Towards Poisoning of Federated Support Vector Machines with Data Poisoning Attacks

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Abstract: Federated Support Vector Machine (F-SVM) is a technology that enables distributed edge devices to collectively learn a common SVM model without sharing data samples. Instead, edge devices submit local updates to the global machine, which are then aggregated and sent back to edge devices. Due to the distributed nature of federated learning, edge devices are vulnerable to poisoning attacks, especially during training. Attackers in adversarial edge devices can poison the dataset to hamper the global machine's accuracy. This study investigates the impact of data poisoning attacks on federated SVM classifiers. In particular, we adopt two widespread data poisoning attacks for SVM named label flipping and optimal poisoning attacks for F-SVM and evaluate their impact on the MNIST and CIFAR10 datasets. We measure the impact of these poisoning attacks on the precision of global training. Results show that 33% of adversarial edge devices can reduce accuracy up to 30%. Furthermore, we also investigate some basic defense strategies against poisoning attacks on federated SVM.

1 INTRODUCTION

Federated Learning is a promising solution that enables numerous decentralized edge devices to jointly build a common prediction model while maintaining all of the training data on the edge device. The edge devices train the model using their data and then send it to the global machine, which combines the models to generate the global model. Though initially designed for Deep Neural Networks, federated learning concepts are currently being investigated for other machine learning models, such as Support Vector Machine (SVM). In Federated Support Vector Machine (F-SVM) frameworks (Kabir and Adnan, 2019; Zhang and Zhu, 2017), edge devices create local hyperplanes utilizing their data and only share them with the global machine. The global hyperplane is then created by combining the local hyperplanes on the global machine.

However, edge devices are susceptible to poisoning attacks due to the distributed nature of federated learning. Data poisoning attacks introduce poisoned data into the training dataset and disrupt the machine learning training process, endangering the model's integrity. This attack modifies the learned classifier and compromises the model's ability to generate accurate predictions. As a result, the accuracy of the classifier is reduced, and the model may categorize malicious instances into desirable classes (e.g., labeling spam e-mails as safe). Numerous studies (Doku and Rawat, 2021; Shejwalkar et al., 2022; Tolpegin et al., 2020; Sun et al., 2021) have examined the effects of poisoning attacks on federated deep neural networks and federated convolutional neural networks. However, none of the research investigated the effects of poisoning attacks on F-SVM.

Another type of attack in a federated system is where adversarial edge devices may attack the local model to be trained instead of training data. This strategy is more effective than the data poisoning attack, according to research (Bagdasaryan et al., 2020; Bhagoji et al., 2019; Fang et al., 2020). However, to launch a model poisoning attack, the attackers need access to the edge device's learning process, which is difficult to achieve in practice. For example, a virus or malicious user can poison the dataset but can not change the model or training process. Therefore, although model poisoning attacks are an important research topic, it is not the focus of this research.

This study investigates the impact of two popular data poisoning attacks on SVM classifiers, namely

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(1) label flipping attack, and (2) optimum poisoning attack (Biggio et al., 2012; Xiao et al., 2015; Demontis et al., 2019). Our contributions can be summarized as,

- We develop a framework for the collaboration of multiple clients, including both adversarial and non-adversarial, in a Federated Support Vector Machine (SVM) training process.
- We evaluated the effectiveness of this framework by implementing and evaluating two attack strategies: label flipping and optimum poisoning. We also assessed the impact of varying numbers of adversarial edge devices on the accuracy of the Federated SVM for the MNIST and CIFAR10 datasets.
- Finally, we tested three outlier detection algorithms as basic defense mechanisms to determine their efficacy.

We measured the negative impact of adversarial edge devices on global F-SVM accuracy. One adversarial edge device, for instance, can decrease the overall performance by 2%. If 33% of edge devices are adversarial, accuracy is reduced by 30%. All our programs are open-source and written in Python on Google's Colab Notebook platform.

The rest of this paper is structured as follows. Section 2 provides a summary of the related works. An outline of the foundational ideas employed in this research is given in Section 3. An F-SVM with poisoning attacks is then briefly described in Section 4. The effects of poisoning attacks are detailed in Section 5. The discussion of various defense strategies against poisoning attacks in F-SVM is presented in Section 6. Finally, we conclude in Section 7.

2 RELATED WORKS

Google introduced the concept of federated learning (Konečnỳ et al., 2016a; Konečnỳ et al., 2016b) for the first time in 2016. After that, several researchers (Kabir and Adnan, 2019; Zhang and Zhu, 2017) began implementing federated learning concepts for privacy-enabled SVMs. F-SVM is utilized for various purposes, including the detection of Android malware (Hsu et al., 2020), and wireless networks (Wang et al., 2020; Chen et al., 2020), amongst many others. However, data poisoning attacks remain a significant concern for any federated learning system (Muñoz-González et al., 2017). Several researchers (Sun et al., 2021; Fang et al., 2020) discussed poison attacks and defense against them for federated deep neural networks.

2.1 Data Poisoning Attacks

Data poisoning attacks remains one of the major threat for any machine learning systems (Zhu et al., 2022; Bovenzi et al., 2022; Radford et al., 2018; Pitropakis et al., 2019; Ding et al., 2021; Anisetti et al., 2022). This attack does not create any suspicious data points. Rather it works by altering the existing data points (Biggio et al., 2011; Paudice et al., 2019). Data poisoning attacks can be targeted (misclassifying positive data points) or untargeted (accuracy reduction). Our focus is on untargeted accuracy reduction of Federated SVM. Currently, there are two major types of data poisoning attacks for untargeted accuracy reduction in SVM:

Label Flipping Attack: A label-flipping attack (Barreno et al., 2010; Paudice et al., 2018) is an attack in which an attacker creates poisonous samples by altering the labels of specific training samples. (Barreno et al., 2010) demonstrate that label-flipping attacks increase both false positives and false negatives. (Paudice et al., 2019) outlined their effects on SVM and also discussed the defense mechanisms.

Optimal Poisoning Attack: (Biggio et al., 2012) demonstrated poisoning attacks against SVM for the first time using the MNIST dataset. The authors proposed an algorithm to compute optimal poisonous points using gradient descent and then injected these custom-designed poisonous points into the training data. They demonstrated that incorporating these poisonous points into subsequent training significantly affects accuracy. Consequently, further studies (Xiao et al., 2015; Mei and Zhu, 2015; Jagielski et al., 2018; Biggio and Roli, 2018; Muñoz-González et al., 2017) improved the generation of poisonous points by utilizing additional datasets.

Most poisoning attack researches against federated learning system target deep neural networks or logistic regressions. However, our research indicates that the non-federated SVM data poisoning attacks are adaptable to F-SVM. In particular, in this research, we demonstrate that existing poisonous point generation algorithms can be applied to F-SVM also.

2.2 Defense Against Poisoning Attacks

Numerous defense strategies against data poisoning attacks on SVM rely on data pre-filtering, in which poisoned samples are detected, filtered out, and then cleaned datasets are used to retrain the model. (Dalvi et al., 2004) presented a formal framework and algorithms for outlier detection where the authors viewed classification as a game between the classifier and the adversary. Then they produced an optimal naive Bayes classifier based on the adversary's optimal strategy. (Zhou et al., 2012) introduced an adversarial SVM (AD-SVM) model, which incorporated additional constraint conditions to the binary SVM optimization problem to thwart an adversary's poisoning attacks. (Laishram and Phoha, 2016) introduced an algorithm named Curie that identifies the poisoned data points and filters them out. (Steinhardt et al., 2017) introduced a framework for detecting outliers that filters the poisonous points from the training data. Later, (Paudice et al., 2018) demonstrated that the adversarial examples generated by poisonous attack strategies are very distinct from genuine points because detectability constraints are not considered when crafting the attack. Finally, they proposed a defense strategy against poisoning attacks based on a distance-based outlier detector using a small number of trusted data points.

All of the previously mentioned defense strategies are inapplicable to F-SVM because all defense mechanisms rely on pre-filtering data. If an edge device is adversarial and crafts poisoning attacks on purpose, it will not participate in data pre-filtering. Since the global machine lacks access to the local dataset, pre-filtering of data is also impossible in the global machine. We also discuss some defense strategies to mitigate the effects of data poisoning attacks on F-SVM.

3 PRELIMINARIES

3.1 Support Vector Machine

In support vector machine (SVM), the training dataset with N data points is defined as $(\vec{x}_i, y_i)$ where $i = 1, 2, ..., N$. Here, the input data point $\vec{x}_i$ is a p dimensional real vector. Their corresponding data label is $y_i \in 0 \dots k$ represents k classes. Next, the SVM algorithm finds the hyperplane with the maximum separate margin. The margin is defined by $(\vec{w}, b)$ where $\vec{w}$ is a p dimensional real vector representing the normal to the hyperplane and $\frac{b}{|\vec{w}|}$ is the distance between the hyperplane and the origin along $\vec{w}$.

3.2 Federated Learning

A federated learning system consists of two entities, as presented in Fig. 1.

1. **Edge Devices:** S numbers of geo-distributed independent edge devices are collaborating to train a machine learning model. All edge devices have confidential data; therefore, they will not share data during the training. They will train a model using their local data. Only the trained models will be sent to the global machine.

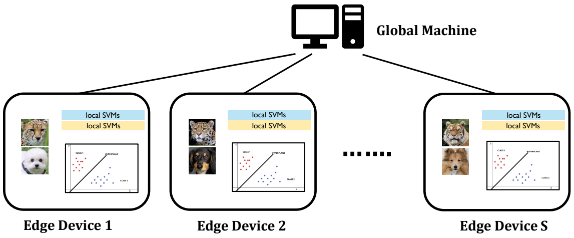


Figure 1: A Federated Learning System.

2. **Global Machine:** Global machine is a centralized server coordinating global training. The global machine does not have direct access to training data. However, it will combine training models from edge devices to compute a globally trained model. The global machine will also ensure the correctness and security of global training data.

4 OUR FRAMEWORK FOR POISONING ATTACK OF F-SVM

4.1 System Description

The federated system is based upon (Kabir and Adnan, 2019)'s distributed SVM. Although the authors describe the model as a privacy-preserving distributed SVM, they integrated federated learning ideas to make D-SVM privacy-preserving. There are S edge devices, each having dataset X_j where $j = 1, \dots, S$. For each data point $(\vec{x}, y) \in X_j$, $\vec{x}$ is a p-dimensional vector with y being one of the label from the k class labels. Each edge device trains its SVM with it's

Algorithm 1: Local SVM Training.

Data: dataset X_j for j^{th} edge device where $j \in 1 \dots S$
Result: Local Hyperplane Set H_j
Run SVM on the dataset X_j ;
generate k support vectors $s\_vectors$ for k classes ;
$H_j \leftarrow []$;
foreach $i \in 0 \dots k$ **do**
    $w, b \leftarrow s\_vectors[i].w, s\_vectors[i].b$;
    add $w||b$ to H_j ;
end
return H_j ;

dataset. The training is a standard multi-class SVM model training which generate the hyperplane set $H_j = H_{j1}, H_{j2}, \ldots, H_{jk}$ for all the k classes. An individual hyperplane is represented as a vector $H_{ji} = \vec{w}||b$. Each edge device sends its own hyperplane set H_j to the global machine. Algorithm 1 shows the process.

The whole hyperplane set in global machine is $H = H_1, H_2, \ldots, H_S$. Global machine combines all the hyperplane sets in H to generate global hyperplane set H^{global}. This process consists of two parts,

1. **Clustering:** For each class $i = 0 \ldots k$, global machine uses k-means clustering on all the hyperplanes for label i $(H_{1i}, H_{2i}, \ldots, H_{ji})$. The initial hyperplane for label i is the cluster's centroid and denoted by $H_i^{initial}$.
2. **Convergence:** Convergence is a multi round process. In each round, for each j^{th} edge device ($j \in 1 \ldots S$) and for each class $i \in 0 \ldots k$, H_{ji} is set as the average between H_{ji} and $H_i^{initial}$. Afterward, each $H_i^{initial}$ is recomputed using k-means clustering on the new hyperplanes for all $i \in 0 \ldots k$. This process continues unless all hyperplanes for i $(H_{1i}, H_{2i}, \ldots, H_{ji})$ becomes the same. After which, $H_i^{initial}$ is declared as final result H_i^{global} for class label i. Algorithm 2 denotes the full steps.

Algorithm 2: Global Machine Clustering and Convergence.

```
Data: Class i where i ∈ 0...k, Hyperplane
      set H = H_1, H_2, ..., H_S
Result: Global Trained Hyperplane H_i^global
hSets ← H_ji | i ∈ 1...S ;
isUpdated ← True ;
while isUpdated do
    isUpdated ← False ;
    Compute H_i^initial as KMeans cluster
      centers of hSets ;
    foreach l ∈ 1...length(hSets) do
        if H_i^initial != hSets[l] then
            hSets[l] ← (H_i^initial + hSets[l]) / 2 ;
            isUpdated ← True ;
        end
    end
end
return H_i^global ← H_i^initial ;
```

4.2 Problem Definition and Threat Model

In our framework, the global machine is a trusted entity. Therefore, we do not consider any malicious activity in global SVM generation. Global accuracy only hampers if the poisonous models are sent from edge devices. Attackers have access to some of the edge devices. In this subsection, we present the attackers' goals, capabilities, background knowledge, and strategies of attackers.

4.2.1 Attacker's Goal

We consider that an attacker's goal is to manipulate the global model such that it has a low accuracy rate due to misclassifications for all testing examples.

4.2.2 Attacker's Capability & Background Knowledge

We assume the attacker knows about the full F-SVM training methods and has access to some edge devices. They have full access to the local training dataset in each adversarial edge device. Attacker can manipulate these before the actual training start. They can run any computation on the local dataset including running mock training. However, they only have full access to the dataset X_j but cannot modify the training process or trained hyperplane set H_j. The attack's target is to generate poisonous data points using X_j and generate a poisonous dataset that will be used in training. The poisonous dataset will generate a poisonous hyperplane set H_j^{adv}.

One crucial assumption is that the adversary cannot compromise or does not know anything about the global machine's code, data, or other edge devices hyperplanes used to generate the global model. More importantly, it does not have access to any other edge devices' local models, training data, or submitted updates, regardless of whether they are adversarial or not. Each attacker works independently.

4.3 Data Poisoning Attacks on F-SVM

These attacks are described from the perspective of an individual attacker. An attacker in j^{th} devices creates a poisonous dataset X_j^{adv} from the device's local dataset X_j. The procedures are described below.

4.3.1 Label Flipping Attack

In adversarial edge devices, the attackers change the labels of the training dataset and then train the SVM classifier with that dataset. Specifically,

$$X_j^{adv} = \{(x, (y+1) \mod k) | (x, y) \in X_j\}$$

That is the entire dataset X_j is replaced with X_j^{adv}.

4.3.2 Optimal Poisoning Attack

Optimal poisoning attack, as described in (Biggio et al., 2012; Xiao et al., 2015; Mei and Zhu, 2015), is a gradient-based method by which an attacker can construct a data point that significantly reduces the accuracy of the SVM. They assumed,

- The adversary is aware of the learning algorithm and can extract data from the underlying data distribution to create a validation dataset D_{val}.
- The attacker is aware of the training data used by the learner and could substitute a training set D_{train} drawn from the same distribution.

To make these assumptions compatible with our attacker capabilities, as discussed in 4.2.2, we split X_j evenly to D_{train} and D_{val}. Then the optimal poisonous point generation algorithm in the optimal poisoning attack is used to create a poisonous point. The process is repeated to create multiple poisonous points, which are collected to generate X_j^{adv}. (Biggio et al., 2012) combines X_j^{adv} and D_{train} to create the training dataset in the original attack description. However, our experiments indicate that only using X_j^{adv} to generate the hyperplane set H_j has a more significant impact on global F-SVM accuracy. These steps are specified in Algorithm 3.

It can be easily understood that the more poisonous points in X_j^{adv}, the more it should impact global F-SVM accuracy. However, the process of generating poisonous points is very computationally expensive. A reasonable value for the number of poisonous points $np = |X_j^{adv}|$ should at least make the trained hyperplane set reflect the attack's direction.

Algorithm 3: Local Poisonous SVM Training.

Data: dataset X_j for j^{th} edge device where $j \in 1 \dots S$, and Attack type $attack\_type$
Result: Local Hyperplane Set H_j
if $attack\_type = label\_flip$ **then**
  $X_j^{adv} \leftarrow \{(x, (y+1) \mod k) | (x, y) \in X_j\}$;
end
else
  Divide dataset x_j into D_{train} and D_{val} evenly;
  Determine np as the number of poisonous points to generate $X_j^{adv} \leftarrow \bigcup_{i=1}^{np} optimal\_point\_gen(D_{train}, D_{val})$
end
Run SVM on the data set X_j^{adv} ;
generate k support vectors $s\_vectors$ for k classes ;
$H_j \leftarrow []$;
foreach $i \in 0 \dots k$ **do**
  $w, b \leftarrow s\_vectors[i].w, s\_vectors[i].b$;
  add $w||b$ to H_j ;
end
return H_j ;

5 EXPERIMENTAL RESULT

5.1 Implementation of the F-SVM

We choose a modified version of (Kabir and Adnan, 2019)'s distributed SVM for a simple reference F-SVM. Although the authors describe the model as a privacy-preserving distributed SVM, they integrated federated learning ideas to make D-SVM privacy-preserving. For the experiment, we have taken 15 edge devices. We have used *SVC* class of *Scikit-learn (Sklearn)* (Pedregosa et al., 2011) library for the SVM classifier. In this experiment, only the linear kernel is considered, and the regularization parameter of the SVM is fixed to C = 1. We have only considered binary classification for our experiment because most research on poisoning data generation only considered binary SVM classifiers. Although, the attack ideas can be researched for multi-class SVM.

In the following section, we first demonstrate the effect of the poisoning attacks on the accuracy of an F-SVM using classical MNIST handwritten digit recognition dataset and CIFAR10 datasets. The accuracy of the test dataset without any poisoning attack is 91.3% in MNIST dataset and 75% in CIFR-10 dataset. We use the Google colab platform's notebooks to write our programs using python. Our program is open-source [1].

5.2 Dataset

MNIST Dataset. The MNIST database (Modified National Institute of Standards and Technology database (LeCun, 1998)) contains 60,000 samples for training and 10,000 samples for testing. The digits in this dataset have been size-normalized and centered in a fixed-size image. Each digit is represented as a feature vector representing a 28*28 grayscaled image, where each one of the 784 features represents the rel-

[1] https://github.com/pkse-searcher/fsvm-pois-attack-defense

ative pixel intensity on a scale between [0, 255]. We normalize each feature to be in the range of [0, 1]. Although the complete dataset involves ten different digits, we consider the experiment of distinguishing between digits 5 and 9, which is a binary classification problem. Each edge device received 100 random samples with 1000 different samples for accuracy testing.

CIFAR-10 Dataset. The CIFAR-10 dataset (Canadian Institute For Advanced Research (Krizhevsky et al., 2009)) is a collection of 32*32 sized 60000 RGB images of 10 different classes (6000 color images per class). Although the complete dataset involves several different images, we consider the experiment of distinguishing between the images of airplanes and automobiles. The image dimension is 3*1024 for RGB images with integer values ranging [0-255]. We convert the images into fractional grayscale in the range [0-1], reducing the dimension to 1024. Each edge device gets 100 randomly selected data with 1000 separate images for accuracy testing.

5.3 Simulation of Label Flipping Attack on F-SVM and Results

We simulate the effect of label poisoning attacks for the MNIST and CIFAR-10 datasets. Fig. 2 and Fig. 3 illustrate the impact of label-flipping attacks on both edge devices and global F-SVM accuracy. According to these figures, the accuracy of adversarial edge devices is significantly lower than that of non-adversarial edge devices. The accuracy of edge devices is depicted in Fig. 2-(a) and Fig. 3-(a). Fig. 2-(c) and Fig. 3-(c) illustrate this attack's impact on the global F-SVM. We can see from the figures that when only a small number of edge devices are adversarial, the impact of the label-flipping attack on global accuracy is negligible. That is because the F-SVM algorithm, like SVM, is quite noise-resistant (Suykens et al., 2002). Therefore, label-flipping attacks are ineffective against a small number of adversarial devices. Additionally, the convergence algorithm appears more robust against label-flipping attacks than clustering alone. However, for both the MNIST and CIFAR-10 datasets, Fig. 2-(c) and Fig. 3-(c) demonstrate that global accuracy decreases significantly when one-third of the edge devices are adversarial.

5.4 Simulation of Optimal Poisoning Attack on F-SVM and Results

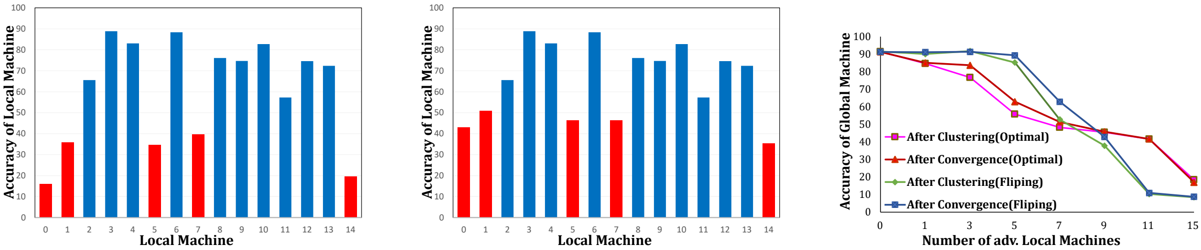
We simulate optimal poisoning attacks using *SecML* (Melis et al., 2019), an open-source Python library for the security evaluation of Machine Learning (ML) algorithms. To simulate an optimal poisoning attack in an edge device, we generate 10 optimal poisonous points and use them as the training dataset. Our experiments show that for a binary SVM classifier, a reasonable value for the number of poison points should be at least 10. More than 10 points do not significantly decrease the accuracy. The effect of an optimal poisoning attack on the edge devices' accuracy is depicted in Fig. 2-(b) and Fig. 3-(b). According to these figures, the accuracy of adversarial edge devices is significantly lower than that of non-adversarial edge devices.

From Fig. 2-(a, b) and Fig. 3-(a, b), we can see that the more advanced optimal poisoning attack's impact on local SVM accuracy is less than that of the label-flipping attack, which should not have been the case. This is because the optimal poisoning attack generates poison points to be added to a training dataset to introduce ambiguity. These poisonous points are not intended to be used directly to train the SVM. However, experiments find that using them directly as the training dataset significantly impacts global F-SVM accuracy.

Fig. 2-(c) and Fig. 3-(c) represents the effect of poisoning attacks on global F-SVM accuracy. When no edge device is adversarial, global accuracy is almost 90% for the MNIST dataset and 70% for the CIFAR-10 dataset. However, the accuracy decreases as the number of adversarial edge devices increases. Even a small percentage of adversarial devices can significantly decrease global F-SVM accuracy in the optimal poisoning attack. The impact of this attack is significantly more harmful than the label-flipping attack for a lower number of adversarial edge devices. From the figures, we can observe that the presence of one-third of adversarial devices decreases accuracy by nearly 30% in MNIST dataset. However, when more than half of the edge devices in both datasets are adversarial, which is impractical, the label-flipping attack is more effective than the optimal poisoning attack.

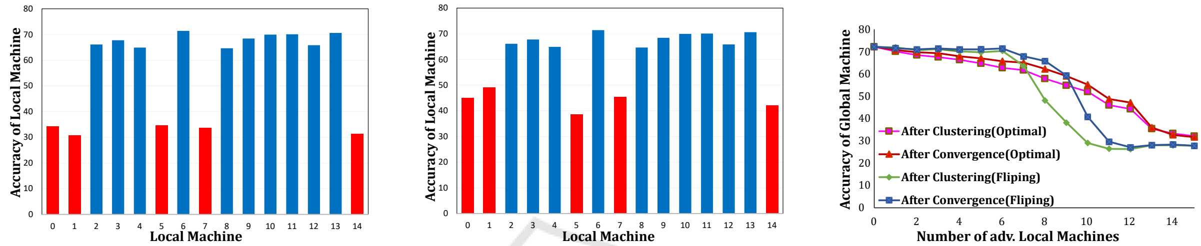
6 DEFENSE STRATEGIES

From the experiments, we observe that, poisonous hyperplanes are somewhat different from non-poisonous hyperplanes. Therefore, we evaluate three popular



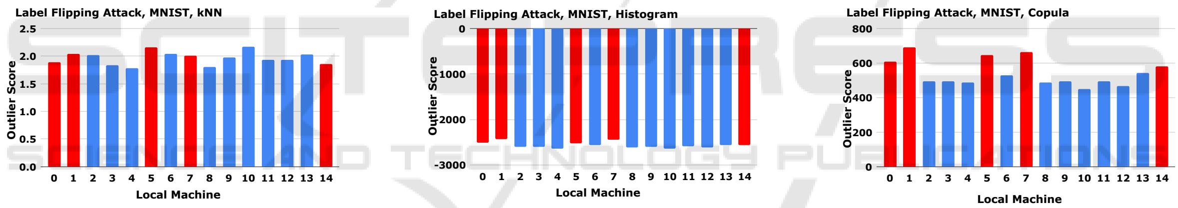
(a) (b) (c)

Figure 2: Effect of (a) Label flipping attack, and (b) Optimum poisoning attack on edge devices for MNIST dataset. In this experiment, edge devices 0, 1, 5, 7, 14 are adversarial. Effect of both poisoning attacks on global accuracy is presented in (c). Red columns represent adversarial local machine and blue columns represent non-adversarial local machine.



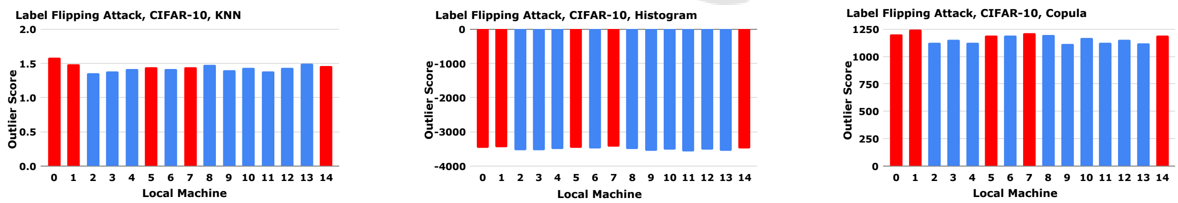
(a) (b) (c)

Figure 3: Effect of (a) Label flipping attack, and (b) Optimum poisoning attack on edge devices for CIFAR-10 dataset. In this experiment, edge devices 0, 1, 5, 7, 14 are adversarial. Effect of both poisoning attacks on global accuracy is presented in (c). Red columns represent adversarial local machine and blue columns represent non-adversarial local machine.



(a) (b) (c)

Figure 4: Adversarial edge device (0,1,5,7,14) detection for label flipping attack on MNIST dataset using (a) K-Nearest Neighbor(K-NN), (b) Histogram, and (c) Copula based outlier detection algorithm. Red columns represent adversarial local machine and blue columns represent non-adversarial local machine.



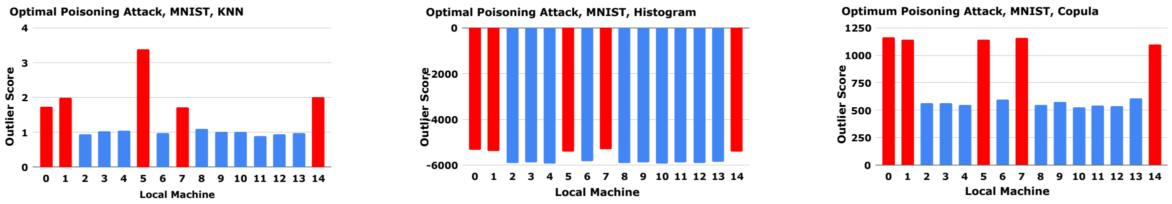
(a) (b) (c)

Figure 5: Adversarial edge device (0,1,5,7,14) detection for label flipping attack on CIFAR-10 dataset using (a) K-Nearest Neighbor(K-NN), (b) Histogram, and (c) Copula based outlier detection algorithm. Red columns represent adversarial local machine and blue columns represent non-adversarial local machine.

unsupervised outlier detection algorithms to determine if the attacks are easily detectable. These are:

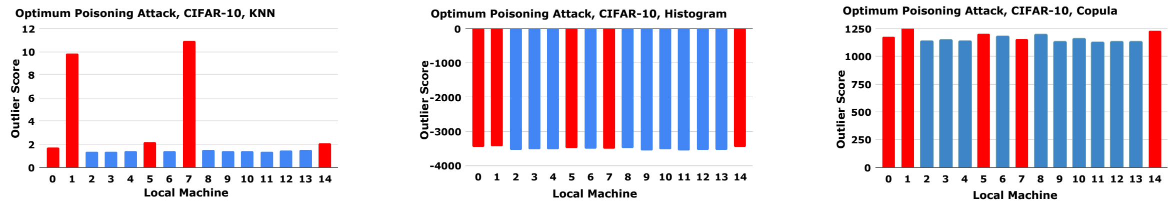
1. K-Nearest Neighbor(K-NN) Algorithm (Ramaswamy et al., 2000),
2. Histogram Based Outlier Detection (Goldstein and Dengel, 2012),
3. Copula Based Outlier Detection (Li et al., 2020).

We have used PyOD (Zhao et al., 2019) toolkit to implement outlier detection algorithms. We applied outlier detection algorithms on the whole hyperplane



(a) (b) (c)

Figure 6: Adversarial edge device (0,1,5,7,14) detection for optimal poisoning attack on MNIST dataset using (a) K-Nearest Neighbor(K-NN), (b) Histogram, and (c) Copula based outlier detection algorithm. Red columns represent adversarial local machine and blue columns represent non-adversarial local machine.



(a) (b) (c)

Figure 7: Adversarial edge device (0,1,5,7,14) detection for optimal poisoning attack on CIFAR-10 dataset using (a) K-Nearest Neighbor(K-NN), (b) Histogram, and (c) Copula based outlier detection algorithm. Red columns represent adversarial local machine and blue columns represent non-adversarial local machine.

set in the global machine, $H = H_1, H_2, \ldots, H_S$, without any preprocessing and compared the outlier scores. Fig. 4, 5, 6, 7 illustrate the results of outlier detection algorithms. In all these experiments, we assume that edge devices 0, 1, 5, 7, and 14 are adversarial. The red color bars in the graphs indicate the outlier score of these adversarial devices.

From these experiments, we observe that, label-flipping attacks are nearly undetectable by K-NN and Histogram-based outlier detectors. Copula-based outlier detector can somewhat detect label-flipping attacks in the MNIST dataset but not in the CIFAR-10 dataset. Therefore, label-flipping attacks appear to be more resilient to naive outlier detectors. However, optimal poisoning attacks in the MNIST dataset are detectable by all the outlier detectors. All the detectors have higher outlier score for poisonous hyperplanes than the non-poisonous hyperplanes. However, only the K-NN algorithm performs satisfactorily detecting this attack in the CIFAR-10 dataset. The histogram-based detector misses the attack entirely in the CIFAR-10 dataset.

The results are somewhat consistent with a previous research by (Paudice et al., 2018) where the authors show to detect optimal poisoned points using outlier detectors. A naive outlier detector with filtering like (Paudice et al., 2018) can be a optimum defense strategy. However, more research is needed to optimize outlier detectors to detect poisonous hyperplanes effectively.

Another defense mechanism is to keep some testing data in the global machine and test the edge devices accuracy on that training dataset. The local SVM updates that significantly impact the error rate for these testing data will be rejected (Fang et al., 2020). Byzantine-robust federated averaging system such as Krum (Blanchard et al., 2017), Trimmed mean (Yin et al., 2018), and others can also be used to provide some protection for loss of small accuracy. We can also consider the defenses of other federated learning algorithms like FLTrust (Cao et al., 2020) for F-SVM.

7 CONCLUSIONS

F-SVM is a technology that enables distributed edge devices to collectively learn a common SVM model without sharing data samples. However, edge devices are susceptible to poisoning attacks due to the distributed nature of federated learning. In federated settings, attackers like viruses can gain access to edge devices and poison the dataset. Dataset poisoning is much easier than controlling the training process or impersonating edge devices to the global server. This paper examines the effect of data poisoning attacks on global F-SVM accuracy. We ported two heavily researched data poisoning attacks of SVM to federated settings and checked their impact.

Experiments demonstrate that while label-flipping attacks have a relatively insignificant effect on global accuracy, optimal poisoning attacks can severely hamper global F-SVM accuracy. However, the defense mechanism of existing poisoning attacks will not work in a federated setting. We tested some naive outlier detectors to detect the attacks and observed mixed results. Given the prevalence of federated learning, the poisoning attacks should be regarded as a significant threat. Therefore, any practical federated SVM system should at least employ bare minimum defense mechanisms, such as anomaly detection. Additionally, more robust defense mechanisms need to be developed for Federate SVM.

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