JAYPEE INSTITUTE OF INFORMATION TECHNOLOGY, NOIDA

Department of CSE & IT

Bachelor of Technology, 7th Semester

TERM PAPER

Data Poisoning Attacks in Linear Regression Models

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INTRODUCTION

As machine learning is widely used for automated decisions, the results and models created by machine learning algorithms are exploited by attackers with strong incentives. Recent studies have shown that machine learning models are vulnerable to numerous attacks that compromise the protection of the models and the application systems themselves.

Poisoning is to add a fraction of poisoning points in training to degrade model accuracy (availability attack).In poisoning attacks, in order to exploit the results of a predictive model, attackers intentionally influence the training data. This gives attackers power to manipulate the training dataset in order to control the prediction behavior of a trained model such that the model will label malicious examples into desired classes.

Attacker Knowledge is of two types –

1. White box: full knowledge of the ML system .
2. Black-box: query access to the model.

This is a huge security threat and needs countermeasures to make the model robust against poisoned data. Examples where poisoning attacks have been studied so far include attacks against sentiment analysis, malware clustering, malware detection, worm signature detection, DoS attack detection, intrusion detection and social media chatbots.

PROBLEM STATEMENT

We study the security issues present in machine learning models and focus on poisoning attacks and their countermeasures for linear regression models. A model can be poisoned/broken during various stages of model building and we focus on the attacks done during the training phase.

LITERATURE REVIEW

Paper 1

Title: **Manipulating Machine Learning: Poisoning Attacks and Countermeasures for Regression Learning**

Citation: *Jagielski, Matthew, et al. "Manipulating machine learning: Poisoning attacks and countermeasures for regression learning." 2018 IEEE Symposium on Security and Privacy (SP). IEEE, 2018.*

Link: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8418594

Summary: In this paper, the first systematic study of poisoning attacks and their countermeasures for linear regression models was conducted. It shows the following contributions:

- It considers the problem of poisoning linear regression under different adversarial models;
- Starting from an existing baseline poisoning attack for classification, it proposes a theoretically-grounded optimization framework specifically tuned for regression models;
- A fast statistical attack is designed that requires minimal knowledge on the learning process;
- A principled defense algorithm is proposed with significantly increased robustness than known methods against a large class of attacks;
- Extensively evaluate the attacks and defenses on four regression models (OLS, LASSO, ridge, and elastic net), and on several datasets from different domains, including health care, loan assessment, and real estate.

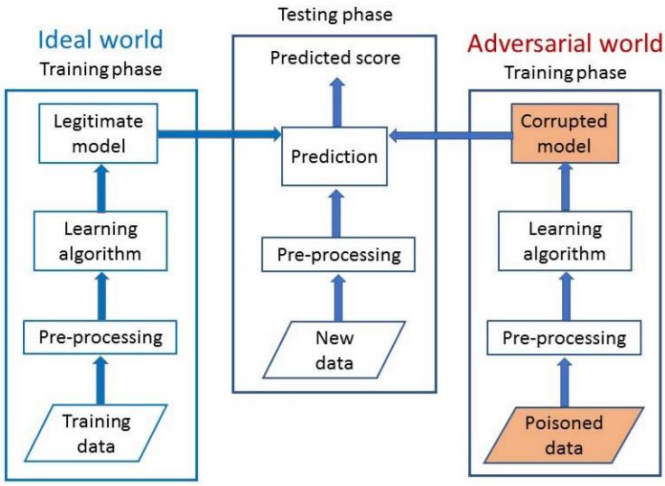


Fig. Overview of working of the model

Paper 2

Title: **ML-Leaks: Model and Data Independent Membership Inference Attacks and Defenses on Machine Learning Models**

Citation: *Salem, Ahmed, et al. "Ml-leaks: Model and data independent membership inference attacks and defenses on machine learning models." arXiv preprint arXiv:1806.01246 (2018).*

Link: https://arxiv.org/pdf/1806.01246.pdf

Summary: In several real-world applications, machine learning (ML) has become a central component, and training data is a key factor driving current development. This tremendous success has prompted the introduction of machine learning as a service (MLaaS) by Internet businesses. Recently, the first membership inference attack has shown that in such MLaaS environments, extracting information on the training set is feasible, which has significant security and privacy implications. At low cost, such attacks are very widely applicable and thus pose a serious risk. Though several ML models are widely popular, they are susceptible to various security and privacy attacks like model inversion, adversarial examples, and model extraction to name a few.

The paper primarily concentrates on the Membership Inference attack. In this attack, an adversary is used to find out whether a given data point or item was used in the training of an ML model or not. This may lead to severe consequences. For example, if a machine learning model is trained on data collected from people with a certain disease through recognizing that the data of a victim belongs to the model's training data, the attacker will learn the health status of this victim immediately.

The paper suggests two methods of protection to resolve the situation. We analyze strategies designed to minimize overfitting, as we demonstrate the link between overfitting and vulnerability to membership inference attacks. In each training iteration in a completely linked neural network, the first one, namely dropout, randomly deletes a certain proportion of edges, while the second method, namely model stacking, organizes multiple ML models in a hierarchical way. The extensive assessment suggests that our defensive tactics are still worthy of being able to largely reduce the efficiency of the membership inference attack while retaining high-level usefulness, i.e. the prediction accuracy of the high target model.

Paper 3

Title: SoK: Security and Privacy in Machine Learning

Citation: Papernot, Nicolas, et al. "SoK: Security and privacy in machine learning." *2018 IEEE European Symposium on Security and Privacy (EuroS&P)*. IEEE, 2018.

Link: http://www-personal.umich.edu/~arunesh/Files/Other/Papers/18-eurosp-adv-ml-sok.pdf

Summary: A dizzying array of applications such as data analytics, autonomous systems, and security diagnostics have been made possible by developments in machine learning (ML) in recent years. ML is now prevalent, with new systems and models being implemented in any conceivable domain, leading to the widespread implementation of inference and decision making based on software. The security and privacy of machine learning is an active yet nascent area.

- A unifying threat model to allow structured reasoning about the security and privacy of systems that incorporate ML is introduced. Considers the entire data pipeline, not just algorithms.
- Attacks and defenses found by the various technological communities are taxonomized.
- Systematize desirable properties to improve the security and privacy of machine learning

Take-away from the paper is that, information systematisation points towards varying, but connected, sensitivity notions. Characterizing the sensitivity of learning algorithms to their training data is important for ML to maintain privacy. Similarly, for secure ML, it is required to control the sensitivity of deployed models to data on which they perform inference. The sensitivity of generalisation error (i.e., the difference between training results and test data) remains poorly understood for many models at the centre of these two principles, and calls for further study.

Paper 4

Title: **Explaining Vulnerabilities to Adversarial Machine Learning through Visual Analytics**

Citation: *Ma, Yuxin, et al. "Explaining vulnerabilities to adversarial machine learning through visual analytics." IEEE transactions on visualization and computer graphics 26.1 (2019): 1075-1085.*

Link: https://arxiv.org/pdf/1907.07296.pdf

Summary: In a number of real-world applications, machine learning models are currently being applied where model forecasts are used to make health care decisions, bank loans, and many other important tasks. Adversaries have started developing strategies to exploit models of machine learning to their benefit.In this article, we present a framework for visual analytics to clarify and explore model vulnerabilities for adversarial attacks. Our architecture employs a multi-faceted visualisation system designed to support the study from the perspective of models , data instances, functions, and local structures of data poisoning attacks.

Under the assumptions of static environments, many of the Machine Learning models were created, where new data instances are presumed to be from a statistical distribution close to that of training and test data. Unfortunately, the real-world implementation of these models creates a complex environment that is home to malicious individuals who in the machine-learning models may wish to manipulate these underlying assumptions; E-mail spam filtering is an example where unwanted mails bypass the spam section and reach the inbox of the user.

The paper proposes a framework for visual analytics to explore vulnerabilities and adversarial attacks against machine learning models. Our system helps users to analyse possible weak points in the training dataset and explore the impacts of poisoning attacks on model efficiency by focusing on targeted data poisoning attacks. Via collaboration with domain experts, task and design criteria were established to support the study of adversarial machine learning attacks. Our system serves as a mechanism for iterative proactive defence, as opposed to conventional reactive defence techniques that respond when attacks are detected. Users can model poisoning operations and explore attack vectors in historical documents that have never been used. This will help domain scientists to design more accurate models of machine learning and pipelines for data processing.

Paper 5

Title: **Machine Learning Security: Threats, Countermeasures, and Evaluations**

Citation: *Xue, Mingfu, et al. "Machine Learning Security: Threats, Countermeasures, and Evaluations." IEEE Access 8 (2020): 74720-74742.*

Link: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9064510

Summary: Recent studies have shown that machine learning models are vulnerable to numerous attacks that compromise the protection of the models and the application systems themselves.This survey extensively analyzes machine learning security problems, concentrating on current attacks on machine learning systems, effective protections or safe learning strategies, and methods of safety assessment. This paper addresses all aspects of machine learning safety from the training phase to the test phase, instead of concentrating on one stage or one form of attack.

The security threats along the life cycle of machine learning systems can be divided into five categories: 1) Poisoning attacks; 2) Backdoor attacks; 3) Adversarial example attacks; 4) Model theft; 5) Recovery of sensitive training data. The first two attacks occur during the training phase, while the last three attacks occur during the test phase.

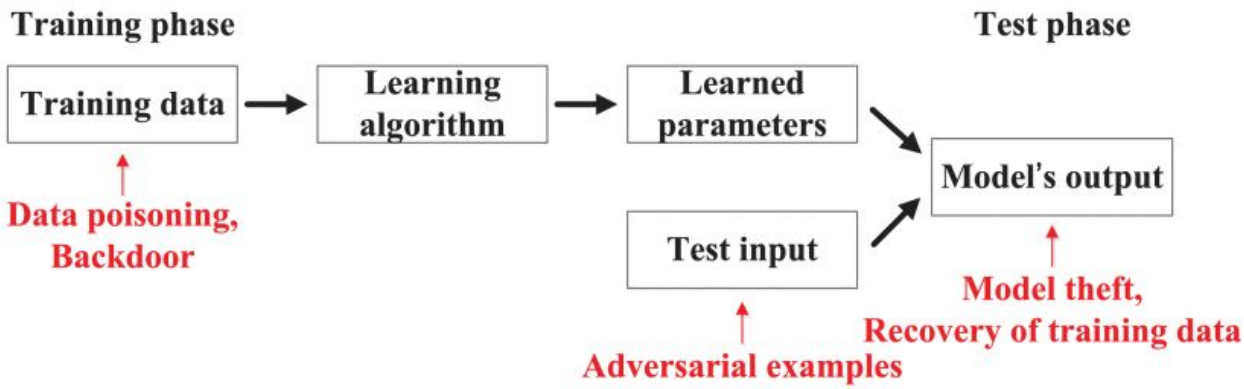


Fig. Overview of all types of attacks

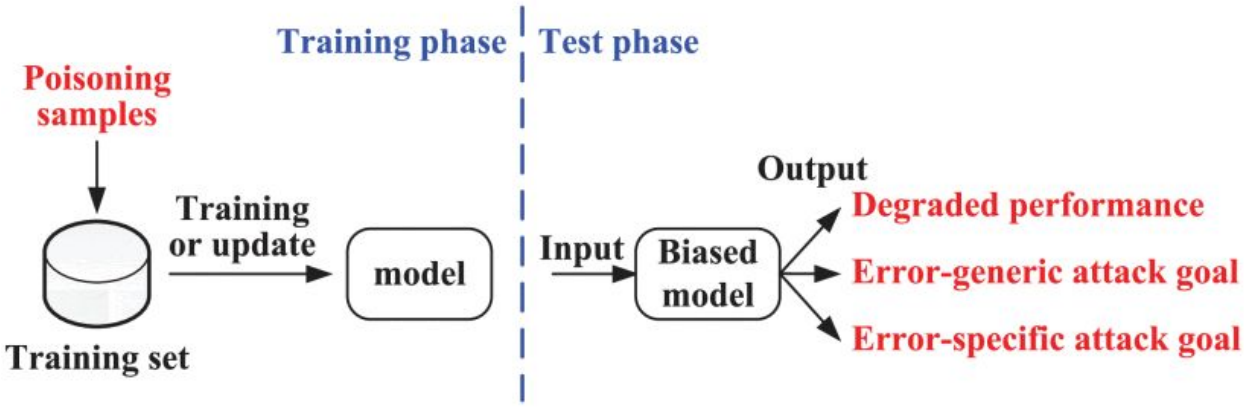


Fig. Overview of poisoning attack

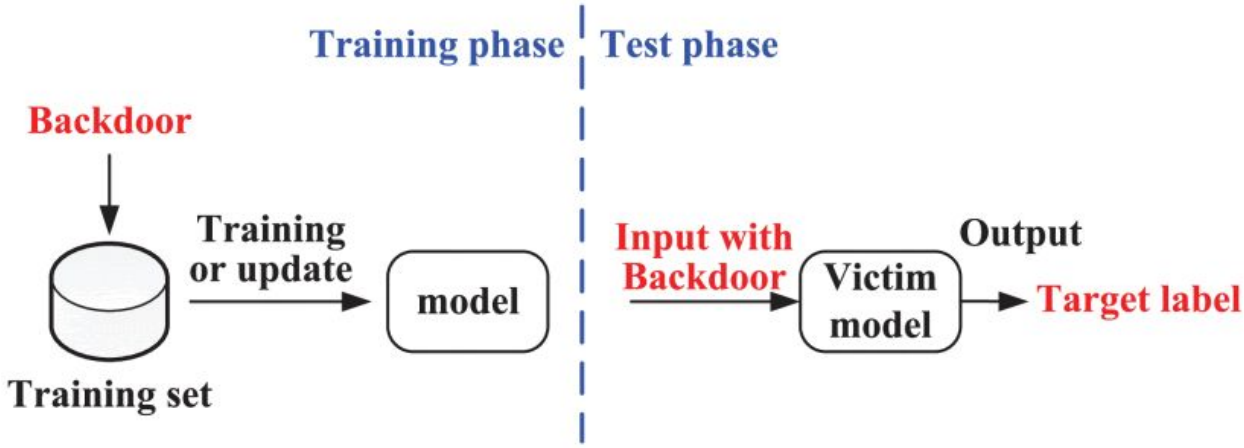


Fig. Overview of backdoor attack

Defense against poisoning attacks on various algorithms include:

- Anomaly detection or security detection by using robust statistical methods such as bagging ensembles , self-adaptive learning camouflage detector.
- SVM- game theory and rejection method
- Robust linear regression , data provenance on contextual information
- In Neural networks check the loss of the model, identify features with abnormal distributions.
- In healthcare based data monitor the accuracy deviations on the training set.

In the training phase, the defensive works against poisoning attacks or backdoor attacks, can be called *data sanitization*, in which the anomalous poisoned data is filtered out first before feeding into the training phase. The anomaly detectors are usually based on training loss, nearest neighbors, and so on

In the test phase, the defense techniques against adversarial examples can be called *smoothing model outputs* , i.e., reduce the sensitivity of the model's output to the changes in the input.

Paper 6

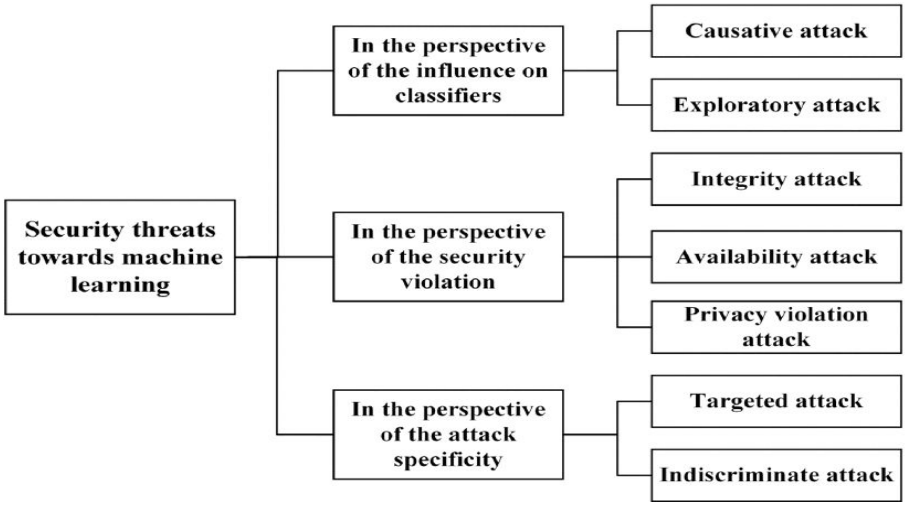
Title: **A Survey on Security threats and Defensive Techniques of Machine Learning: A Data Driven view**

Citation : *Liu, Qiang, et al. "A survey on security threats and defensive techniques of machine learning: A data driven view." IEEE access 6 (2018): 12103-12117.*

Link : https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8290925

Summary : Machine learning has been widely applied in image processing, natural language processing , pattern recognition, cryptography, and other fields, and is one of the most prevalent techniques in computer science. These algorithms and related training data are vulnerable to a number of security threats, causing a substantial performance decrease, regardless of effective implementations of machine learning algorithms in many scenarios, such as facial recognition, malware detection, automatic driving, and intrusion detection. It is therefore necessary to call for more attention to security threats and corresponding machine learning defensive techniques, which motivates a detailed survey in this paper.

This paper discusses current security threats and provides two dimensions, the training process and the testing / inferring process, with a comprehensive survey on them. The paper subsequently categorises existing protective machine learning strategies into four groups: safety evaluation mechanisms, training phase countermeasures, testing or implied phase countermeasures, data protection, and privacy. Finally , the paper presents five notable developments in research into safety risks and machine learning protective strategies that are worth doing in-depth studies in the future.



Paper 7

Title: Robust Linear Regression Against Training Data Poisoning

Citation: *Liu, Chang, et al. "Robust linear regression against training data poisoning." Proceedings of the 10th ACM Workshop on Artificial Intelligence and Security. 2017.*

Link: https://www.ccis.northeastern.edu/home/alina/papers/RobustRegression.pdf

Summary: Supervised learning typically relies on dimensionality reduction in high-dimensional settings to enhance efficiency and recognise the most significant factors in predicting results. However, it has become a natural target for adversarial exploitation of training data, which we call poisoning attacks. Prior approaches to dealing with stable supervised learning, such as feature independence and sub-Gaussian noise with low variance, rely on clear assumptions about the existence of the feature matrix. This paper suggests an integrated robust regression approach that relaxes these assumptions, assuming only that a low-rank matrix can approximate the feature matrix well. In this paper, the techniques combine improved robust low-rank matrix approximation and robust principal component regression, and provide strong performance guarantees. In addition, this paper experimentally shows that the techniques outperform state-of-the-art substantially in both running time and prediction error.

The poisoning attack for linear regression issue with dimensionality reduction is considered in this paper. The paper addresses the issue in two steps:

1. Implementation of a new robust method of matrix factorization to recover the true subspace, and
2. Novel robust regression of the principle variable to prune adversarial instances based on the basis recovered in step (1).

In order to be efficient in recovering the true subspace, this paper defines required and adequate conditions for our approach and presents a bound on expected prediction loss compared to ground truth.

Paper 8

Title: Online Data Poisoning Attacks

Citation : *Zhang, Xuezhou, Xiaojin Zhu, and Laurent Lessard. "Online data poisoning attacks." Learning for Dynamics and Control. 2020.*

Link : http://proceedings.mlr.press/v120/zhang20b.html

Summary : In the online learning environment, where training data arrives sequentially, this paper research data poisoning attacks where the attacker listens to the data stream and has the potential to contaminate the current data point to influence the process of online learning. As a stochastic optimal control problem, this paper formulate the optimal online attack problem and provide a systematic solution using techniques from model predictive control and deep reinforcement learning.Theoretical analysis of the remorse experienced by the attacker for not understanding the true data sequence is also presented.

The online attacker faces some specific challenges compared to the offline environment: In the offline setting, it is often presumed that the entire dataset is observed by the attacker. However, in the online world, when making decisions, the attacker can only observe the current data. The attacker only needs to make one decision in the offline setting, while the attacker is expected to make a series of decisions in the online setting to execute the attack over time. These particular problems make the online regime applicable to the classic data poisoning attack structure.

The paper thus formulates online poisoning attacks as an adaptive control problem. Based on model-based planning and deep reinforcement learning, it proposed two attack algorithms, and showed that both are able to achieve near clairvoyant-level efficiency.

Paper 9

Title : **Why do adversarial attacks transfer? explaining transferability of evasion and poisoning attacks**

Citation : *Demontis, Ambra, et al. "Why do adversarial attacks transfer? explaining transferability of evasion and poisoning attacks." 28th {USENIX} Security Symposium ({USENIX} Security 19). 2019.*

Link : https://www.usenix.org/system/files/sec19-demontis.pdf

Summary :The ability of an attack against a machine-learning model to be successful against another, theoretically unknown, model is captured by transferability.The paper presents a comprehensive analysis aimed to investigate the transferability of both test-time evasion and training-time poisoning attacks.Evasion is to add a minimum amount of perturbation to a test point to change prediction.Poisoning is to add a fraction of poisoning points in training to degrade model accuracy (availability attack).
Attacker Knowledge is of two types –

1. White box: full knowledge of the ML system .
2. Black-box: query access to the model.

Model complexity is the capacity of the classifier to fit the training data (can be controlled through regularization).

Extensive experiments on 3 datasets and 12 classifiers have shown that:

- High-complexity models are more vulnerable to both evasion and poisoning attacks
- Low-complexity models are better surrogates to perform evasion attacks.
- The complexity of the best surrogate is the same as the one of the target for availability poisoning.

Paper 10

Title : Mitigating poisoning attacks on machine learning models: A data provenance based approach

Citation : *Baracaldo, Nathalie, et al. "Mitigating Poisoning Attacks on Machine Learning Models: A Data Provenance Based Approach." (2017).*

Link:https://www.researchgate.net/profile/Nathalie_Baracaldo/publication/320836025_Mitigating_Poisoning_Attacks_on_Machine_Learning_Models_A_Data_Provenance_Based_Approach/links/5aa03719aca272d448b0197d/Mitigating-Poisoning-Attacks-on-Machine-Learning-Models-A-Data-Provenance-Based-Approach.pdf

Summary :A protection risk is posed by the dependence of machine learning methods on quality training data in which adversaries can insert poisonous samples into the training dataset to exploit the trained classifier. Provenance meta-data is used to segment the untrusted data into groups where the probability of poisoning is highly correlated across samples in each group. A specific video camera, a Twitter account, or a specific firmware version. etc., is called a provenance signature.

- A new technique for detecting and filtering poisonous data collected to train an arbitrary supervised model of learning is presented in the paper. The training data has been segmented appropriately, data points in each segment are evaluated together by comparing the performance of the classifier trained with and without that group.
- Two flavors of our provenance-based defense for cases when partially trusted and fully untrusted datasets are available. By partially trusted, it is meant that some of the data points are believed to be genuine (not poisoned) in the collected data.

Trusted provenance information is available in many application scenarios such as in environmental sensing or even some social media environments. The paper assumes that data sources are independent.

Paper 11

Title: Adversarial Security Attacks and Perturbations on Machine Learning and Deep Learning Methods

Citation: *Siddiqi, Arif. "Adversarial security attacks and perturbations on machine learning and deep learning methods." arXiv preprint arXiv:1907.07291 (2019).*

Link: https://arxiv.org/ftp/arxiv/papers/1907/1907.07291.pdf

Summary: This paper first briefly explains the different kinds of machine learning models like Logistic Regression, SVM, Decision Tree, Random Forest, Hidden Markov Model, etc.
Then it tells us the categories of security attacks which are:

- Causative attack. Targets the training process or the training data is altered. The model trained on the altered data provides the manipulated output. It is sometimes also called the poisoning attack.
- Exploratory attack. Targets after the training process. Explores or probes the learner for useful information. Can exploit misclassifications but do not alter the training process.
- Evasion attack. Targets after the training process. Modifies the input data to the learner that results in an incorrect prediction or evade detection.
- Targeted attacks. Targets the specific points, instances, or exploits that are continuous streams.
- Indiscriminate. Targets the general class of points, instances, or exploits in a random non-targeted manner.
- Integrity attack. A successful attack on assets via false negatives and that is being classified as normal traffic.
- Availability attack. A broad class of an attack that makes the system unusable with classification errors, denial of service, false negatives and positives, etc.
- Privacy violation attack. An exploratory attack type that reveals sensitive and confidential information from the data and models. Also known as model extraction, inversion, or hill-climbing attack.

Then it explains most of the terminologies used in this area of research so that it is easier for new researchers like us to get started. Even though several research papers exist that review adversarial security attacks and perturbations, there is always room to grow due to the dynamic nature of ML and DL methods. The learning models that are ideal and produce satisfying results remain an open and a lasting challenge. This includes the issue of adversarial security attacks and perturbations because of its relation to the DM and ML methods.

Paper 12

Title: Decision-Based Adversarial Attacks: Reliable Attacks Against Black-Box Machine Learning Models

Citation: *Brendel, Wieland, Jonas Rauber, and Matthias Bethge. "Decision-based adversarial attacks: Reliable attacks against black-box machine learning models." arXiv preprint arXiv:1712.04248 (2017).*

Link: https://arxiv.org/pdf/1712.04248.pdf

Summary: This paper emphasises the importance of attacks which solely rely on the final model decision. Such decision-based attacks are (1) applicable to real-world black-box models such as autonomous cars, (2) need less knowledge and are easier to apply than transfer-based attacks and (3) are more robust to simple defences than gradient- or score-based attacks. It introduces something called the Boundary Attack, a decision-based attack that starts from a large adversarial perturbation and then seeks to reduce the perturbation while staying adversarial. The attack is conceptually simple, requires close to no hyperparameter tuning, does not rely on substitute models and is competitive with the best gradient-based attacks in standard computer vision tasks like ImageNet.

At its core the Boundary Attack follows the decision boundary between adversarial and non-adversarial samples using a very simple rejection sampling algorithm in conjunction with a simple proposal distribution and a dynamic step-size adjustment inspired by Trust Region methods. Its basic operating principle— starting from a large perturbation and successively reducing it—inverts the logic of essentially all previous adversarial attacks. Besides being surprisingly simple, the Boundary attack is also extremely flexible in terms of the possible adversarial criteria and performs on par with gradient-based attacks on standard computer vision tasks in terms of the size of minimal perturbations. The mere fact that a simple constrained iid Gaussian distribution can serve as an effective proposal perturbation for each step of the Boundary attack is surprising and sheds light on the brittle information processing of current computer vision architectures. Nonetheless, there are many ways in which the Boundary attack can be made even more effective, in particular by learning a suitable proposal distribution for a given model or by conditioning the proposal distribution on the recent history of successful and unsuccessful proposals. Decision-based attacks will be highly relevant to assess the robustness of machine learning models and to highlight the security risks of closed-source machine learning systems like autonomous cars.

Paper 13

Title: Robust Physical-World Attacks on Machine Learning Models

Citation: *Evtimov, Ivan, et al. "Robust physical-world attacks on machine learning models." arXiv preprint arXiv:1707.08945 2.3 (2017): 4.*

Link: https://s3.observador.pt/wp-content/uploads/2017/08/08133934/1707-08945.pdf

Summary: Deep neural network-based classifiers are known to be vulnerable to adversarial examples that can fool them into misclassifying their input through the addition of small-magnitude perturbations. This paper proposes a new attack algorithm—Robust Physical Perturbations (RP2)— that generates perturbations by taking images under different conditions into account. This algorithm can create spatially constrained perturbations that mimic vandalism or art to reduce the likelihood of detection by a casual observer. It shows that adversarial examples generated by RP2 achieve high success rates under various conditions for real road sign recognition by using an evaluation methodology that captures physical world conditions. It evaluates two attacks, one that causes a Stop sign to be misclassified as a Speed Limit sign in 100% of the testing conditions, and one that causes a Right Turn sign to be misclassified as either a Stop or Added Lane sign in 100% of the testing conditions.

Previous algorithms assume that the inputs of DNNs can be modified digitally to achieve misclassification, but such an assumption is infeasible, as an attacker with control over DNN inputs can simply replace it with an input of his choice. Therefore, adversarial attack algorithms must apply perturbations physically, and in doing so, need to account for new challenges such as a changing viewpoint due to distances, camera angles, different lighting conditions, and occlusion of the sign. Furthermore, fabrication of a perturbation introduces a new source of error due to a limited color gamut in printers. It shows the use of RP2 to create two types of perturbations: subtle perturbations, which are small, undetectable changes to the entire sign, and camouflage perturbations, which are visible perturbations in the shape of graffiti or art. When the Stop sign was overlaid with a print out, subtle perturbations fooled the classifier 100% of the time under different physical conditions. When only the perturbations were added to the sign, the classifier was fooled by camouflage graffiti and art perturbations 66.7% and 100% of the time respectively under different physical conditions. Finally, when an untargeted poster printed camouflage perturbation was overlaid on a Right Turn sign, the classifier was fooled 100% of the time.

Paper 14

Title: Data Security Issues in Deep Learning: Attacks, Countermeasures, and Opportunities

Citation: *G. Xu, H. Li, H. Ren, K. Yang and R. H. Deng, "Data Security Issues in Deep Learning: Attacks, Countermeasures, and Opportunities," in IEEE Communications Magazine, vol. 57, no. 11, pp. 116-122, November 2019, doi: 10.1109/MCOM.001.1900091.*

Link: https://ink.library.smu.edu.sg/cgi/viewcontent.cgi?article=5676&context=sis_research

Summary: This paper focuses on data security issues in deep learning. It investigates the potential threats and the latest countermeasures based on various underlying technologies, where the challenges and research opportunities on offense and defense are also discussed.

We focused on studying the defense against poisoning attacks which is explained in the paper as follows:

- Defense against Poisoning Attack: In general, one of the main ways to defend against poisoning attacks is to design efficient detection mechanisms, which can rapidly detect abnormal samples and eliminate these poisoned data during training.

Existing research on this-

- Method1: First use influence functions to trace and explain the correlation between prediction and training sets. The influence functions can be widely used for malicious data detection in poisoning attacks even in nonconvex and non-differentiable models.
- Method2: A defense scheme by constructing approximate upper bounds on the loss across a broad family of attacks. Further, design two efficient defense strategies called sphere defense and slab defense to remove outliers (i.e., data suspected of being injected by the adversary) that are outside the applicable set. In this way, the false data in the DNN model can be effectively detected and filtered.
- Method3: It uses key sharing protocols to protect the integrity of training samples, thereby preventing malicious adversaries from tampering with training samples and calculation results.

Then, it proposes SecureNet, the first verifiable and privacy-preserving prediction protocol to protect model integrity and user privacy in DNNs. It can significantly resist various security and privacy threats during the prediction process. The researchers simulate SecureNet under a real dataset, and the experimental results show the superior performance of SecureNet for detecting various integrity attacks against DNN models.

Paper 15

Title: Preventing Data Poisoning Attacks By Using Generative Models

Citation: *Aladag, Merve, Ferhat Ozgur Catak, and Ensar Gul. "Preventing Data Poisoning Attacks By Using Generative Models." 2019 1st International Informatics and Software Engineering Conference (UBMYK). IEEE, 2019.*

Link:https://www.ozgurcatak.org/files/papers/2019-data-poison.pdf

Summary: In this paper, a data poisoning attack towards classification method of machine learning models is conducted and a defense algorithm which makes machine learning models more robust against data poisoning attacks is also proposed. The authors have conducted data poisoning attacks on MNIST, a widely used character detection data set. Using the poisoned MNIST dataset, they built classification models which were more reliable by using a generative model such as AutoEncoder. Auto-encoder is a generative model of the artificial neural network that reproduces the data by learning the structure of the data with no labels. The structure and features of the data are learned with this model and the data is tried to be re-created.

An optimization based data poisoning attack which manipulated the training stage of the classification method from machine learning models was performed. Before the training phase of the classification model, manipulated data was added on the true data so that the model could learn the manipulated data as well. The auto-encoder model to make the classification models more robust to such attacks was then proposed, and by observing the classification performance, the authors showed that the model marked the manipulated data as it should have.

Paper 16

Title: With Great Dispersion Comes Greater Resilience: Efficient Poisoning Attacks and Defenses for Online Regression Models

Citation: *Wen, Jialin, et al. "With Great Dispersion Comes Greater Resilience: Efficient Poisoning Attacks and Defenses for Online Regression Models." arXiv preprint arXiv:2006.11928 (2020).*

Link: https://arxiv.org/pdf/2006.11928.pdf

Summary: The need to ensure the safety of the resulting machine learning models has become an increasingly important subject with the rise of third parties in the machine learning pipeline, the Machine Learning as a Service (MLaaS) service provider, or external data contributors in online learning, or the retraining of existing models.

The study examines how adversaries can threaten by poisoning the training datasets with the outcomes of regression learning. A new grey-box poisoning attack algorithm is developed. In comparison to previous poisoning attack algorithms, this attack algorithm, called Nopt, can generate larger mistakes with the same proportion of poisoning data-points. Conceptually, the main difference between the state of the art attack method and the proposed is that the optimization measured for each subsequent poisoning point is carried out on a dataset that contains all previous poisoning points. This creates a new poisoning point that maximises the loss of the original clean and poisoning points collective training dataset.

The paper also revised the TRIM algorithm further and claims to propose the most successful defense against poisoning attacks, called Proda, to date. In this algorithm, the idea of probability estimation of unpolluted data-points is implemented.

Paper 17

Title: Data Poisoning Attacks on Regression Learning and Corresponding Defenses

Citation: *Müller, Nicolas Michael, Daniel Kowatsch, and Konstantin Böttinger. "Data Poisoning Attacks on Regression Learning and Corresponding Defenses." arXiv preprint arXiv:2009.07008 (2020).*

Link: https://arxiv.org/pdf/2009.07008.pdf

Summary: Regression learning is used in various fields in today's world. It is used for the production of pharmaceuticals in medicine, for predictive analysis in the financial sector, such as hedge fund management and cash forecasting, and also for predictive maintenance and quality control. These systems are prone to two types of attacks; attacks done during testing time which is called evasion, and attacks done during training time which is termed poisoning. This paper focuses on the attacks done during the training time. The poisoned samples which are introduced during the testing time confuse the learner which leads to either the system not working with respect to its initial intent or providing the attacker control over the machine learning model. In a broad empirical test over seven regressors and 26 datasets, the paper illustrates the utility of the proposed attack and defense algorithm. Realistic restrictions are assumed by both attack and defence: the attack is black-box and does not presume access to the true dataset, but rather a substitution dataset. On the other hand, the defence does not presume any knowledge of the rate of poisoning, but calculates it using an iterative strategy.

Paper 18

Title: Certified Defenses for Data Poisoning Attacks

Citation: *Steinhardt, Jacob, Pang Wei W. Koh, and Percy S. Liang. "Certified defenses for data poisoning attacks." Advances in neural information processing systems. 2017.*

Link: https://arxiv.org/pdf/1706.03691.pdf

Summary: The most important aspect of all the training data in machine learning comes directly from the outside world. An intruder can insert malicious data by merely building a user account for a device trained on user data. This attacks on data poisoning force one to re-think what it means for a device to be secure. One might take a clean dataset at the time of creation and test a defence against a variety of poisoning techniques on that dataset. However it is difficult to infer from empirical success alone, owing to the near-limitless space of potential threats, that a defence working against an established series of attacks would not fail against a new threat. This paper tackles this challenge by providing a method for analysing the entire space of attacks against a given security. This paper's structure extends to defenders who (i) exclude outliers located beyond a feasible range, then (ii) reduce the remaining details to a margin-based loss.

Paper 19

Title: Certified Defenses against Adversarial Examples

Citation: *Raghunathan, Aditi, Jacob Steinhardt, and Percy Liang. "Certified defenses against adversarial examples." arXiv preprint arXiv:1801.09344 (2018).*

Link: https://openreview.net/pdf?id=Bys4ob-Rb

Summary: In the face of minor imperceptible yet adversarial disruptions, classifiers also struggle catastrophically notwithstanding the remarkable (and often sometimes superhuman) accuracies of machine learning on diverse tasks such as object recognition, voice recognition, and playing Go. In addition to being an interesting phenomena, a significant flaw in existing ML systems is revealed by the presence of such adversarial examples. In this paper, they introduced a method for generating neural network robustness certificates and training against these certificates in order to obtain networks that are known to be robust against opponents.

Paper 20

Title: Defending Regression Learners Against Poisoning Attacks

Citation: *Weerasinghe, Sandamal, et al. "Defending Regression Learners Against Poisoning Attacks." arXiv preprint arXiv:2008.09279 (2020).*

Link: https://arxiv.org/pdf/2008.09279.pdf

Summary: A fundamental class of supervised learning, with applications in healthcare, industry, protection, and engineering, is linear regression models. Recent works in the literature show that in the presence of poisoned training results, the performance of regression models degrades significantly. Adversaries try to push the learner into certain attacks to end up with a prediction model with compromised prediction capability. Any application based on regression models for automatic decision-making could theoretically be corrupted and decisions could have significant implications. While adversarial manipulations pose a major challenge to important regression applications, only a few previous studies have tried to address this question. Most works in the literature are related to robust regression, where regression models are educated instead of maliciously contaminated data in the face of stochastic noise. However several articles have recently proposed linear regression models that consider the existence of samples of adversarial evidence.

The topic of increasing the attack resistance of linear regression models to data poisoning attacks is discussed in this article. It is noted that the prediction performance of regression models could be dramatically weakened by deliberately designed attacks, and stable regression models do not survive targeted adversarial attacks on large-scale data sets. This paper proposed a novel LID metric that takes into account the LID values of the neighbours of a data sample and introduced multiple weighting schemes that modify the effect of each sample on the learned model. Experimental findings show that the suggested protection mechanisms are very powerful and in terms of precision and computational costs, outperform prior art substantially.

In order to explore the impact of poisoning attacks on non-linear regression models and how N-LID will work in those situations, more study should be done.

Paper 21

Title: Novel Defenses Against Data Poisoning in Adversarial Machine Learning

Citation: *Weerasinghe, Prameesha Sandamal Liyanage. Novel Defenses Against Data Poisoning in Adversarial Machine Learning. Diss. 2019.*

Link:
https://minerva-access.unimelb.edu.au/bitstream/handle/11343/240543/4244c26a-9411-ea11-94b1-0050568d7800_final_thesis.pdf?sequence=1&isAllowed=y

Summary: In a wide variety of areas, such as defence, finance, and communications, machine learning models are increasingly being used for automatic decision making. On the premise that the training data and test data have the same underlying distribution, machine learning algorithms are designed. This assumption collapses as data changes spontaneously, allowing the distribution of test data to diverge from the distribution of training data, and hostile opponents misrepresent the training data (i.e., poisoning attacks), which is the subject of this study.

This work provides new defences for algorithms for machine learning to avert the consequences of poisoning attacks. This paper analyse the effect on machine learning algorithms such as Support Vector Machines (SVMs), one-class Support Vector Machines (OCSVMs) and regression models of sophisticated poisoning attacks, and add new protections that can be integrated into these models to achieve safer decision-making. In specific, in order to solve the issue of learning under adversarial circumstances, two innovative methods are described as follows.

The first method is focused on data forecasts that compact the data, and the influence of the projections on adversarial disturbances is analysed. The paper strive to reduce the influence of adversarial function disruptions on the training model by projecting the training data to lower-dimensional spaces in selective directions. Local Intrinsic Dimensionality (LID), a metric that characterises the dimension of the local subspace in which data samples lie, is used in the second method to identify data samples that may have been interrupted (feature perturbation or label flips). In the form of sample weights, this information is then integrated into current learning algorithms to decrease the effect of poisoned samples.

Paper 22

Title: Adversarial Machine Learning

Citation: *Vorobeychik, Yevgeniy, and Murat Kantarcioglu. "Adversarial machine learning." Synthesis Lectures on Artificial Intelligence and Machine Learning 12.3 (2018): 1-169.*

Link: https://www.morganclaypool.com/doi/abs/10.2200/S00861ED1V01Y201806AIM039

Summary: Combined with substantial technological advancements over the last few decades, the growing proliferation of vast high-quality datasets has made machine learning a major instrument used in a wide variety of activities, including vision, vocabulary, finance, and defence. Progress, though has been followed by significant new challenges: many machine learning systems are adversarial in nature. Some are adversarial, such as autonomous vehicles, and they are vital to safety. In these implementations, an attacker may be a hostile party aiming at causing congestion or incidents, or can even model unexpected scenarios in the prediction engine that reveal vulnerabilities. Other apps are adversarial since their mission and/or the knowledge they use is adversarial. For eg, detection, such as ransomware, spam, and intrusion detection, is an essential form of security concern.

The area of adversarial machine learning has developed to investigate the limitations in adversarial settings in machine learning techniques and to build methods to make learning stable for adversarial exploitation. A technical outline of this area is given in this book. We provide a general categorisation of attacks on machine learning after examining machine learning principles and methods, as well as typical usage cases of these in adversarial environments. We then present two key types of attacks and related defences: decision-time attacks, in which an opponent alterations the essence of instances seen at the time of prediction by a trained model to trigger mistakes, and poisoning or training time attacks, in which the real training dataset is maliciously changed. Recent strategies for deep learning attacks, as well as approaches to enhancing the robustness of deep neural networks, are explored in the final chapter devoted to technical material.

Paper 23

Title: Is Feature Selection Secure against Training Data Poisoning?

Citation: *Xiao, Huang, et al. "Is feature selection secure against training data poisoning?." International Conference on Machine Learning. 2015.*

Link: http://proceedings.mlr.press/v37/xiao15.pdf

Summary: The number of interconnected users and computers, along with the available number of resources, has grown exponentially with the introduction of the digital Internet. Not only did this simplify our lives by simplicity and ease-of-use of novel resources, but it also presented attackers with fantastic opportunities to conduct novel and lucrative malicious operations. Machine learning has been adopted in security-sensitive settings such as spam and intrusion identification, web page rating and network protocol verification to deal with this phenomenon. While much of the literature has concentrated on evaluating classification and clustering algorithm vulnerabilities, only recent work has considered intrinsic vulnerabilities introduced by the use of methods of feature selection. In particular, it has been shown that if features are not chosen according to an adversary-aware process that specifically allows for adversarial data manipulation at test time, classifier evasion may be encouraged. Although these attacks do not target the collection of features explicitly, but rather the resulting classification system, they illustrate the need for procedures to pick adversarial features. Attacks that threaten the collection of features more specifically fall under the range of poisoning attacks. The attacker has access to the training data in this environment and contaminates it in order to subvert or monitor the collection of the reduced feature set.

This paper has established a structure that enables one to reliably model possible attack scenarios against feature selection algorithms, making clear assumptions about the goal, expertise and capabilities of the attacker. In order to describe the related hazard of poisoning attacks against function selection algorithms, this paper used this context and documented a comprehensive case study on the susceptibility to these attacks of common embedded methods (LASSO, ridge, and elastic net). Our security research on a real-world security application involving PDF malware detection has shown that the collection of reduced feature subsets can be fully regulated by attackers even by only inserting a small fraction of poisoning training points especially if the feature selection algorithm enforces sparsity.

Paper 24

Title: Towards the science of security and privacy in machine learning

Citation: *Papernot, Nicolas, Patrick McDaniel, Arunesh Sinha, and Michael Wellman. "Towards the science of security and privacy in machine learning." arXiv preprint arXiv:1611.03814 (2016).*

Link: https://arxiv.org/pdf/1611.03814.pdf

Summary: Combined with developments in computing and storage capabilities, the coming of age of machine learning software (ML) has changed the technology environment. For starters, the practise of health care and financial management has been profoundly transformed by ML-driven data analytics. Detection and surveillance devices today ingest vast quantities of data within the security context and collect actionable information that would have been difficult in the past. Yet, despite these spectacular developments, the understanding of the vulnerabilities inherent in the architecture of systems based on ML by the engineering community and the means to protect against them is still in its infancy. There is a large and urgent call for the advancement of security and privacy research in ML.
In investigating these aspects of assaults on machine learning and
Protection, the inputs this paper makes are the following:

- This paper presents a unified threat model to allow for formal thinking on the security and privacy of machine learning systems. By considering the entire data pipeline, of which ML is a portion, instead of ML algorithms in isolation, this model departs from previous efforts.
- This paper taxonomizes attacks and defences described as knowledgeable elements of the PAC learning theory by the various technical communities. In adversarial environments, this paper details the challenges of data poisoning and also considers trained and applied programmes. This offers desirable properties to strengthen ML's security and privacy.
- The no free lunch theorem for adversarial machine learning is discussed in this article. It characterises, when learning from minimal data, the tradeoff between precision and robustness for adversarial efforts.

Paper 25

Title:On the (Statistical) Detection of Adversarial Examples

Citation: *Grosse, Kathrin, et al. "On the (statistical) detection of adversarial examples." arXiv preprint arXiv:1702.06280 (2017).*

Link: https://arxiv.org/pdf/1702.06280.pdf

Summary: Machine learning algorithms are typically built under the basis that models are trained on samples from a distribution that is representative of test samples for which they can make predictions later. Ideally, the distributions of training and testing should be similar. In the face of enemies, however this does not hold. Either the training or test distribution of an ML device can be abused by a motivated adversary. When ML is added to security-critical matters, this has significant implications. As seen by the variety of techniques possible to escape malware detection developed with ML, attacks are increasingly elaborate. The hypothesis that adversarial examples can be defined using statistical tests before they are even fed as inputs to the ML model was empirically tested by this article. Their malicious properties are thus, paradigm agnostic. In addition, this paper shows how ML models can be increased with an additional class in which the model is equipped to distinguish all adversarial inputs. This results in adversary robustness, including those using transferability-based attack strategies, a type of attacks that are considered to be harder to protect against than gradient-based strategies. Furthermore if adversarial cases with minor disruptions are not marked as outliers, the initial class is always restored and the disrupted data is appropriately categorised.

Paper 26

Title:Stateful Detection of Black-Box Adversarial Attacks

Citation: *Chen, Steven, Nicholas Carlini, and David Wagner. "Stateful detection of black-box adversarial attacks." Proceedings of the 1st ACM Workshop on Security and Privacy on Artificial Intelligence. 2020.*

Link:https://dl.acm.org/doi/pdf/10.1145/3385003.3410925

Summary: It has proved to be incredibly difficult to protect neural networks against adversarial examples. It has been found that most reported defences have major weaknesses, and even the few defences that have withstood validation still provide partial robustness. In a completely black-box threat model, adversarial examples can also be created, in which an adversary can only query the model and obtain the expected classification as performance. In comparison to attempting to (statelessly) detect whether or not any individual input is malicious, this paper studies the issue of detecting the generation of adversarial examples, which has proved to be challenging. The role of defining the sequence of queries made to the classifier when constructing an adversarial example is taken into account in this article. This paper introduces a defence that uses a similarity detector neural network to recognise certain query patterns based on the fact that current black-box attacks allow a series of strongly self-similar queries (i.e. each query in the sequence is similar to previous queries in the sequence), and finds that the current state-of-the-art blackbox attack algorithms can be identified by this strategy. To date, protections against white-box adversarial examples have proved to be elusive; this paper therefore encourages expanded analysis of blackbox defences against adversarial examples. The scholarly community has analysed only stateless defences in the black-box environment thus far. This paper claims that stateful defences offer the defender a new advantage and warrant consideration. To the end, this paper proposes a simple scheme that senses the adversarial example creation mechanism and implements query blindness, an adaptive attack on such schemes that breaks prior work effectively. This paper builds the first cohesive defence that could have black-box robustness by integrating the paper's proposed solution with current defences that resist transferability attacks.

Paper 27

Title: Blackbox attacks on reinforcement learning agents using approximated temporal information

Citation: *Zhao, Yiren, et al. "Blackbox attacks on reinforcement learning agents using approximated temporal information." 2020 50th Annual IEEE/IFIP International Conference on Dependable Systems and Networks Workshops (DSN-W). IEEE, 2020.*

Link:https://arxiv.org/pdf/1909.02918.pdf

Summary: On a wide range of functions, deep neural networks (DNNs) perform well, ranging from image analysis, target identification and emotion recognition to language processing. Recent developments in reinforcement learning (RL) show that by mapping raw environment inputs directly to an action space, DNNs can learn policies that solve complex problems. In playing Go and Atari games, trained deep RL agents demonstrate human-level or even superhuman results. Following this success, in safety-critical fields such as robotics, as well as in advisory systems and trading, RL agents are beginning to be exploited. When inputs are injected with minor irregularities that are not perceptible to humans, DNN-based image classifiers may generate incorrect results. Adversarial examples may also be generated by attackers that cause DNN-based systems to misbehave, like facial recognition and autonomous driving systems. Their transferability is one characteristic of adversarial samples. Adversarial inputs that influence one paradigm very frequently influence others. Adversarial samples can also easily impact on-scale machine learning (ML) programmes. Three points are offered in this paper: an improvement in the state of the art, a criticism of the analysis methods used so far and a new challenge to research. First of all, this paper used seq2seq models to forecast and use a series of possible acts to be taken by an agent to yield highly transferable adversarial samples. Second, while these adversarial samples are transferable, as a way of reducing the game scores of qualified RL operators, they do not outperform random Gaussian noise. However, this paper's adversarial attacks have one benefit over spontaneous jamming: they can be used to cause a qualified person to misbehave in the future at a given time. This is the paper's third finding, and it seems to be a truly new form of attack; it theoretically allows an intruder to use time-bombing equipment operated by RL agents.

Paper 28

Title:Just How Toxic is Data Poisoning? A Unified Benchmark for Backdoor and Data Poisoning Attacks

Citation: *Schwarzschild, Avi, et al. "Just how toxic is data poisoning? a unified benchmark for backdoor and data poisoning attacks." arXiv preprint arXiv:2006.12557 (2020).*

Link:https://arxiv.org/pdf/2006.12557.pdf

Summary: Data poisoning is a security vulnerability to machine learning systems in which, by modifying their training data, an attacker influences a system's actions. For deep learning systems, this class of threats is especially germane since they require massive volumes of data to practise and are so therefore trained (or pre-trained) on large web-scraped datasets. For eg, there are approximately 9 million and 233 million samples in the Open Photos and Amazon Items databases respectively, that are scraped from a wide variety of potentially unreliable and in many cases, unknown sources. It is also difficult to accurately vet material on this scale. The dependency on datasets that are not manually reviewed by industrial AI systems has led to concerns that compromised training data could generate defective models. A recent study of 28 industry organisations showed that these firms fear data poisoning considerably more than other risks from adversarial machine learning. For benchmarking and analysing a wide variety of poison attacks, this paper develops a coherent structure. The purpose of this paper is to discuss in the existing literature the following vulnerabilities. First this paper states that the recorded performance in the literature of poisoning attacks is sometimes based on particular (and often unrealistic) network design and training protocol choices, making it impossible to determine the feasibility of attacks in real-world scenarios. Second, this paper finds that the percentage of training knowledge that an attacker can change, the typical budget calculation in the literature on poisoning, is not a reliable reference metric. Third, the paper considers that
It is not like any attacks pretending to be "clean label," so that poisoned information still remains normal and correctly labelled upon human examination, are not.

Paper 29

Title: Security and Machine Learning in the Real World

Citation: *Evtimov, Ivan, et al. "Security and Machine Learning in the Real World." arXiv preprint arXiv:2007.07205 (2020).*

Link:https://arxiv.org/pdf/2007.07205.pdf

Summary: In real-world applications of important social and market importance, machine learning (ML) models are being implemented in the analysis of visual, voice, and other digital data signals. As for any information technologies implemented on a scale or in critical domains, ML systems face mobilised opponents that seek to trigger undesired behaviours or breach security constraints. Latest analysis reveals that, due to structural weaknesses in deep neural networks, so-called adversarial examples breach the security properties of individual models. These adversarial inputs are important because they allow the model outputs to be absolutely regulated by adversaries. This has sparked much research on this threat, primarily based on standalone models of computer vision and adversaries that are limited to direct, tiny pixel input shifts. This paper suggests that these shortcomings can be filled by learning from interactions with ML implemented systems and carefully thinking about how closely they follow best practises in classical defence. This calls for two advances. In the one hand, to understand complete systems and the actual challenges they are likely to encounter in an adaptive environment, machine learning needs to evolve. In the other hand, it is important to establish technical strategies to adapt system protection best practises to ML applications.
Some of the approaches for the model this paper suggests are-

- Boost the cost of an attack by adding several models that review each other for fitness.
- Consider how vulnerabilities in ML lead to exploits of the overall framework and investigate whether attackers in adversarial environments benefit from the programming logic.

Paper 30

Title: Addressing adversarial attacks against security systems based on machine learning

Citation: *Apruzzese, Giovanni, et al. "Addressing adversarial attacks against security systems based on machine learning." 2019 11th International Conference on Cyber Conflict (CyCon). Vol. 900. IEEE, 2019.*

Link: https://ccdcoe.org/uploads/2019/06/Art_21_Addressing-Adversalial-Attacks.pdf

Summary: In different areas, applications focused on machine and deep learning algorithms are becoming widespread, with reported achievements in computer vision, speech recognition, monitoring of social media and healthcare. However some shortcomings that hinder their usefulness in actual environments also impact the application of these approaches to cyber defence. Recent findings indicate that when considering defence strategies based on machine learning to defend current organisations, the greatest caution and due diligence should be taken. There are many explanations for these problems: attacks are comparatively uncommon compared to the vast amount of events created by modern businesses; they grow quickly, with repercussions for confirmation of potential ground truth; and attackers are not limited by rules such as gaming with artificial intelligence. This paper considers the additional problem raised by the inherent susceptibility to adversarial attacks of machine-learning techniques, by which adversaries can thwart the mechanism by causing incorrect or unexpected results to be produced. The different variants of malicious behaviour that can be done during the training or testing period of the machine-learning algorithms aggravate this problem. This paper provides a taxonomy of adversarial attacks that demonstrates which cyber defence fields have been evaluated against which type of threat and which machine learning algorithms have been evaluated.

INTEGRATED SUMMARY

Papers which study existing work:

S.No.	Paper title	Work Done
1.	Why do adversarial attacks transfer? explaining transferability of evasion and poisoning attacks(9)	A comprehensive analysis aimed to investigate the transferability of both test-time evasion and training-time poisoning attacks
2.	Adversarial Security Attacks and Perturbations on Machine Learning and Deep Learning Methods (11)	Basic knowledge on the machine learning and deep learning models and algorithms, as well as some of the relevant adversarial security attacks and perturbations
4.	A Survey on Security threats and Defensive Techniques of Machine Learning: A Data Driven view(6)	Emphasis on data distribution drift caused by adversarial samples and sensitive information violation problems in statistical machine learning.
5.	Machine Learning Security: Threats, Countermeasures, and Evaluations(5)	Covers all the aspects of machine learning security. From the training phase to the test phase, all types of attacks and defenses are reviewed in a systematic way.
6.	SoK: Security and Privacy in Machine Learning (3)	Study of a threat model that considers characteristics of the attack surface, adversarial goals, and possible defense and attack capabilities for it.
7.	Data Poisoning Attacks on Regression Learning and Corresponding Defenses (17)	Evaluate all aspects of data poisoning attacks on regression learning. Presents realistic scenarios in which data poisoning attacks threaten production systems.
8.	Certified Defenses for Data Poisoning Attacks (18)	Study on the worst-case loss of a defense in the face of a determined attacker across a broad family of attacks.
9.	Adversarial Machine Learning Synthesis Lectures on Artificial Intelligence and Machine Learning (22)	This book provides readers with the tools necessary to successfully engage in research and practice of machine learning in adversarial settings.
10.	Is Feature Selection Secure against Training Data Poisoning? (23)	Provides a framework to investigate the robustness of popular feature selection methods, including LASSO, ridge regression and the elastic net.
11.	SoK: Towards the Science of Security and Privacy in Machine Learning (24)	It articulates a comprehensive threat model for ML, and categorize attacks and defenses within an adversarial framework.

12.	Just How Toxic Is Data Poisoning? A Benchmark For Backdoor And Data Poisoning Attacks (28)	The researchers develop standardized benchmarks for data poisoning and backdoor attacks.
13.	Security and Machine Learning in the Real World (29)	It describes novel challenges to implementing systems security best practices in software with ML components.
14.	Addressing Adversarial Attacks Against Security Systems Based on Machine Learning (30)	This paper contains several performance evaluations that are based on extensive experiments using large traffic datasets.The results highlight that modern adversarial attacks are highly effective against machine-learning classifiers for cyber detection, and that existing solutions require improvements in several directions.

Papers which propose solutions:

S.No.	**Paper title**	**Type of model targeted**	**Type of attack**	**Proposed Attack mechanism**	**Proposed Defence mechanism**
1.	Robust Linear Regression Against Training Data Poisoning(7)	Linear regression	Data Poisoning	--	Trimmed principal component regression (T-PCR) algorithm
2.	Preventing Data Poisoning Attacks By Using Generative Models (15)	Classification	Data Poisoning	--	Auto-Encoder Model
3.	Mitigating poisoning attacks on machine learning models: A data provenance based approach (10)	General	Poisoning	--	Data provenance based defense
4.	Manipulating Machine Learning: Poisoning Attacks and Countermeasures for Regression Learning (1)	Regression	Poisoning	Statistical-based Poisoning Attack (StatP)	TRIM
5.	ML-Leaks: Model and Data Independent Membership Inference Attacks and Defenses on Machine Learning Models (2)	General	Model and data independent membership inference attacks	--	Dropout, Model stacking
3.	Data Security Issues in Deep Learning: Attacks,	Deep learning	General	--	SecureNet - privacy-preserving prediction

	Countermeasures, and Opportunities (14)				protocol to protect model integrity and user privacy in DNN
4.	With Great Dispersion Comes Greater Resilience: Efficient Poisoning Attacks and Defenses for Online Regression Models (16)	Regression	Poisoning	Nopt	Proda
5.	Certified Defenses Against Adversarial Examples (19)	Neural Networks	General	--	Defense method based on a relaxation that for a given network, no attack can force the error to exceed a certain value
6.	Defending Regression Learners Against Poisoning Attacks (20)	Regression	Poisoning	--	Local Intrinsic Dimensionality (LID) based defense
7.	Novel Defenses Against Data Poisoning in Adversarial Machine Learning (21)	All	Poisoning	--	1.Projecting data to lower dimensional spaces and 2.LID based defense.
8.	On the (Statistical) Detection of Adversarial Examples (25)	General	Poisoning	--	Introduces a complimentary approach to identify specific inputs that are adversarial using statistical approach.
9.	Stateful Detection of Black-Box Adversarial Attacks (26)	General	General	Query blinding attack	Defense to detect the process of generating adversarial examples.
10.	Blackbox Attacks On Reinforcement Learning Agents Using Approximated Temporal Information (27)	Reinforcement Learning	Black-box attacks	Use of RL agents to trigger a trained agent to misbehave after a specific time delay.	--

CONCLUSION

We have systematically analyzed the security issues of machine learning, focusing on existing attacks on machine learning systems, corresponding defenses or secure learning techniques, and security evaluation methods. Instead of focusing on one stage or one type of attack in the starting only, we tried to understand the basics of all kinds of attacks from the training phase to the test phase. Finally, we decided to focus on data poisoning attacks on linear regression models in detail and plan to work on making these models robust against poisoning attacks.

MEMBER CONTRIBUTIONS

Papers 1-5: Shivam
Papers 6-10: Soumya
Papers 11-15: Meetanshi
Papers 16-20: Shivam
Papers 21-25: Meetanshi
Papers 26-30: Soumya

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