

Security risk assessment of Machine-Learning Systems.

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Abstract—This document aims to identify top three cybersecurity risks associated with Machine Learning systems. In the context of cybersecurity, Risk is defined as follows: $Risk = Threat * Vulnerability * Consequence$ [3]
Document outline:

- 1) First part of the document will summarize the most recent work on the topic.
- 2) Second part will identify three primary Risks associated with Machine Learning systems. The Risks will be described in a table with columns presenting the constituent Asset, Vulnerability and Threat.
- 3) Third part will summarize risk mitigation strategies discussed in academic literature from reputed publications and journals.

I. INTRODUCTION

The goal of this document is to identify three primary risks associated with Machine Learning technology.¹

In today's era, ML is ubiquitous component in systems that are built with Information Technology. The popularity of ML, attracts researchers from diverse academic fields. Identification and categorization of top three risks associated with ML will be of fundamental value to the researchers who are interested in ML.

II. BACKGROUND

A. Problem Description

The overarching problem targeted in this work is the security and privacy vulnerabilities inherent in Machine Learning (ML) systems. The most recent work on this is presented in a paper published in 2018 [1]. Our focus is on identification of the top three risks of attack on ML systems.

¹abbreviated as ML; going forward

In this section we will describe "Consequence", "Vulnerability" and "Threat" specific to the technology domain of Machine Learning.

To establish a context of the application areas pertaining to prevalent use of ML, we have referred to the documents mentioned in Appendix A.

B. Adversary Model

We model adversary in terms of threat and threat agent.

III. RELATED WORK

The most recent work that is related to the security assessment of machine learning systems is presented in 2018 [1]. Appendix B summarizes this work.

IV. METHODOLOGY

The methodology deployed in this work is based on a categorization theory [4]. The visual representation of risk will be in the form of three dimensional layers.

The depth of layers will be plotted along Z dimension, which represents the "Consequence" in our Risk assessment model. A point in risk diagram will have 0 in its z co-ordinate, if customer is farthest from the risk. X axis will represent "Vulnerability" and Y axis will represent "Threat".

This survey instigates papers related to various threat models for different machine learning algorithms that were published in top conferences on cybersecurity and machine learning.

V. CONCLUSION

The result of the survey of potential risks associated with machine learning systems is presented as follows:

Risk Factors Domain	Threat	Vulnerability	Consequence	On Vulnerability ML Category	Attack	Defense
Healthcare	NaN	NaN	NaN	Supervised	NaN	NaN
Finance	NaN	NaN	NaN	Unsupervised	NaN	NaN
Governance	NaN	NaN	NaN	Reinforcement	NaN	NaN
Defense	NaN	NaN	NaN			
Environment	NaN	NaN	NaN			
Society	NaN	NaN	NaN			

VI. APPENDICES

A. Appendix A

This section of the document summarizes the literature that were referenced to establish the context of Machine Learning systems. [2]

- 1) Machine Learning is described as a technology that address the need of automated data analysis.

Target audience, as described in the book - "This book is suitable for upper-level undergraduate students and beginning graduate students in computer science, statistics, electrical engineering, econometrics, or any one else who has the appropriate mathematical background. Specifically, the reader is assumed to already be familiar with basic multivariate calculus, probability, linear algebra, and computer programming. Prior exposure to statistics is helpful but not necessary."

- 2) (ML) is categorized in three major areas, viz. "Supervised Learning", "Unsupervised Learning" and "Reinforcement Learning". Vulnerability of an ML system is seen as an information flow pipeline that begins with input features, digital representation of input features, learning mechanism to learn from input features, deployment of learned system. [1]

B. Appendix B

The SoK [1], presents valuable information on "attack" and "defenses" as applicable to machine learning systems. The following table puts the summary of the paper in perspective.

VII. REFERENCES

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