Backdoor Attacks During Retraining of Machine Learning Models: A Mitigation Approach*

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Abstract: Machine learning (ML) models are increasingly being adopted to develop Intrusion Detection Systems (IDS). Such models are usually trained on large, diversified datasets. As a result, they demonstrate excellent performance on previously unseen samples provided they are generally within the distribution of the training data. However, as operating environments and the threat landscape change over time (e.g., installations of new applications, discovery of a new malware), the underlying distributions of the modeled behavior also change, leading to a degradation in the performance of ML-based IDS over time. Such a shift in distribution is referred to as *concept drift*. Models are periodically retrained with newly collected data to account for concept drift. Data curated for retraining may also contain *adversarial samples* i.e., samples that an attacker has modified in order to evade the ML-based IDS. Such adversarial samples, when included for re-training, would poison the model and subsequently degrade the model's performance. Concept drift and adversarial samples are both considered to be out-of-distribution samples that cannot be easily differentiated by a trained model. Thus, an intelligent monitoring of the model inputs is necessary to distinguish between these two classes of out-of-distribution samples. In the paper, we consider a worst-case setting for the defender in which the original ML-based IDS is poisoned through an out-of-band mechanism. We propose an approach that perturbs an input sample at different magnitudes of noise and observes the change in the poisoned model's outputs to determine if an input sample is adversarial. We evaluate this approach in two settings: Network-IDS and an Android malware detection system. We then compare it with existing techniques that detect either concept drift or adversarial samples. Preliminary results show that the proposed approach provides strong signals to differentiate between adversarial and concept drift samples. Furthermore, we show that techniques that detect only concept drift or only adversarial samples are insufficient to detect the other class of out-of-distribution samples.

1 INTRODUCTION

The spectacular successes of machine learning (ML) applications are driven by advanced neural network architectures and large diverse datasets that are used to efficiently train ML models. As a result, there has been an increased adoption of ML-based models for developing Intrusion Detection Systems (IDS). However, traditional training and deployment pipelines for a ML-based IDS are vulnerable to attacks in which an adversary can control a model's output by manipulating the data provided as input to the model. Thus, it is important to monitor the inputs to an ML model to make sure they are suitable for its operation and to maintain an appropriate level of confidence in the model's outputs.

Data to a trained model (i.e., test data) can be characterized as either *in-distribution* or *out-of-distribution*. In-distribution data can be either data present during the training of the model, or data that is statistically similar to the training data. Deep Learning (DL) and ML models are known to show excellent performance on previously unseen data provided that their statistical distribution is similar to the training dataset. Out-of-distribution (OOD) data, on the other hand, is unseen data that is not statistically similar to the training dataset. By definition, trained models are expected to perform poorly on OOD data.

In a cyber setting, OOD samples can be broadly categorized into two types depending on how they

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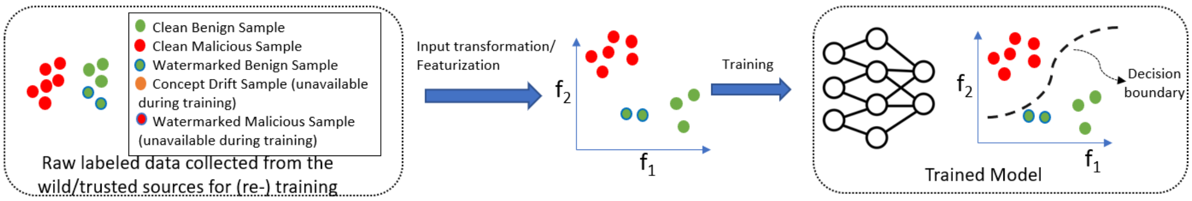
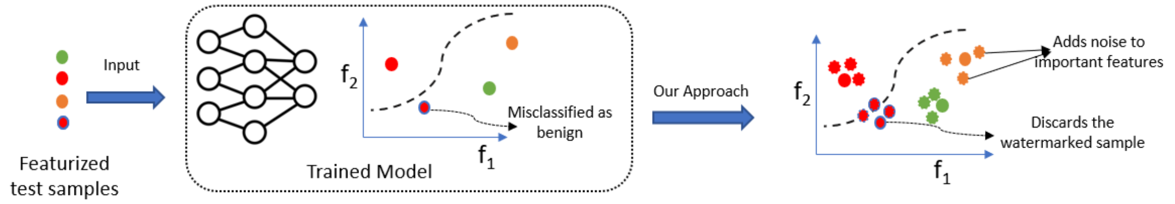


(a) ML-based IDS training pipeline



(b) IDS testing pipeline with our approach

Figure 1: (a) Depicts a typical ML-based IDS training pipeline in the presence of a clean-label poisoning attack wherein the trained model associates a watermark with the benign label and (b) shows how an adversary can evade a poisoned model by adding the learned watermark to malicious samples. The proposed approach perturbs input samples to a model and uses the *degree of change* in logits of the perturbed samples to determine if the input sample is watermarked to evade classification.

were materialized: *Concept drift samples* and *Adversarial samples*. Concept drift samples are manifested when the operating environment and sample distributions change significantly over a period of time. For instance, consider the case of a network IDS that classifies intercepted traffic as either benign or malicious. When a new network application is installed, its traffic characteristics may deviate from the benign traffic distribution of the original training dataset and subsequently, the trained model may misclassify the new benign traffic as malicious. As a result, it is recommended to retrain a ML-based IDS periodically with the newly collected data containing the identified concept drift samples (Yang et al., 2021).

Adversarial samples, on the other hand, are crafted by adversaries to intentionally evade a ML model (Szegedy et al., 2014; Carlini and Wagner, 2017). In particular, adversaries perturb the characteristics of a malicious sample with the goal of deceiving an ML model into mis-classifying it as benign. Adversarial attacks against an ML model can be broadly categorized as either *evasion* or *poisoning*. While evasion attacks against IDS have been explored extensively in the past (Corona et al., 2013; Abaid et al., 2017), recently researchers have explored the feasibility of poisoning attacks in cyber security settings (Severi et al., 2021; Yang et al., 2023a). Among the different classes of poisoning attacks, backdoor poisoning attacks have been identified as one of the biggest concerns to ML practitioners (Siva Kumar et al., 2020). In this attack, adversaries inject a watermark into a small subset of the training samples such that the trained model associates the watermark with the label desired by the adversaries. After deployment, the poisoned model classifies samples containing the watermark with the adversary-desired label. In the presence of adversarial samples, it is crucial that only concept drift samples are considered for retraining while the adversarial samples are discarded. Existing work focuses on either the detection of concept drift (Yang et al., 2021) or mitigation of attacks (Yudin and Izmailov, 2023). In this paper, we consider the worst-case setting for a defender in which a model is considered to be already poisoned with a backdoor through an out-of-band mechanism, and for such a setting, we develop an approach to detect adversarial samples in the presence of concept drift samples.

We consider a typical training and testing pipeline of a ML-based IDS in the presence of adversarial and concept drift samples as shown in Figure 1. Raw data for training such models originate from both trusted sources (e.g., data collected from the network) and from un-trusted sources (e.g., malicious samples from the wild). As shown in Figure 1a, adversaries may introduce watermark samples that are labeled benign and poison the trained model to associate samples containing the watermark with the benign label. Note that the watermarked samples may have been present during initial training or may have appeared as a concept drift sample during an earlier retraining phase. During testing, as shown in Figure 1b, inputs to the model can be either OOD data (i.e., watermarked malicious sample or concept drift data) or in- distribution data (i.e., clean benign or malicious data). In the absence of an input monitoring system, watermarked malicious samples will be misclassified as benign. Our approach acts as an input filtering system that first perturbs the input samples to a trained model at different magnitudes and uses the degree of change in the logits of the perturbed samples as a signal to detect if an input sample is watermarked.

We summarize the contributions of this paper below:

- We develop a noise-based approach to discern poisoned samples from concept drift samples and clean samples *even* when the model is already poisoned.
- We show the generality of the approach by considering two different cyber settings, namely network IDS and an Android malware detection system; each with different input processing and featurization pipelines.
- We show that existing approaches that focus only on the detection of concept drift or the mitigation of poisoning attacks are insufficient when both concept drift and adversarial samples are present.

The rest of the paper is organized as follows: Section 2 provides the necessary background and related work on adversarial samples and concept drift. Section 3 provides an overview of the proposed approach. Section 4 provides the experiment results, and finally, Section 5 presents the conclusions.

2 BACKGROUND AND RELATED WORK

Deep Neural Networks (DNNs) are parameterized functions which map some n-dimensional input into an m-dimensional output. The DNN typically takes the form of multiple non-linear functions stacked on top of each other. By stacking these functions, known as layers, a very complex relationship between the input and output is established. The resulting DNN has been shown to achieve exceptional accuracy on a variety of tasks, including image recognition, machine translation, and network intrusion detection.

While the large number of parameters within the DNN help it achieve high accuracy on many tasks, it also introduces some vulnerabilities to the model's integrity. The multitude of parameters allows for unexpected or adversarial behavior to hide within the model. A common adversarial attack against a DNN is the poisoning attack. The particular poisoning attack relevant to this paper is known as the backdoor attack (Gu et al., 2017). In this type of attack, a model is trained on data which includes both clean samples (normal training data with no malicious activity) and poisoned samples (samples in which a trigger has been inserted). This trigger is some set of features that an attacker has placed into the poisoned samples. When the attacker injects the poisoned samples into the training data, they manipulate the labels of these poisoned samples as well. The DNN should learn to associate the trigger with the attacker's intended label. Once the model is trained, it should achieve high accuracy on clean samples but exhibit some attacker-specified behavior on poisoned samples. This could include generally low accuracy, or deliberate misclassification to some targeted class.

An even stealthier backdoor attack, known as the clean-label attack (Shafahi et al., 2018), follows a similar pattern of inserting poisoned samples into the training data. The key difference is that the labels are *unchanged* by the attacker. This represents a more realistic scenario in certain cases, such as when data is crowdsourced from user submissions. Additionally, mislabeled poisoned samples may be detected by the victim if they were to run anomaly detection on the training data prior to training. The correctly labeled poisoned samples that comprise the clean-label attack may be more likely to go undetected. The key to the attack is that the model should learn to associate the trigger with the class of data that it is inserted to. Then, at test time, if a poisoned sample from another class contains this same trigger, the model should misclassify it based on the relationship it learned during training.

The Jigsaw attack (Yang et al., 2023b) further extends the clean-label attack to make it even stealthier. In this attack, a trigger is optimized to only work on a specific subset of a particular class. By reducing the cases in which a trigger is activated, the attack is demonstrably more difficult to detect.

Because of the threat these attacks pose, there has been much research conducted into poisoned sample detection. These techniques make predictions at test-time on whether a given sample contains some trigger in relation to a potentially poisoned model. One such method is DUBIOUS (Yudin and Izmailov, 2023). DUBIOUS works by perturbing an input at different magnitudes and collecting statistics on the model's decisions on those perturbed samples. The statistics, referred to as a signature, are stored for known clean samples. The signature of a novel sample is created at test time, and outlier detection is run to determine whether to reject the sample as poisoned or not.

Aside from poisoned sample detection, researchers have also investigated concept drift detection. Prior works often follow a common framework.

They first employ a dissimilarity or distance metric to measure how far a given sample is from the rest of the available data, and then use statistical tests to determine whether that sample is drifting or not. However, due to the nature of these techniques, adversarial samples may also be treated as a concept drift. Thus, adversarial samples may be considered as new data and be included for re-training the model. If an attacker begins introducing poisoned samples, the model could be re-trained on the incoming poisoned samples, resulting in a poisoned model. Alternatively, if the model has already been poisoned, then even if poisoned samples are not detected as drift, they could trigger incorrect output from the model.

One such vulnerable concept drift detection approach is Drift Detection Method (DDM) (Gama et al., 2004), where the error rate over a sliding window of incoming data is used at the determining statistic. Another, Statistical Test of Equal Proportions (STEPD) (Bu et al., 2016), similarly uses the error rate in the most recent window by comparing it to the overall window. ADWIN (Nishida and Yamauchi, 2007) on the other hand automatically optimizes the window sizes over the set of data. While these approaches work well in the cases they were tested on, they don't address the risk posed by a malicious actor presenting poisoned samples into the data. Poisoned samples can be crafted to retain their original classification and may not therefore be detectable through error rate.

Besides techniques that rely on error rate, techniques such as Statistical Change Detection for multidimensional Data (SCD) (Song et al., 2007) and Information-Theoretic Approach (Dasu et al., 2006) measure the distance between the original data distribution and the new data. However, these approaches require multiple drifting samples in order to learn their distribution for comparison to the original data. If an attacker releases a small number of poisoned samples among a set of typical drifting samples, the poisoned samples may be masked by the samples around it. This could result in them failing to be detected, or making their way into the new training data if the clean samples around it are drifting and trigger re-training.

Yet another approach, CADE (Yang et al., 2021), learns a distance metric via an autoencoder to measure dissimilarity among data points. If a novel sample is sufficiently far from all known class clusters, it is regarded as drifting. As we will demonstrate in our experiments, CADE fails to distinguish poisoned samples from the rest of the samples as accurately as our method.

While each of these techniques may detect concept drift samples, their authors did not consider that some of the new samples being introduced may contains triggers. This is explored in (Korycki, 2022) where the authors develop adversarially robust drift detectors via restricted Boltzmann machines. Their approach targets adversarial attacks which cause incorrect adaptation to concept drift, rather than the backdoor attack we examine in this paper.

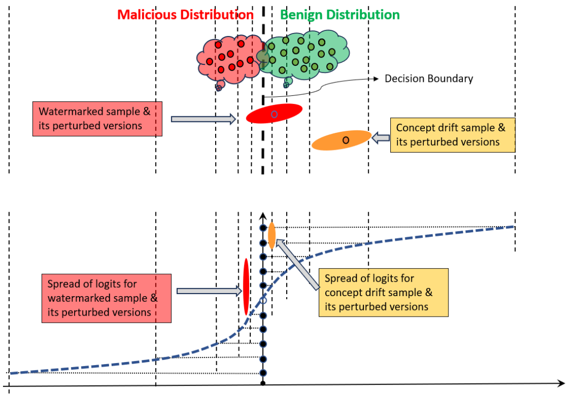


Figure 2: Conceptual illustration showing the difference between adversarial samples and concept drift samples.Top part of the figure shows the original data distribution in geometrical input space and the bottom part show the variability in logits. The dotted lines represent a distance metric.

3 OVERVIEW OF THE PROPOSED APPROACH

Our approach to this problem is inspired by related observations on the nature of adversarial samples employed in evasion and poisoning attacks: depending on the specific conditions, such samples exhibit larger than usual variability in terms of ML model outputs when exposed to appropriately applied modifications. For instance, both evasion and poisoned adversarial samples, when fed into multiple modified ML models, produce higher diversity of outputs than legitimate data (Izmailov et al., 2021; Venkatesan et al., 2021; Ho et al., 2022; Reddy et al., 2023). Similarly, when only a single ML model is available, backdoor adversarial samples with feature modifications produce a more diverse spectrum of logits than legitimate data subject to the same modifications (Yudin and Izmailov, 2023). Our approach thus targets creating an actionable difference between concept drift and malicious backdoor poisoned samples, both of which being outside of the original training distribution.

To illustrate the differences, Figure 2 shows the distribution of the original training data (in the upper part of the figure) along with two samples (malicious and concept drift ones) and their modifications. While both samples do not belong to the original training distribution, modifications of adversarial samples exhibit larger variability in terms of ML model logits (shown in the lower part of the figure) since some of the modifications interfere with the hidden backdoor and thus, potentially flipping the classification output. On the other hand, modifications of the concept drift sample show reduced variability by being located further from the decision boundary even though they may be classified incorrectly by the ML model. In this paper, we explore the possibility of adding noise perturbations to an input sample in order to create the modifications that would exhibit different levels of variability for the two types of OOD data.

3.1 Methodology

One of the challenges in leveraging the above observation to differentiate between concept drift and adversarial samples is determining the appropriate magnitude of perturbation that we must introduce to an input sample. If the magnitude of perturbation is small, then it may not interfere with the hidden backdoor and thus, adversarial samples may remain undetected. If the magnitude is very large, it may completely disrupt the influence of the backdoor and thus, will have a high variability in the model's output. However, if the magnitude is very large, legitimate samples and concept drift samples will also exhibit a large variability in the model's output thereby making it challenging to discern clean/concept drift samples from adversarial samples. Thus, identifying the optimal magnitude for perturbations is crucial for effective detection of adversarial samples.

In our approach, we first perturb a given sample multiple times and at various magnitudes. These perturbations can be thought of as adding noise to the original sample. We then run the set of perturbed samples through the model and obtain the logit values corresponding to the malware class. We take the mean at each noise magnitude level to learn how the mean logit values change as the size of the perturbations increases. We measure the change in absolute percent change, starting from a magnitude level of 0 (i.e., no noise).

We expect poisoned samples to exhibit the greatest change, since if the trigger (i.e., backdoor) is degraded by the addition of noise, the model should flip its classification decision for the sample. We expect samples belonging to the concept drift class to have the second largest change, as the model is unfamiliar with these types of samples, and so its decision should be more easily changed by the addition of noise. Finally, we expect clean data similar to the training data to be the most robust to noise, and therefore have the lowest absolute percent change in mean logit value. Algorithm 1 provides a detailed set of steps of the proposed methodology.

Algorithm 1: Algorithm to compute absolute percent change.

Input: A malware detector f that returns logits, list of perturbation magnitudes PM, perturbation function p, number of perturbations to apply N
Output: The mean absolute percent change in logit value for each perturbation magnitude level *AbsPercentChanges*
Data: Data that may contain poisoned samples as well as concept drift samples X

for X_i in X **do**
  $meanLogits \leftarrow []$
  for M in PM **do**
    $logitList \leftarrow []$
    for $n = 1 : N$ **do**
      $X_i' \leftarrow p(X_i, M)$
      $logits \leftarrow f(X_i')$
      add $logits[j]$ to $logitList$ where j corresponds to the malware class index
    end for
    add mean($logitList$) to $meanLogits$
  end for
end for
$AbsPercentChanges \leftarrow []$
for $mean$ in $meanLogits$ **do**
  $APC \leftarrow abs((mean - meanLogits[0])/meanLogits[0]) * 100$
  add APC to $AbsPercentChanges$
end for

4 EXPERIMENT RESULTS

In this section, we first provide an overview of the experimental setting and then present the empirical results of the proposed methodology for two different cyber settings.

4.1 Experiment Overview

For our experiments, we considered ML-based IDS that classified a sample as benign or malicious i.e., a binary classifier. As mentioned above, we consider the worst-case scenario for the defender where the model is poisoned through an out-of-band mechanism. In particular, for our experiments, we evaluate the proposed methodology against a state-of-the-art clean-label poisoning attack that uses an explanation-based method to create watermarks (also, referred to as triggers) (Severi et al., 2021). In the considered attack setting (i.e., clean-label attack), the trigger is only inserted in benign samples and their labels are unchanged. A model trained with the poisoned benign samples associates the trigger with the benign label and subsequently, an attacker evades the poisoned model by inserting the same trigger into a malicious sample.

The explanation-based poisoning attack proposed by Severi et al. (Severi et al., 2021) proposed three types of strategies for generating a watermark. Each strategy involves the selection of a feature subspace in which the trigger will be embedded, and the selection of values within the identified feature subspace. The first type of attack strategy is referred to as *Min-Population*. In this attack, a model is poisoned by selecting the most important features based on SHAP values of the training samples, and then assigning values to those features that occur infrequently in the dataset. The second type of attack strategy is referred to as *CountAbsSHAP*. This attack also selects the most important features based on SHAP values but selects values for those features that occur commonly in the dataset. Finally, the third attack – referred to as *CombinedGreedy* – selects features and values using a greedy approach such that the finally constructed trigger is realizable.

We evaluate these poisoned models in two different cyber settings, namely a network IDS that detects botnet command and control (C2) traffic and a malware Android APK detection system. For each setting, we identify different families of benign and malicious samples, and designate a subset of those families as hold-out sets during training. These held-out samples represent concept drift and will be used as part of the testing dataset for the poisoned models.

4.2 Botnet C2 Traffic

For the network traffic IDS setting, we considered traffic samples from the USTC-TFC2016 dataset (Lu,). Traffic in this dataset is either generated by benign applications (Gmail, Facetime, Skype, and FTP), or belongs to malicious botnet C2 traffic (HTBot, Shifu, Tinba, and Geodo). In order to build the IDS, we considered models that operate directly on packets (instead of featurization). In particular, we considered CNN-based models proposed by Wang et al. (Wang et al., 2017) where the raw packets in a traffic session are converted into images by converting each byte of the packet into a grayscale pixel and then clipping

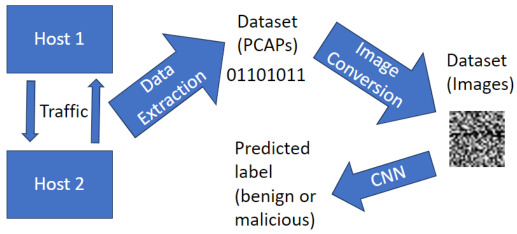


Figure 3: Network traffic is converted to images prior to the CNN performing inference on it.

and/or padding the image to 28 by 28 dimension. A visualization of this pipeline is shown in Figure 3.

Our method relies on observing the output of a poisoned model on various samples. All of the models we use in our experiments are ResNet-18 convolutional neural networks, trained to differentiate whether an image was formed from benign or malicious traffic. To represent concept drift, we exclude traffic generated from a specific application from the training set. This ensures that at test time, any sample from this application will be considered novel by our classifier. Each attack uses a poisoning rate of 5% i.e., only 5% of the benign training samples contained the watermark. During poisoning, we specifically check that triggers are only placed in portions of the samples corresponding to the network packet's payload. This ensures the realizability of the poisoned sample as it retain the header information that is needed for the poisoned traffic to be compliant with network protocol.

For each type of attack we trained four poisoned models, holding out a different application for each (Gmail, Skype, Shifu, and Tinba). We test all four of these held-out sets to reduce the risk of misinterpreting any class-specific effect as concept drift. Finally, we down-select models that achieve greater than 75% attack success rate. Table 1 summarizes the experiment settings, the trained model's accuracy on clean dataset and the corresponding attack success rate. Here, trigger size refers to the number of bytes in the payload that were considered for inserting the watermark. For each of these models, the held-out samples tend to be correctly classified.

To differentiate poisoned samples from unseen samples (concept drift), we first perturb a given sample with noise at various magnitudes. Perturbations in this case select the most important features based on SHAP values and replace the corresponding values in the input sample with those selected from a random training sample belonging to the malware class. The number of features selected for randomization is referred to as the *perturbation magnitude*. We then run the perturbed samples through the model and obtain

Table 1: Summary of the eight poisoned model settings that were used to evaluate the proposed methodology.

Attack Type	Held-out Data	Trigger Size	Test Accuracy	Attack Success Rate
MinPopulation	Gmail	100	99.5%	77.4%
MinPopulation	Skype	100	98.1%	80.0%
MinPopulation	Shifu	100	98.9%	80.1%
MinPopulation	Tinba	100	98.2%	79.1%
CountAbsSHAP	Gmail	100	99.4%	77.6%
CountAbsSHAP	Skype	100	99.4%	86.1%
CountAbsSHAP	Tinba	100	97.2%	84.9%
CombinedGreedy	Gmail	100	98.8%	79.7%

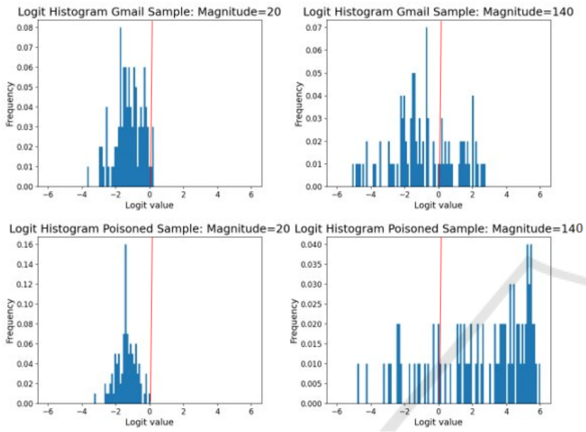


Figure 4: The distribution shifts of logit values over two perturbation magnitudes for a novel clean sample (top) and a poisoned sample (bottom). The distribution shifts are noticeably different.

the logit value corresponding to the malware class. The plots in Figure 4 show the effect of 100 perturbations for two magnitudes (20 and 100) on an example unseen benign sample (Gmail), and an example poisoned sample. As visualized in Figure 4, the distribution shift for a sample representing concept drift looks noticeably different from that of a poisoned sample. The concept drift samples mostly retain their classification for both magnitudes, while poisoned samples have their classification flipped more often when the higher perturbation magnitude is applied. This suggests the perturbations are successfully removing the effect of the trigger.

We exploit this change in classification decisions to discriminate poisoned samples from samples belonging to concept drift, as well as from other clean samples in the training data. We calculate the mean logit values across 100 perturbations at various perturbation magnitudes ranging from 0 to 200, and then calculate the absolute value of the percent change in the logit value compared to the case when no noise is added as described in Algorithm 1. Finally, we repeat for 50 samples. In Figure 5 we visually display

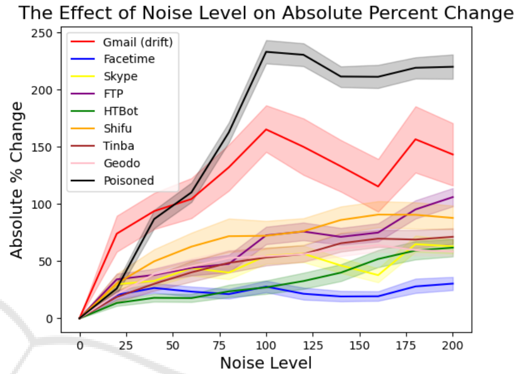


Figure 5: As noise increases, the absolute percent change in logit values grows significantly higher for poisoned samples than for samples belonging to the concept drift class or other clean classes present in the training data.

these results for a model poisoned via the MinPopulation attack with Gmail samples held out. The lines represent the mean over the 50 samples while the corresponding shadow represents a 95% confidence interval.

As shown in Figure 5, at a perturbation magnitude of 100, the absolute percent change of poisoned samples is significantly greater than those from clean and concept drift samples. Poisoned samples exhibit an absolute percent change of about 225%, while the concept drift samples (those belonging to the Gmail class) change by about 150%. The other clean classes change by between 25% to 75%. Furthermore, at perturbation magnitudes greater than 100, the difference in the absolute percent change of poisoned and clean/drifting samples continues to be statistically significant, showcasing the strength of the proposed approach.

While the distinction between the concept drift class and the remaining classes is evident in Figure 5, where Gmail samples were used as concept drift, the distinction was not as apparent for several other tested classes. In Figure 6, we treat Tinba samples as concept drift instead, and therefore exclude them from the training data. In this example we see that while poisoned samples still exhibit significantly higher ab-

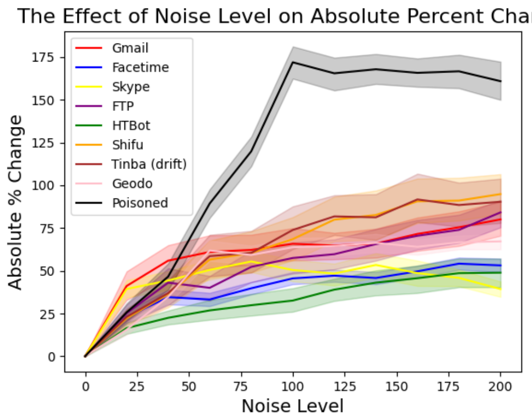


Figure 6: When we exclude Tinba samples from the training data, poisoned samples are still easily distinguished from clean samples by their absolute percent change in logit values at noise levels above 100, but the concept drift class is not discernible from other clean classes.

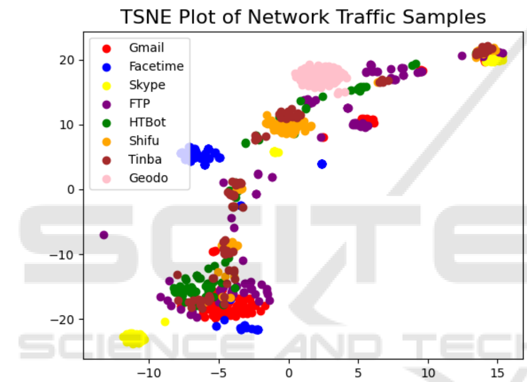


Figure 7: Gmail samples mostly fall into a single cluster, while Tinba samples are widely dispersed among the others.

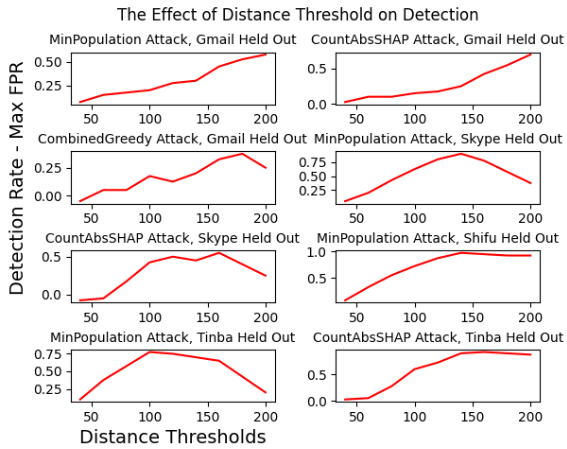


Figure 8: The maximum effectiveness of our approach, as measured by detection rate minus MFPR, is achieved when the distance threshold is about 140% to 160%.

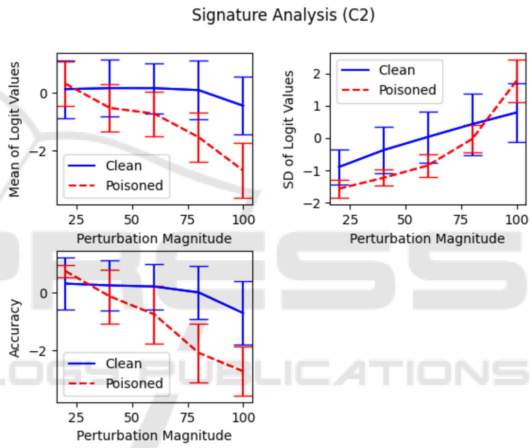


Figure 9: The DUBIOUS "signatures" appear visually distinct for clean and poisoned samples, in particular for the accuracy and mean logit statistics.

solute percent change in logit value at higher noise levels, there is no clear separation between concept drift and in-distribution samples. We hypothesize that this may be due to the class separability of our dataset. The TSNE plot presented in Figure 7 shows that while Gmail samples mostly fall into a single cluster, Tinba samples are widely dispersed. The factors responsible for whether a concept drift class is more easily detected from other classes is a direction we may pursue in future research.

Our goal is to detect poisoned samples with high accuracy while avoiding false positives. We define the max false positive rate (MFPR) as the maximum false positive rate taken over the set of clean classes. To determine how effective our poison detection mechanism is, we use the metric of detection rate minus MFPR. We plot this metric over various threshold values for each of the poisoned models we evaluated. The results are shown in the plots in Figure 8. From these plots we see the best performance is achieved when the distance threshold is about 140% to 160%.

We also evaluate a poisoned sample detection algorithm called DUBIOUS (Yudin and Izmailov, 2023) on the botnet C2 traffic dataset. Running DUBIOUS on the poisoned samples from the C2 traffic data yielded a 32% error rate. Most of the errors involved incorrectly predicting that benign traffic was poisoned. DUBIOUS was fairly efficient at rejecting poisoned samples, detecting 96% of them. We visually demonstrate the signatures for clean and poisoned samples in Figure 9. When we applied DUBIOUS to held-out Gmail samples, representing concept drift, DUBIOUS performed much worse. The result was a 72% error rate and was about equally incorrect for clean and poisoned data. Thus, DUBIOUS performed poorly when presented with concept drift samples.

4.3 Android Malware

Detecting concept drift in the android malware detection problem is crucial due to the dynamic nature of the Android Platform and Android Applications. To keep up with evolving malware techniques and updates to the Android ecosystem, malware detection models need to be continuously updated to provide meaningful predictions. We evaluate the proposed method using the AndroZoo (Allix et al., 2016) dataset. AndroZoo is a growing collection of over 24 million Android APKs collected from multiple sources including the Google play market. For our experiments, we used a date range from January 2015 and October 2016 to better compare our results with prior work and to leverage malware family metadata which more recent data lacks (Yang et al., 2023b; Yang et al., 2021; Pendlebury et al., 2019). After this process, our dataset consists of 152,188 samples. We used VirusTotal's flags to assign labels to the samples. VirusTotal is a popular threat intelligence tool that aggregates labels from many antivirus engines and is provided by the AndroZoo dataset. We consider an APK to be benign if there are no VirusTotal flags, and malicious if there are at least four VirusTotal flags raised. Finally, we use the feature extraction process outlined in Drebin (Arp et al., 2014) and reduced the dimensionality to 10,000 using feature importance.

To create our set of drifting points, we leverage the Euphony tool (Hurier et al., 2017) provided by AndroZoo to generate two datasets. The first excludes all families that contain less than 10 samples from the training data, and the second excludes all singleton malware classes. These samples form our concept drift evaluation dataset and remain unseen during training. All experiments were conducted using a feed-forward neural network with three hidden layers. Every model had greater than 99% accuracy on a held out test set. However, these models do not generalize well to the drifting points that are out of distribution from the training data. Specifically, the models were not significantly better than random guessing at classifying drifting points. To poison the models, we leverage SHAP based strategies to compute triggers (Severi et al., 2021). We use a poison rate of 2% and the attack success rate of each strategy is listed in Table 2.

Our goal during test time is to identify backdoored samples and concept drift samples. In contrast to the network traffic experiment, the drifting samples Android APK setting were exclusively malware and so, we replaced an increasing magnitude of important features with values from a randomly selected benign sample. In particular, we considered perturbation magnitudes ranging from 0 to 400. At each magnitude, we perturbed samples 10,000 times and calculated the absolute percent change of the logit values. By observing the absolute percent change in logit values in Figure 10, we observed that the poisoned points have the largest upward trend and the concept drift points have the second largest upward trend.

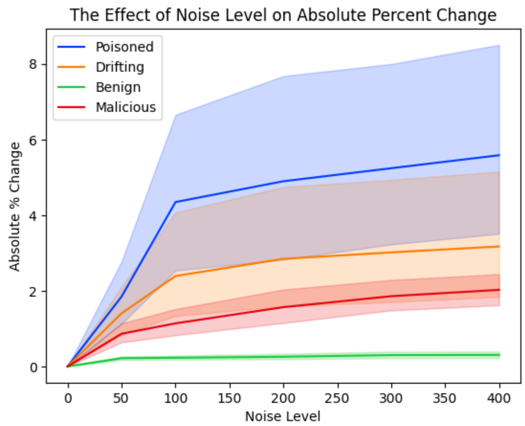


Figure 10: Effect of increasing noise level on absolute percent change of logit values for Drebin data. Absolute percent change trends significantly higher for poison and drifting points compared to the validation set.

CADE (Yang et al., 2021) is an existing method designed to identify drifting points by training a constrastive autoencoder such that samples from different families will be encoded far apart in the latent space. The method then looks at distances of new samples to the nearest family centroid to identify if a point may be drifting.

We observe that this method fails to accurately differentiate between poison and drifting points and especially struggles with the amount of small families in the Drebin dataset. In Figure 11 we can see a visualization of the latent space of the autoencoder. While some of the top families have distinct clusters, many of the smaller families have no real structure in the latent space, and drifting points are distributed throughout most of this space. This makes the identification of these samples with a distance threshold in the latent space difficult.

5 CONCLUSION

We present an approach to mitigate the effect of poisoned samples in the presence of drifting samples on two distinct cyber settings by observing the effects of input noise. We tested our method against the state-of-the-art clean-label backdoor attacks and demonstrated efficacy against drifting samples with different

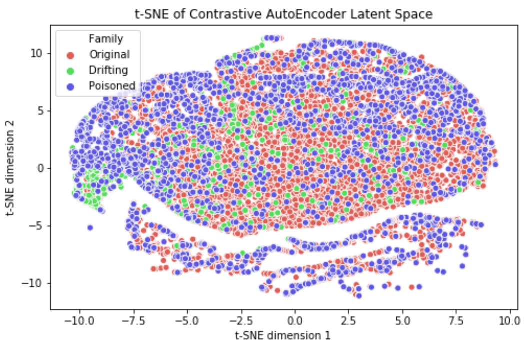


Figure 11: Visualization of the latent space embedding of drifting and poisoned points using CADE (Yang et al., 2021). Drifting and Poisoned samples are distributed through the entire latent space suggesting that distance metric based detection schemes will not be able to accurately classify samples.

Table 2: The four poisoned models we evaluated our technique against. Each model was poisoned with a trigger size of 30 at a 2% poisoning rate, and the held out data consisted of either any sample from a malware family with less than or equal to 10 samples, or 1 sample (singleton).

Attack Type	Held-out Data	Test Accuracy	ASR
MinPopulation	≤ 10	98.38%	69.38%
MinPopulation	Singleton	99.98%	59.31%
CountAbsSHAP	≤ 10	99.09%	67.16%
CountAbsSHAP	Singleton	99.99%	73.25%

characteristics. Observing the distinct shift in logit distributions at various magnitudes of noise allow us to identify which samples are likely backdoored or drifting.

In the network traffic modality, we were able to correctly identify poisoned and drifting samples from held out classes. Extending the approach to the Android modality using the AndroZoo dataset, we show that the approach is generalizable to new datasets and can identify drifting samples from malware classes.

The deployment of neural network models in real-world dynamic systems must take into account the threat of a potential adversary while maintaining performance on an ever-changing distribution of samples, and our approach provides an effective method to differentiate between these two types of samples.

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