.
There is a lot of literature on attacking autonomous vehicle (from white hat hackers) but an unexplored area is how safety protocol measures could prevent such attacks. Current test drivers are well educated and trained on the protocol once control is given to the user; however those users with lower technical ability and who are unsure about what the safety implications are might have issues with the change in protocol. Also the attentions need to be paid to how the driver should be alerted to issues in order to act quickly and safely [102].

6.3.3 User trust measurement.
There are many limitations in studying trust and user acceptance of autonomous vehicles and healthcare. The main limitation is the newness of the technology and limited means in which to test real life uses of the technology. Current studies only examine user intent to use through surveys [135] or simulations [86]. More attention needs to be paid to how trust is measured, as currently there are no appropriate scales in which to measure trust in autonomous vehicle technology [86].

6.3.4 Informed consent over the disclosure of data.
Data gathered during or after real world usage of the technology would be valuable. An issue of note is the discussion over the amount of personal data automated vehicles will generate, and the ownership and security protocols around this. Much of the literature is focused on the need for robust anonymization as well as strong encryption [102], but there are also issues at play here which could lead into discussions of informed consent over the disclosure of data, and what types of data are necessary (i.e. location data gathered from smartphones compared to user preference data gathered from web browsers) as well as how to disclose when that personal data has been compromised.

7 EMPIRICAL ROBUSTNESS ASSESSMENT
It is well recognized that an objective and comprehensive assessment, which covers a set of aspects of the quality of a system including system robustness and human factors, is crucial to building trustworthy systems [23]. A
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A trained ML model should be measured by the model performance on prediction accuracy and equally important by the capability to resist adversarial attacks [78]. Independent and standard assessment methodologies and metrics for ML model resilience should be devised to support trustworthy ML system development.

7.1 Quantitative Analysis

Quantitative analysis is a key tool to assess robustness of ML algorithms against adversarial attacks [62], in terms of attacker’s constraints, strategy of attacking optimization, and adversarial impacts. A realistic assessment of ML security risk is a “reasonable-case” analysis which is based on reasonable assumptions on attacker’s capacity, resource and constraints. Such assumptions, e.g. the fraction of the training data can be controlled or the content of network traffic can be manipulated, may vary among ML systems. Threat modeling discussed in section 3 can be leveraged to systematically identify these assumptions.

Researchers have devised various attacking methods, as discussed in section 4, to uncover the weaknesses and vulnerabilities in machine learning algorithms. The efficiency of the attack methods typically are measured by the level of negative impacts on an ML system performance. For binary classifiers, most performance metrics are derived from four distinctive classification outcomes: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) [113]. The commonly used performance metrics include:

- **Accuracy** = (TP + TN)/(TP + FP + FN + TN): represents the ratio of correctly predicted samples to the total samples;
- **Precision** = TP/(TP + FP): represents the ratio of correctly predicted positive samples to the total predicted positive samples;
- **Recall** = TP/(TP + FN): represents the ratio of correctly predicted positive samples to the all positive samples; and
- **F1 score** = 2×(Recall × Precision)/(Recall + Precision): represents the weighted average of Precision and Recall that takes into account both false positives and false negatives.

These metrics have been widely used by researchers to demonstrate performance decrease when an ML system suffers due to various adversarial attacks for various ML algorithms and applications. Depending on the factors such as security violation (e.g. integrity vs. availability), attack vectors (e.g. evasion attack vs. poisoning attack), and application scenarios, the suitable metrics may vary. For instance, in [32] the metrics Accuracy, Precision, False Positive, and True Positive were used to measure the negative impacts of the poisoning attacks to four ML models’ integrity, including gradient boosted machines, random forests, naive Bayes statistical classifiers, and feed forward deep learning models, in the application of IoT environments; in [110], the evaluation was focused on the Recall metric to study the robustness of a Deep Learning-based network traffic classifier by applying several Universal Adversarial Perturbation based attacks against various traffic types including chat, email, file transfer, streaming, torrent, and VoIP; in [9], several metrics including Area Under the Curve (AUC, a type of false positive metric), Genuine Acceptance Rate (GAR) and False Acceptance Rate (FAR) were proposed to evaluate pattern classifiers used in adversarial applications like biometric authentication, network intrusion detection, and spam filtering.

7.2 Assessment Methodologies

It is a very challenging task to perform ML system security evaluation, especially when assessing the efficiency of defense mechanisms. Studies have reported that many defense mechanisms that were claimed efficient have been found out either less efficient (lower robust test accuracy) or even broken when enhanced, diversified attacks were used [17, 25, 45], which led to wrong impression of ML system robustness.

Researchers have proposed novel methods to address this challenge. Biggio et al. proposed an empirical security evaluation framework that can be applied to different classifiers, learning algorithms, and classification
tasks [9]. The framework, which consists of an adversary model to define any attack scenario, a corresponding data distribution model, and a method for generating training and testing sets used for empirical performance evaluation, provides a quantitative and general-purpose basis for classifier security evaluation.

They provided three examples of using their framework by attacking different systems, namely, spam filtering, biometric authentication, and network intrusion detection. In the case of an IDS, they designed an anomaly detector using one-class SVM with a radial basis function (RBF) kernel. Each network packet was considered an individual sample to be labeled as normal (legitimate) or anomalous (malicious) and represented as a 256-dimensional feature vector. They assumed the attacker had knowledge of the feature set and the algorithm used, but no access to the training data and the classifiers’ parameters or any feedback from the classifier. Samples injected were on purpose made to emulate other existing network traffic (same histogram of payload’s bytes), so that they are not excluded as anomalous during detector re-training. As a result, the authors managed to compromise more than half the accuracy of the system.

Goodfellow et al. introduced the concept of “attack bundling” [45]. While various attack algorithms can be used to generate adversarial samples, the attack bundling is devised to measure the true worst-case error rate within the threat model under consideration by choosing the strongest adversarial sample among the ones generated using all the available attack algorithms for each clean example. While the approach of attack bundling is considered suitable for white-box attacks, the author also described the way to apply it in the black-box setting. Attack bundling may help to alleviate the problem of ML robustness overestimation.

In [25], Croce and Hein presented their work on ML robustness evaluation method. The authors designed a new gradient-based scheme called Auto-PGD which remedies the standard Projected Gradient Descent (PGD) attacks, the most popular adversarial algorithm, by (i) automatically adjusting the hyperparameter “step size” and (ii) using an alternative loss function. Auto-PGD is then combined with the white-box FAB-attack and the black-box Square Attack to form an ensemble of complementary attacks call AutoAttack to increase attack diversities. AutoAttack has been studied in a large-scale evaluation on over 50 classifiers from 35 papers that claimed the models are robust. The reported result demonstrates the efficiency of the tool with the majority of the tests yielding lower robustness than the ones claimed in the original papers and several identified broken defenses.

Carlini et al. in their paper [17] discussed the methodologies and best practices in ML robustness evaluation, including the principles of rigorous evaluation, the common flaws and pitfalls, and the recommendations on evaluation tasks and analysis. The live document may help ML security practitioners as a guidance to develop and evaluate defensive ML technologies.

The fact that lack of suitable robustness metrics hinders widespread adoption of robust ML models in practice [41] attracted some researchers’ interests. In [11], Biggio et al. proposed to assess and select ML learning algorithms and models based on the security evaluation curve, which measures the extent to which the performance on prediction accuracy of a trained model drops under attacks of increasing attack strength (for example, the amount of input perturbation for evasion attacks or the number of adversarial samples injected into training data for poisoning attack). The authors further discussed that while the metric of minimally-perturbed adversarial samples can be used to analyze the sensitivity of a trained model, maximum-confidence attacks are more suitable for assessing model resilience. That is, using the security evaluation curve to demonstrate that if attack strength is not larger than $\epsilon$, then the model prediction performance should not drop more than $\delta$.

Katzir et al. proposed a formal metric called model robustness (MRB) score to evaluate the relative resilience of different ML models, as an attempt to quantify the resilience of various ML classifiers applied to cyber security [58]. The method is based on two core concepts - total attack budget and feature manipulation cost to model an attacker’s abilities. The researchers reported that MRB provides a concise and easy-to-use comparison metric to compare the resilience of different classification models trained using different ML learning algorithms against simulated evasion attack and availability attack. MRB method relies on domain experts to estimate feature
manipulation costs, which is considered a limitation of the method as it is prone to subjective variation of domain experts’ estimation.

8 ROBUST AND TRUSTWORTHY MACHINE LEARNING SYSTEM DEVELOPMENT

In the previous sections, we presented various technologies that can be used to support robust and trustworthy ML system development. However, our literature review found little studies on how to leverage these technologies from a security engineering perspective, which in general encompasses tools, methods and processes to support system development to protect the system and its data from malicious attacks [7]. In this section, we attempt to push our effort forward above and beyond a survey by exploring how to address this gap of knowledge. Based on the literature we have studied, we developed a metamodel to formalize and generalize the body of knowledge. We choose to use UML, a de facto general-purpose development and modeling language in the field of software engineering, to specify the core concepts, the fundamental entities and their intricate relationships captured in the metamodel. We then further illustrate how to perform ML threat analysis and security design following a systematic process based on the metamodel.

8.1 Robust and Trustworthy ML Development: Metamodel

Figure 4 shows the UML metamodel for robust and trustworthy ML development that captures the entities and the relationships between them from three different aspects: ML Vulnerability, Threat Modeling, and Security Analysis.

The ML Vulnerability sub-model presents assets to be protected across a typical ML pipeline and vulnerabilities that are exploitable and therefore will bring risks against the assets. By analyzing the data flow along the pipeline, a set of assets has been identified including raw data; feature vectors; information pertinent to model training such as learning algorithms, model architecture and hyperparameters; trained model parameters (weights and biases); and input/output for model prediction. The Threat Modeling sub-model captures the adversarial aspects of threat modeling in the context of ML system development that have been discussed in section 3. It models a comprehensive profile of potential adversaries who pose threats to an ML system. The Security Analysis sub-model includes three types of key entities in secure ML development: attack vectors, defense mechanisms, and robustness assessment that have been discussed through section 4 to 7. An attack vector represents a path to exploit an ML system by using various attack methods and usually with the help of tools to increase the power of attacking. At each ML pipeline phase there may exist multiple feasible attack vector(s). Correspondingly, different defense mechanisms are available to defeat the attacks and mitigate the risks. Robustness assessment, a critical tool to assure a system’s security posture, follows a systematic approach and uses a set of suitable quantitative and qualitative metrics to gauge the performance and efficiency of the applicable attack vectors and adopted defense mechanisms.

The metamodel provides ML developers with an expressive model in a standard and visualized method for robust and trustworthy system development. In the following subsections, we will illustrate how we can perform systematic threat analysis and security design in the context of a generic ML system development by leveraging the metamodel.

8.2 Threat Modeling

Threat modeling is a process to define the security objectives for a system, identify potential attackers and their goals and methods, and conclude potential threats that may arise. The security objectives is the first artifact we developed during threat modeling. It is set to protect all the assets identified in the “ML Vulnerability” sub-model including the ML system itself, including:

- protect the authenticity, integrity, and confidentiality of raw data;
Based on the “ML Vulnerability” sub-model, we further developed the attack surface, as shown in Figure 5, which identifies all the potential attacking points along the entire pipeline where an ML system may be exposed to adversaries. Then with the identified attack surface, we developed attack trees against the defined security objectives, as shown in Figure 6. The attack trees are derived from the potential attack vectors specified in the “Security Analysis” sub-model. The attack trees present at high level an intuitive and visualized view of the threats an ML system may face. It is a very useful tool to further derive attack scenarios that can be used during the system security design phase to help identify appropriate defense mechanisms as well as to validate the system’s security compliance during the system implementation phase.

8.3 Security Design

We used the attack trees to effectively identify appropriate defense mechanisms based on the available defense methods specified in the “Security Analysis” sub-model. Figure 7 shows an outcome of the security design that adopts various defense methods across the entire ML pipeline to defeat the attacks and protect the system assets.

It is worth noting that the aforementioned analysis of the threat modeling and security design is based on the context of a generic ML system development. The “Threat Modeling” sub-model identifies various characters of potential adversaries that can be used to depict the adversaries against an ML system. These characters can be used to develop a taxonomy of the attack-defense methods, so that feasible attacks and applicable countermeasures can be easily identified in the context of a specific, concrete ML system.

9 CONCLUSION: OPEN PROBLEMS AND FUTURE RESEARCH DIRECTIONS

Machine Learning technologies have been widely adopted in many application areas. Despite the benefits enabled by applying the ML technologies, it is a challenge to ensure that the ML systems are sufficiently robust against security attacks and privacy breaches and users have trust in the systems. Robust and trustworthy ML system development has not yet been widely adopted in industry. From the security engineering perspective, this is due to a number of reasons including the lack of (i) general guidance with key principles and best practices; (ii) efficient ML defensive technologies; (iii) ML robustness assessment methodologies and metrics; and (iv) dedicated tool support.

In this article, we summarized our findings on the survey of the state-of-the-art technologies that can be leveraged to support the development of robust and trustworthy ML systems, including threat modeling, common offensive and defensive technologies, privacy-preserving machine learning, user trust in the context of machine learning, and empirical evaluation for machine learning robustness. We then explored an engineering effort to push forward our studies above and beyond a survey. We created a metamodel specified in UML to represent the body of knowledge acquired in the survey. We further illustrated how the metamodel can be used to guide a systematic approach to threat analysis and security design in ML system development.

In many research work that we reviewed, the authors emphasized the importance of offensive-defensive ML technologies and proposed the design of robust ML algorithms as a direction to future research. The results of our investigations only reinforce that view. In addition, we believe the engineering of ML system development, which is currently at its incipient stage, is critical to ensure ML system’s robustness and trustworthiness. In section 8, we demonstrated what a systematic approach to ML threat modeling and security design may look like, by extending and scaling up the classical process. Our results in this area and their analysis are still preliminary since a more thorough treatment would be beyond the scope of this work. Hence, we propose the following two
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Future research directions that we expect could shed light on the research of the robust and trustworthy ML system development for both industrial and academic practitioners in the near future.

9.1 Develop a comprehensive ML metamodel

Figure 4 presents a preliminary result of the modeling effort that is limited to the scope of our survey. A comprehensive metamodel should represent the body of knowledge considering all of the following aspects:
- different machine learning approaches such as supervised learning, unsupervised learning, and reinforcement learning;
- different machine learning architectures including classic, "shallow" models and deep neural network learning models; and
- all phases in the ML pipeline including data collection, feature extraction, model training, prediction, and model retraining.

In addition, while plenty of research on the ML offensive-defensive technologies are primarily based on various adversarial sampling algorithms, there exist simple and direct attacks across the process of ML system implementation and integration, e.g., last layer attack, GPU overflow attack, tainted open source models and datasets [60, 121, 137], which should be included in the scope of the modeling as well.

9.2 Develop an ontology for machine learning robustness and trustworthiness

The ontology of a certain domain, e.g., cyber security, is about its terminology, essential concepts in the domain, their classification and taxonomy, their relations, and domain axioms [31]. Cyber security ontology describes the body of knowledge in the domain, which was first coined in 2012 by the Software Engineering Institute at Carnegie Mellon University. Efforts have been made since then to develop cyber security ontology, including the recent progress on the ontology for network security [120]. Another example of applying ontology in building trustworthy systems is an ontology-based metric framework proposed in [23].

UML, originally was developed as a software engineering tool, is considered also a suitable language for knowledge representation [31]. UML provides a standard way to specify and visualize information system. It can be used to develop structural models that emphasize the organization of a system, or behavioral models that emphasize the dynamics of the system. The metamodel we created is constructed using class diagram - a type of structural model. There are many other types of UML models available to extend the metamodel to further represent the body of knowledge in the domain.

The development of an ontology for ML robustness and trustworthiness is to capture and represent basic concepts, key entities and intricate relationships between them in a formal way. A proper and coherent ML ontology can facilitate the ML community to communicate and exchange profound knowledge, develop and share innovative ideas, and open the door to developing tools that support proper system development. Such an ontology can also guide ML developers to follow a more systematic and efficient development process.

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Fig. 4. Robust and Trustworthy Machine Learning Development: MetaModel
Towards a Robust and Trustworthy Machine Learning System Development

**Fig. 5. Attack Surface**

**Attack Data Authenticity**
- Attack against data collection
  - Stealthy channel
- Attack against model training (Poisoning)
  - Label-flipping
  - Backdoor & Trojaning
  - Gradient descent
  - Memory

**Attack ML Integrity**
- Attack against model prediction (Evasion)
  - Transferrable samples

**Attack ML Availability**
- Attack against model training (Poisoning)
  - Label-flipping
  - Gradient descent

**Attack ML Privacy**
- Attack against model training
  - Reconstruction
- Attack against model prediction
  - Model inversion
  - Membership inference

**Fig. 6. Attack Trees**
Fig. 7. Security Design