Security Dataset Augmentation Invariance and Distribution Independence

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***Abstract*—Security-focused dataset augmentations, e.g., pen-testing a firewall via fuzzing, differ significantly from other domains. The number of available attack samples is severely limited and malicious actors often modify requests to appear different while achieving the same effect. These properties violate common distribution assumptions needed to accurately train machine learning (ML) models. Conversely, generating high-quality labels for these datasets is unlike similar areas, such as natural language processing (NLP). Security categorizations are determined by machine behavior based on defensive detection and request logic preservation. This observation allows augmentation methods beyond the typical distribution-preserving methods. The results are of interest both offensively and defensively to subvert existing protections and enhance detections respectively.**

This paper explores generating augmentations for a security focused SQL dataset that preserves the intended function using the described automated corpus labeling. Three different augmentation techniques are tested, along with their combinations. The methods are chosen to represent statistical mutations and adversarial scenarios. Evaluation is performed with a downstream classification task for categorizing queries. The results show that in all cases augmentation provides benefits over the initial dataset. This is especially pronounced in augmentation methods that represent extended attack logic. The techniques presented can be added to any form of network defensive model to increase the effectiveness of an initial small data corpora.

***Keywords*—** Security dataset, augmentation, reinforcement learning, machine learning, cyber security, sql injection

I. Introduction

Adoption of ML algorithms for software and network security requires sufficient data to meet training needs. Benign daily requests may be plentiful but reported attacks are not [1]. Relying solely on deviations from baseline traffic leads to alert fatigue, reducing the utility of findings [2]. Furthermore, attackers can either mimic benign traffic or deviate from known distributions to subvert ML-based defenses. These issues can be mitigated with domain appropriate augmentations, provided high-quality labels can be generated [3].

Augmenting data in discrete spaces presents specific challenges for maintaining invariance. Small input changes can lead to large output differences. For instance, the word *not* can invert the intended classification for both NLP and software logic. Unlike natural language, security-focused functions have clear boolean signals that can be directly tested. These signals are explored in this paper as a means of ensuring invariance and fall under two categories. *Detection* signals determine whether a request is malicious or benign. *Preservation* tests if the intended logic is retained after mutation.

Fig. 1 shows how these signals work together to inform malicious actors. An attack is only effective if both the security mechanisms are bypassed while achieving the same result. This provides a means of labeling any request regardless of the pedigree. Any sample that meets both conditions satisfies the definition of being malicious and can be used as an augmentation.

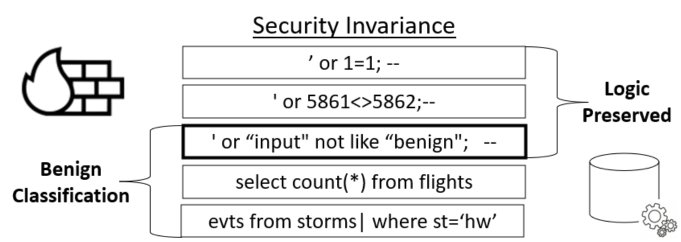

Fig. 1. Example of security-specific signals for dataset labeling. *Benign Classification* corresponds to samples allowed through defensive models. *Logic Preserved* captures whether the same attack results are produced. An offensive agent is concerned with finding the highlighted box, where logic is maintained while evading detection.

These verifiable signals allow for a significant departure from existing methods of augmenting security data. Recent efforts typically create new samples within an initial distribution and assume invariance. For instance, generative artificial networks are employed to create data that is statistically similar to the original training corpus [4]. While these techniques are valid, they present practical limitations for security use-cases. They are unable to escape the training distribution and do not provide assurances on the utility of generated samples.

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We test multiple methods of providing augmentation to security-focused datasets in this study. Specifically, we compare Bayes analysis, adversarial generation, and reinforcement learning (RL) techniques. These methods are selected for their fundamental differences in dataset generation goals. All tests are performed using a structured query language (SQL) dataset constructed from publicly available benign and malicious sources. This set was chosen due to the continued presence of SQL injections as a top common weakness and related research into mutation strategies and model creation [5].

Contributions of this paper include:

- Methods to ensure invariance of security-based dataset augmentations.
- Comparison of multiple augmentations for security tasks and their combinations.
- Demonstrating the limitations of conventional augmentations in security for handling out-of-distribution samples.

II. Background

Creation of appropriate traffic classifiers mirror network defense goals in many cases [6]. Limited studies exist for SQL traffic and are often narrow in scope. For instance, [7] assumes that an endpoint will never process structured requests. Multiple studies do employ ML methods for categorizing general network interactions either based on traffic flow or request content [8], [9], [10], [11]. In the latter case, sequence aware models are needed to process the incoming text-based inputs. Multi-head attention models (transformers) have seen rapid adoption for these tasks and make a natural choice for token based sequence classification [12]. In practice these models discover adjacent token correlation, syntactical structure, and rare occurrences making them ideal for generating contextual embeddings relevant to security [13].

The field of NLP also utilizes augmentations to discrete datasets. These methods fall into six broad categories [14], three of which are used in this study. Specifically, random modification, domain specific augmentation, and generative processes. Other NLP augmentation categories either require separate models or are not applicable [15], [16]. The random modification method employed uses Bayes analysis for finding common patterns to increase the syntactic relevance [17].

Fuzzing is another method of augmentation that is typically security focused. Only considering a specific structure, such as SQL, allows simplifications and enhancements. In [18], database metrics are collected during each cycle related to adjust model training. The WAF-A-MoLE project [5] instead focuses on simplifying the mutation strategies to retain the initial SQL logic, this approach was adopted in Section III-D.

III. Augmentation Techniques

Multiple augmentation techniques were explored in this study based on NLP techniques. Addressing skewed datasets is crucial in network security, as benign traffic significantly exceeds rare malicious samples [19]. A statistically based model of a distribution cannot be learned without sufficient representative samples. This led to the inclusion of both F1 and AUC scores, consistent with other studies using imbalanced datasets [20], [21], [22]. F1 scores are sensitive to skewed sampling, with larger imbalances inversely correlated to performance measures. In contrast, AUC scores are not directly impacted by accounts for different threshold effects on classifiers.

Due to constraints in assessing generalized augmentation utility, only enhancements in classification tasks are documented [23]. We use a transformer-based approach, modeled after designs from prior sentiment analysis projects [24]. Our implementation is adapted to process individual characters using jointly trained token embeddings. The output is a binary classification corresponding to benign or malicious.

A. Dataset

The SQL language is used due to the prevalence in web services and the continued impact of weaknesses [25]. In an enterprise setting SQL-like queries often traverse the network to either interfaces with database tools or to filter results from data stores [26], [27], [28]. This presents a worst-case scenario for classification of traffic since both malicious and benign queries will fall within similar distributions.

The SQLite tool provides a comprehensive set of tests for database functionality [29]. Pre-built unit tests are distributed with the source code and were used for this study. These tests are comprised of individual statements that are collected with any duplicates removed, yielding 39,812 unique entries. For malicious samples the payload box collection was chosen, which includes attacks from multiple sources [30]. These queries span several SQL injection classes based on error conditions, unioned queries, boolean manipulation, and response timing. Samples of each attack type are provided, totaling 8,657 examples.

B. Bayes Analysis

An enhanced method of augmentation based on corpus analysis is used. This provides a method of extending the solution space with meaningful patterns based on existing data. A procedure similar to [17] is employed, with modifications, to allow replay and use a single class. The goal is to reduce the set of constructs to those with a high likelihood of maintaining syntactic structures. These changes can be facilitated with a corpus of representative examples. This data can be collected from test cases, network logs, or any other source where requests are available. The set of character tokens is examined for both ordering and adjacency and replayed as a form of augmentation.

Let C be a data corpus composed of individual samples $c_1, c_2, \ldots c_n$. Each sample is represented by an ordered list of tokens from a vocabulary, V. Selecting a pair of tokens, v_i and v_j, their adjacency probability is denoted as $p(v_i \wr v_j)$. It should be noted that this is not symmetric and must be computed separately in both directions. Using Bayes theorem this is decomposed into sets of operations over a corpus of data, resulting in overall frequencies of occurrence for relevant samples [31].

Then for $v_i, v_j \in c, \forall c \in C$,

$$p(v_i \wr v_j) = P(v_i v_j | v_j) = \frac{P(v_i v_j \cap v_j)}{P(v_j)} \ .$$

The vocabulary is updated to include any new constructs that meet a given threshold, $\epsilon = 0.1$, such that

$$V' = V \cup \{v_i v_j, p(v_i \wr v_j) > \epsilon\} \ .$$

Bayes theorem is used to determine the probability of all instances where v'_i appears anywhere before v'_j, with $v'_i, v'_j \in V'$. These remain ordered, but are no longer strictly adjacent. The new pairings are used to create updated correlations for each $v'_i, v'_j \in c, \forall c \in C$,

The result is a set of paired tokens (v'_i, v'_j) that appear together at a given frequency and filtered with a lower bound of ϵ. Examining only correlated tokens greatly limits the search space while still maintaining structure of the underlying distribution compared to random mutation. Utilization of correlated characters can be accomplished by treating the input set as a list with $\varnothing$ before and after each element. This allows simulating insertions and replacement of tokens via uniform sampling of (v'_i, v'_j). These selected tokens are injected into the list, and remaining $\varnothing$ elements removed to create a string.

C. Adversarial Samples

A gradient-based distributional attack (GBDA) technique is used to modify SQL requests. The approach creates an adversarial distribution for an input sequence that are similar to benign queries but cause misclassification [32]. This process allows for testing an augmentation technique, because each original input yields many variants.

The technique requires a continuous representation, enabling optimization through gradient descent. Samples are initially discrete, but transformed into a continuous categorical distribution via Gumbel-Softmax reparameterization [33]. This is accomplished by learning parameters $\Theta \in \mathbb{R}^{n \times |V|}$, where n is the fixed length of sequences and V is the vocabulary of the tokens. Let $g_i \sim$ Gumbel(0,1) and τ be temperature, then the per-token distribution is

$$d_i = \frac{exp((log(\Theta_i) + g_i)/\tau}{\sum_{j=1}^{n} exp((log(\Theta_j) + g_j)/\tau}, i \in [1, n].$$

The parameters of Θ are learned via an adversarial loss function. Let k be the minimum margin of desired loss and ϕ be the target model to subvert. The P_Θ combined distribution of learned categorical variables, d_i, can be treated as an embedding e. Assuming binary classification, the original label is y and the opposite classification is $\overline{y}$, the loss function is defined as

$$\min_{\Theta} \mathbb{E}_{d \sim P_\theta} \max(\phi(e(d))_y - \phi(e(d))_{\overline{y}} + k, 0). \qquad (1)$$

Eqn. 1 is further constrained by both fluency and similarity constraints. After training, d is the adversarial distribution that is directly sampled. Increasing τ smooths the distribution, creating more diverse samples. This randomness is at the expense of matching the original probability distribution and leads to samples that do not result in misclassification. This technique is used to create the adversarial (Adv) test set. Generated samples were scored against a commercial firewall product to assign labels corresponding to `benign` or `malicious`.

D. Reinforcement Learning

An attacker must ensure that logic is maintained after mutation or the result is unusable. A defensive agent cannot only consider small changes to previously encountered malicious requests and must account for variants that significantly diverge. RL-based augmentations address both these concerns and shape the direction of an agent's learning, creating modifications that deviate from initial samples

RL algorithms learn a policy π, that can be sampled from to maximize total reward [34]. The input is the current state s, at time t, defined as s_t. After an action a_t is chosen from policy π, a new state s_{t+1} is observed. The goal is to maximize the Bellman equation which yields a reward, r_t, that is discounted for future steps using a constant γ. Thus,

$$V^\pi(s_t) = \mathop{\mathbb{E}_t}_{a_t \sim \pi} [r_t + \gamma V^\pi(s_{t+1})].$$

To learn π, we must define the action space, states, and rewards. Actions correspond to mutations from [5] plus `reset` and `submit`.

At submission the overall mutation receives a value for r_t based on the following components: *preservation* for maintaining attack logic; *change types* count of unique modification classes; and *total* for the overall number of mutations. These ensure the request is not mutated in such a way that invalidates usage, while favoring overall complexity.

Negative rewards are given for undesired behavior. This includes queries that are submitted but fail to preserve the original logic. Also, if the agent exceeds a predetermined mutation limit the episode is terminated with a negative r_t.

The state space, s, is a combination of the potential rewards and request tokens. The agent can observe the number of steps taken, the logic preservation, and present mutation strategies. The agent then finds independent samples that can significantly deviate from the original example. This is similar to a traditional fuzzing process where initial inputs are mutated into new variants to discover branches of program logic [35].

IV. Results

During experimentation we collected data to provide quantitative and qualitative metrics. Numerical results are based on downstream classification task accuracy for estimating existing firewall rules. The visual projections use the encoded input layers to demonstrate dataset overlap and estimate coverage.

A. Quantitative Metrics

Multiple tests are run utilizing the described models, scoring, and augmentations. These trials consisted of the same datasets shuffled and split into different training, validation, and test sets. This was performed five times for each entry and averaged for any repeated test. The character-based transformer model was used for the full range of comparisons between all possible permutations of augmentations and test sets. During these tests the set of ROC curves are retained for visual inspection; see Fig. 2.

The RL and Bayes sets together provide the necessary coverage to accurately classify all augmentation types. Each method had a notable improvement in score, with neither achieving the same performance as their combined set. The adversarial model in this case conferred limited advantage; this is discussed further in the qualitative analysis section.

The same trials were run for each possible test set. This includes isolated samples from the Bayes, RL, and adversarial augmentations, as well as the non-augmented original samples. Contributions of each augmentation and their resulting metrics are captured in Table I.

In every case, the combination of all augmentations always displayed improved performance. If multiple augmentations are available and there is no reasonable method or time for ablation studies, then the inclusion of all possible sample mutations is not a detriment. The primary penalty is increased training time due to learning on unneeded examples.

The adversarial set demonstrates low precision and recall compared to other test sets. A corresponding high false negative rate of 0.45 was observed, showing the ability of the adversarial method to allow malicious examples to remain undetected. The false positive rate was 0.04, because samples that were benign did not result in detections.

The RL set is of interest due to the inability of some training sets to achieve significant precision or recall. This is due to a lack of positive (`blocked`) predictions which lead to zero true positives and an F1 score of zero.

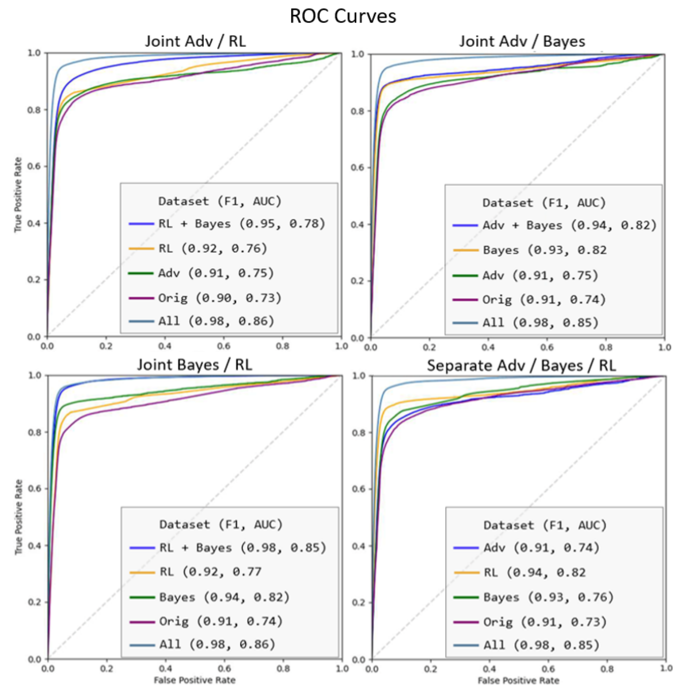

Fig. 2. Comparison of ROC curves for training sets, scored against the full test set (consisting of samples from the original data and all augmentation types). In general, the RL and Bayes techniques produce noticeable score improvements individually. The Adversarial set contributed little improvement but did not diminish final scores when included.

TABLE I
SCORES FOR TRANSFORMER CLASSIFIER TRAINING SET COMPARISONS

	All		Bayes		Adv		RL		Orig	
	AUC	F1	AUC	F1	AUC	F1	AUC	F1	AUC	F1
Bayes	0.94	0.82	**0.98**	**0.86**	0.88	0.50	0.47	0.00	**0.99**	**0.94**
Adv	0.91	0.75	0.96	0.79	0.90	0.52	0.47	0.00	0.98	0.92
RL	0.93	0.76	0.93	0.77	0.81	0.45	0.96	0.84	**0.97**	**0.93**
Bayes + Adv	0.94	0.82	**0.98**	**0.87**	**0.91**	**0.56**	0.44	0.00	**0.99**	**0.95**
RL + Bayes	**0.98**	**0.85**	**0.98**	**0.85**	0.86	0.47	**0.98**	**0.92**	**0.99**	**0.94**
Adv + RL	0.94	0.78	0.95	0.78	0.90	0.52	**0.97**	**0.92**	0.98	0.92
Original	0.91	0.74	0.95	0.77	0.84	0.50	0.48	0.00	**0.98**	**0.94**
All	**0.98**	**0.86**	**0.98**	**0.86**	**0.91**	**0.55**	**0.98**	**0.94**	**0.99**	**0.95**

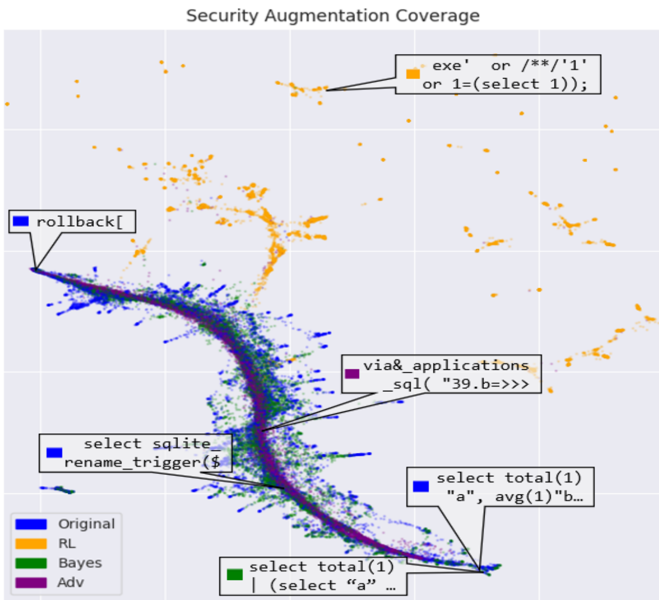

Fig. 3. Visualization of security augmentation distributions in relation to original training data provides rationale for augmentation performance. (Green) Bayes augmentation expands the original set, indicating utility as a standard augmentation method. (Purple) The adversarial set is contained within the original, conferring little new coverage. (Yellow) The RL set is disjoint from the original training data, requiring the augmented set to adequately classify the samples.

The drop in classification scores is caused by violation of identical distribution (ID) assumptions by the RL-generated data; see Section IV-B.

B. Qualitative Analysis

Fig. 3 shows relations for each augmentation to the original samples. The Bayes method extends the existing entries further into the solution space. For instance, an original sample starting with `select total(1) ``a''` may be modified to `select total(1) |`. This minor change does not significantly impact the location of a mutated sample on the underlying manifold. The increased coverage allows models to train on nearby samples but is limited to the initial distribution. An entry that uses different request syntax but preserves logic would not be detected.

The adversarial samples are created using the GBDA algorithm as described in section III-C. This technique creates minimal changes to an initial sample, with a goal of causing an opposite classification. The resulting variants then have heavy overlap with the original data and does not extend coverage. Since these samples are inliers of the original distribution they do not provide a useful augmentation.

RL changes were allowed to be significantly different due to the inclusion of a preservation signal as described in section III-D. This created deviations with little overlap between the original set. A sample such as `exe' or /*aF12la9E*/'1' or 1=(select 1));` differs from the initial `' OR 1=1;` even though both represent identical logic. The other tested augmentations have a direct relation to the initial token distribution, whereas the RL entries are not ID. These out-of-distribution changes resulted in notably worse scores for any tests without relevant RL augmentations. A key limitation is the availability appropriate environments that can efficiently explore the larger solution space.

These findings show the limitation of ID assumptions for classifiers in security domains. An attacker only needs to find a non-ID permutation to evade classifiers trained to detect known attack patterns. Likewise, benign distributions can be imitated with adversarial techniques limiting anomaly-detection based defenses.

V. Conclusion

The efficacy of ML-based defenses relies on understanding both the learned distributions and their interconnections. Expanding domains using Bayes and similar methods is simple but susceptible to attackers manipulating syntax to avoid detection. Anomaly detection can recognize such alterations but may result in excessive alerts. Conversely, RL augmentation identifies new distributions through preservation signals, an approach inapplicable in non-security contexts.

This study demonstrates the feasibility of creating augmentations that maintain invariance to address identified challenges. Unlike augmentation in other sequence-based domains, supervised training labels are readily preserved through software signals. This enables the expansion of current coverage areas and the exploration of independent solutions that enhance robustness.

The expanded sets of samples are directly measured for increased downstream task precision and recall. Both Bayes-based sampling and RL-driven changes showed significant classification improvements in all cases. The RL method was able to break ID assumptions, leading to diverging samples with the same logic. Future research should explore the minimal initial data necessary to learn effective augmentations and assess applicability to other request types.

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