Security risk assessment of Machine-Learning Systems.

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***Abstract*— The outcome of the document would be to recommend top three cybersecurity risks associated with Machine Learning systems. 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.** [1] **[3]**
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. [2]

In todays 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.

[1]Risk will be defined in terms of: $Risk = Threat * Vulnerability * Consequence$

[2]abbreviated as**ML**; going forward

Risk here can be define as follows. $Risk = Threat * Vulnerability * Consequence$
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

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. Specifically, we considered 4 conferences in Table 1.

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
Healthcare	NaN	NaN	NaN
Finance	NaN	NaN	NaN
Governance	NaN	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 ”Reinformcement 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.

On Vulnerability ML Category	Attack	Defense
Supervised	NaN	NaN
Unsupervised	NaN	NaN
Reinforcement	NaN	NaN

VII. References

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