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Foundations and Trends® in Privacy and Security

Published, sold and distributed by:

now Publishers Inc.
PO Box 1024
Hanover, MA 02339
United States
Tel. +1-781-985-4510
www.nowpublishers.com
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Outside North America:

now Publishers Inc.
PO Box 179
2600 AD Delft
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The preferred citation for this publication is

B. Han *et al.*. *Trustworthy Machine Learning: From Data to Models*. Foundations and Trends® in Privacy and Security, vol. 7, no. 2-3, pp. 74–246, 2025.

ISBN: 978-1-63828-549-6

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Volume 7, Issue 2-3, 2025

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Foundations and Trends® in Privacy and Security, 2025, Volume 7, 4 issues. ISSN paper version 2474-1558. ISSN online version 2474-1566. Also available as a combined paper and online subscription.

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Trustworthy Machine Learning: From Data to Models

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ABSTRACT

The success of machine learning algorithms relies not only on achieving good performance but also on ensuring trustworthiness across diverse applications and scenarios. Trustworthy machine learning seeks to handle critical problems in addressing the issues of robustness, privacy, security, reliability, and other desirable properties. The broad research area has achieved remarkable advancement and brings various emerging topics along with the progress. We present this survey to provide a systematic overview of the research problems under trustworthy machine learning covering the perspectives from data to model. Starting with fundamental data-centric learning, the survey reviews learning with noisy data, long-tailed distribution, out-of-distribution data,

Bo Han, Jiangchao Yao, Tongliang Liu, Bo Li, Sanmi Koyejo and Feng Liu (2025), “Trustworthy Machine Learning: From Data to Models”, *Foundations and Trends® in Privacy and Security*: Vol. 7, No. 2-3, pp 74–246. DOI: 10.1561/33000000043.

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and adversarial examples to achieve robustness. Delving into private and secured learning, the survey elaborates on core methodologies differential privacy, different attacking threats, and learning paradigms, to realize privacy protection and enhance security. Finally, it introduces several trendy issues related to the foundation models, including jailbreak prompts, watermarking, and hallucination, as well as causal learning and reasoning. The survey integrates commonly isolated research problems in a unified manner, which provides general problem setups, detailed sub-directions, and further discussion on its challenges or future developments. We hope the comprehensive investigation presented in this survey can serve as a clear introduction for the problem evolution from data to models and also bring new insight for developing trustworthy machine learning.

1

Introduction

As artificial intelligence (AI) and machine learning (ML) experience advancements rapidly, remarkable breakthroughs have been achieved across a variety of scenarios and applications (Jordan and Mitchell, 2015). These technologies of AI and ML have increasingly become cornerstones of innovation, driving progress in the fields such as healthcare diagnostics (Alowais *et al.*, 2023), autonomous vehicles (Betz *et al.*, 2022), financial modeling (Cao, 2022), protein structure prediction (Abramson *et al.*, 2024), and numerous other domains. Despite these impressive achievements, the trustworthiness of AI systems has come under scrutiny, particularly in security-critical and privacy-sensitive domains. Ensuring that AI systems and ML models are reliable, secure, and trustworthy is not merely desirable but essential for their deployment in large-scale real-world applications.

The heart of machine learning is built upon two crucial aspects: data and model. Data serves as the fundamental resource, representing the diverse, complex, and often noisy real-world phenomena. Meanwhile, the model functions as the learner, with specific model architectures that absorb patterns and knowledge from the data, empowering it to make predictions or decisions in previously unseen scenarios (LeCun

et al., 2015). Notably, the emergence of data privacy and security issues arises at the intersection of data and model, as training data may inadvertently include malicious information that implants backdoors in models (Li *et al.*, 2022b), or contain sensitive privacy details that models could unintentionally expose during inference (Liu *et al.*, 2021a). Overall, these challenges highlight the need to understand and develop trustworthy machine learning from data to model, including perspectives of data-centric methods, privacy and security, and foundation models.

In this monograph, we first discuss the trustworthy data-centric learning, which emphasizes the risks associated with noisy (Song *et al.*, 2022a), long-tailed (Zhang *et al.*, 2023e), out-of-distribution (Yang *et al.*, 2024), and adversarial data (Wang *et al.*, 2019). As the foundation of any ML models, the data directly impacts the model's reliability and generalization ability. Trustworthy data-centric learning focuses on exploring the essential mechanisms by which data influences the trustworthiness of ML models, and designing robust approaches to adapt to, defend against, and mitigate the negative effects of such data challenges. This includes developing robust algorithms for learning from noisy data, handling long-tailed distributions, detecting and generalizing across out-of-distribution data, and improving adversarial robustness and defense strategies. Generally, the goal of trustworthy data-centric learning is to ensure the trustworthiness of ML models from data perspectives, enabling them to handle diverse and complex real-world scenarios while maintaining highly accurate performance.

Privacy and security problems are paramount in the deployment of machine learning models, particularly when dealing with sensitive data (Liu *et al.*, 2021a), such as finance and healthcare. In this monograph, we delve deeply into the approaches that attacking and safeguarding ML systems, addressing challenges from both the data and model perspectives. Specifically, we start with discussing differential privacy (Abadi *et al.*, 2016), a key technique that adds controlled noise to protect privacy while maintaining data utility. We then review two major privacy threats: membership inference attacks (Hu *et al.*, 2022b) and model inversion attacks (Song and Namiot, 2022), both of which attempt to aim to leak information from the training data. Next, we cover data poisoning attacks (Fan *et al.*, 2022) that degrade the model perfor-

mance by manipulating the training data. Additionally, we discuss three types of promising approaches, including machine unlearning (Nguyen *et al.*, 2022), non-transfer learning (Niu *et al.*, 2020) and federated learning (Zhang *et al.*, 2021a), all of which offer solutions to alleviate these risks and enhance trustworthiness of models in defending against such attacks. Overall, these research efforts highlight the vulnerabilities of models and contribute to enhancing the robustness and privacy protection.

Recently, the development of large foundation models, such as ChatGPT, Llama, and Gemini, has revolutionized the field of ML, paving the pathway to artificial general intelligence (Zhou *et al.*, 2024a). Despite their remarkable capacities, these foundation models still face various safety concerns. In this monograph, we discuss several potential risks and vulnerabilities of foundation models, aiming to highlight their weaknesses and provide insights for constructing trustworthy foundation models. In particular, we discuss jailbreak prompts that inveigle foundation models to generate harmful content (Yi *et al.*, 2024), and then review watermarking techniques to ensure content provenance and copyright (Liu *et al.*, 2024a). We next introduce hallucination, which is a critical issue for foundation models in generating unreliable and spurious content (Rawte *et al.*, 2023). Moreover, we discuss causal learning and reasoning methods (Chi *et al.*, 2024a) to enhance reliability of the content generated by foundation models. Finally, we compare different trustworthy concerns in open and proprietary foundation models with their distinct properties. In short, this monograph provides a comprehensive review and discussion of the key challenges and advancements in developing trustworthy machine learning systems, from data-centric approaches, privacy and security concerns to foundation models.

Overview. The monograph is organized around core aspects of trustworthy machine learning from data to models, including *data-centric learning*, *private and secured learning*, and *foundation models*.

- **Trustworthy Data-centric Learning.** First, we start with a systematic review of trustworthy data-centric learning, covering *data-noise learning*, *long-tailed learning*, *out-of-distribution learn-*

ing, as well as *adversarial examples and defense*. These research topics cover fundamental problems regarding data-level issues, e.g., label noise, shifted distribution, outliers, and worst-case corruption. We further categorize specific research problems under the general learning paradigms for discussion.

- **Trustworthy Private and Secured Learning.** Second, we focus on aspects of private and secured learning, covering *differential privacy*, *membership inference attack*, *model inversion attack*, *data poisoning attack*, *machine unlearning*, *non-transferable learning*, and *federated learning*. Considering the trustworthy expectation of privacy, security, and usage or ownership protection, we review a series of critical technologies and research problems.
- **Trustworthy Foundation Models.** Finally, we explore building the trustworthy foundation models, covering *jailbreak prompts*, *watermarking*, *hallucination*, *casual learning and reasoning*, as well as comparison on *open and proprietary foundation models*. These research problems reveal the vulnerability of foundation models in usage control and point the way to developing robust and reliable model learning and reasoning.

In each part, we elaborate on the detailed problem setup and methodology or research directions, for which we conduct a further discussion on promising future development in the problem. We hope this monograph can provide a comprehensive investigation from data to models in trustworthy machine learning and more new insights.

Target Audience and Reading Guidelines. This monograph is intended for researchers, professionals, and graduate students working in the fields of ML and AI. Some sections may contain technical descriptions and discussions that assume a basic knowledge of core ML concepts. Target readers are expected to have a foundational understanding of these key concepts, including supervised, semi-supervised and unsupervised learning, optimization methods, representation learning, federated learning, among others. For undergraduate students or

early-year graduate students new to the field, we recommend first referring to conventional textbooks on ML (Jordan and Mitchell, 2015) and deep learning (LeCun *et al.*, 2015) before delving into the specialized topics covered in this monograph. Additionally, readers unfamiliar with trustworthy ML may benefit from the monograph to establish a solid background of key challenges, methodologies, and emerging research directions in the field. Each section is organized to offer a thorough review and perceptive discussions of its respective topic. This structure makes the monograph suitable for both newcomers looking for a thorough grasp of trustworthy ML and seasoned researchers hoping to further advance the field. We hope this monograph serves as a valuable resource for a broad audience interested in developing more trustworthy and reliable ML systems.

Discussion on the Topic Coverage. In this monograph, our primary focus is on the critical technical aspects of trustworthy machine learning, specifically addressing issues of robustness, privacy, security, and reliability. Our goal is to provide a systematic overview of the evolving research landscape from a data-centric perspective, and consider the privacy and security challenges to building trustworthy foundation models. The overall discussion is with a particular emphasis on data quality, privacy protection, and security challenges. However, we should acknowledge that we don't explicitly cover all the topics that are also important and highly relevant to the field of trustworthy machine learning, such as fairness and bias (Mehrabi *et al.*, 2021; Pessach and Shmueli, 2022), ethics (Chen *et al.*, 2021a; Holmes *et al.*, 2022), and explainability (Došilović *et al.*, 2018; Murdoch *et al.*, 2019). For instance, ML systems can often mirror and amplify biases present in their training data and reflect stereotypes in their outputs, causing a broader concern of algorithm discrimination. In essence, without properly examining the training data, the training stage of the model would reinforce historical or societal prejudices that favor or over-present dominant groups and under-present or mischaracterize minorities.

Moreover, the non-transparency property of ML models increases the difficulty of effective auditing for untrustworthy issues. We do not explicitly discuss fairness and bias, ethics, or interpretability in separated

sections because these issues often require a distinct and deep dive into the societal and moral implications of technologies. However, we recognize the strong connections between these research topics and the core themes of our content. For example, issues of fairness and bias are often intertwined with the robustness considerations discussed in the context of adversarial examples and noisy data, as biased data can lead to unfair and unreliable model outcomes. Similarly, the methodologies explored for privacy protection, such as differential privacy, can contribute to ethical practices by safeguarding sensitive information and ensuring compliance with ethical standards in data handling. Finally, the discussion on casual learning and reasoning for trustworthy foundation models also touches on explainability in the sense that building reliable models often requires transparent and understandable methodologies. We hope this work will complement existing literature and encourage further exploration of these important areas within the context of trustworthy machine learning.

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