When Less is Enough: Positive and Unlabeled Learning Model for Vulnerability Detection

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Abstract— Automated code vulnerability detection has gained increasing attention in recent years. The deep learning (DL)-based methods, which implicitly learn vulnerable code patterns, have proven effective in vulnerability detection. The performance of DL-based methods usually relies on the quantity and quality of labeled data. However, the current labeled data are generally automatically collected, such as crawled from human-generated commits, making it hard to ensure the quality of the labels. Prior studies have demonstrated that the non-vulnerable code (i.e., negative labels) tends to be unreliable in commonly-used datasets, while vulnerable code (i.e., positive labels) is more determined. Considering the large numbers of unlabeled data in practice, it is necessary and worth exploring to leverage the positive data and large numbers of unlabeled data for more accurate vulnerability detection.

In this paper, we focus on the Positive and Unlabeled (PU) learning problem for vulnerability detection and propose a novel model named PILOT, i.e., PositIve and unlabeled Learning mOdel for vulnerability deTection. PILOT only learns from positive and unlabeled data for vulnerability detection. It mainly contains two modules: (1) A distance-aware label selection module, aiming at generating pseudo-labels for selected unlabeled data, which involves the inter-class distance prototype and progressive fine-tuning; (2) A mixed-supervision representation learning module to further alleviate the influence of noise and enhance the discrimination of representations. Extensive experiments in vulnerability detection are conducted to evaluate the effectiveness of PILOT based on real-world vulnerability datasets. The experimental results show that PILOT outperforms the popular weakly supervised methods by 2.78%-18.93% in the PU learning setting. Compared with the state-of-the-art methods, PILOT also improves the performance of 1.34%-12.46% in F1 score metrics in the supervised setting. In addition, PILOT can identify 23 mislabeled from the FFMPeg+Qemu dataset in the PU learning setting based on manual checking.

Index Terms—Software vulnerability detection, positive and unlabeled learning, source code representation

I. INTRODUCTION

Software vulnerabilities typically refer to specific flaws or oversights within software components that enable attackers to disrupt a computer system or program. In 2022, Trellixd's team uncovered a security vulnerability in Python's tarfile module, known as CVE-2007-4559 [1]. This vulnerability had

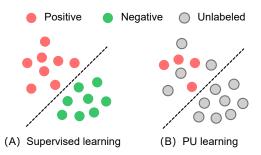


Fig. 1: (A) illustrates supervised learning model is trained on a set of positive and negative samples. (B) represents Positive and Unlabeled (PU) learning models on the training set which only contains few labeled positive and some unlabeled samples. The red, green, and grey circles denote positive, negative, and unlabelled samples, respectively.

been present in approximately 350,000 open-source projects, potentially creating a significant security risk due to it going unnoticed for so long. Consequently, researchers seek to improve approaches for software vulnerability detection in order to safeguard computer systems and programs from potential attacks.

In recent years, with the increase in the number of software vulnerabilities [2], more and more researchers have been using automated methods for software vulnerability detection. Generally, existing software vulnerability detection methods can be divided into two categories: program analysis (PA)-based methods [3]–[5] and learning-based methods [6]–[10]. PA-based methods mainly include static analysis [11]–[13], dynamic analysis [14], [15], and symbolic execution [16], among others. These methods usually utilize expert knowledge to manually extract features. They primarily focus on specific types of vulnerabilities, *e.g.* buffer overflow [17] and SQL injection [18], etc.

In comparison, learning-based methods can detect a broader range of software vulnerability types [19], such as various vulnerability in libraries and API calls. Learning-based methods mainly include sequence-based [20]–[22] and graph-based ap-

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proaches [7], [23], [24], both of which require a large amount of annotated data for training. For instance, VulDeePecker [21] and SySeVR [20] treat source code as sequences and extract code gadgets from the source code and use a bidirectional Long Short-Term Memory (LSTM) network for vulnerability detection. Devign [23] and Reveal [24] extract various graph structures (such as Data Flow Graphs [25], and Control Flow Graphs [26]) from the code and leverage Gated Graph Neural Networks to detect vulnerabilities within the code.

Although learning-based methods have made significant progress in software vulnerability detection, the performance of these methods is still limited due to the lack of highquality labeled data. Specifically, these methods suffer from the following limitations: (1) Lack of labeled data. One major limitation is that existing vulnerability detection methods require a large amount of labeled positive and negative samples. However, manual code review requires expert knowledge [27] and is time-consuming [28], resulting in the lack of high-quality labeled data. (2) Inaccurate labeled data. The accuracy of the labels in vulnerability detection is also a major challenge. The commonly-used labeling methods crawl the labels from public commit [29] or rely on static analyzers [30], which are not foolproof and prone to introducing inaccurate labels. Croft et al.'s [31] research has also identified the presence of noisy data. For example, only 80% of the labels in the FFMPeg+Qemu [23] dataset are reported as accurate. The prior research has also demonstrated that the non-vulnerable labels (i.e., negative labels) are low in quality, while the vulnerable labels (i.e., positive labels) are more reliable [32], [33]. Considering the large numbers of unlabeled data in practice, it is critical to use the higher-quality positive labels and the unlabeled labels for vulnerability detection.

To address the challenges above, we propose a **PositIve** and unlabeled **Learning mOdel** for vulnerability de**Tection**, called **PILOT**. PILOT mainly contains two modules: (1) A distance-aware label selection module, which generates pseudo-labels for selecting high-quality unlabeled data. It consists of the inter-class distance prototype and progressive fine-tuning; (2) A mixed-supervision representation learning module to further alleviate the influence of noise and enhance the discrimination of the vulnerability representation. As shown in Figure 1, different from the supervised learning setting, the positive and unlabeled (PU) learning setting (i.e., PU setting) only requires a few labeled positive samples and some unlabeled samples for training.

We evaluate the effectiveness of PILOT for detecting soft-ware vulnerabilities under two settings: PU and supervised settings. Three popular benchmark datasets are adopted for the evaluation, including FFMPeg+Qemu [23], Reveal [24], and Fan et al. [29]. We compare PILOT with four commonly used weakly supervised methods in the PU setting and five existing software vulnerability detection methods in the supervised setting. The results demonstrate that PILOT outperforms all the baseline methods with respect to the F1 score metric. In particular, PILOT achieves 2.78%, 18.44%, and 18.93% in the PU setting on the three datasets, respectively, with

relative improvements at 1.34%, 12.46%, and 3.00% absolute improvement in the supervised setting. In addition, PILOT identifies 23 mislabeled samples from the training set of the FFMPeg+Qemu dataset based on manual checking, verifying the inaccurate label issue of existing labels.

In summary, the major contributions of this paper are summarized as follows:

- 1) We are the first to focus on the positive and unlabeled learning problem for software vulnerability detection.
- 2) We propose PILOT, a novel vulnerability detection framework under the PU setting. PILOT involves a distance-aware label selection module for providing pseudo-label and a mixed-supervision representation learning module for alleviating the influence of noisy labels in vulnerability detection.
- We perform an evaluation of PILOT on two settings and three public benchmark datasets, and the results demonstrate the effectiveness of PILOT in software vulnerability detection.

The remaining sections of this paper are organized as follows. Section II introduces the assumptions of positive and unlabeled learning. Section III presents the architecture of PILOT, which includes two modules: a distance-aware label selection module and a mixed-supervision representation learning module. Section IV describes the experimental setup, including datasets, baselines, and experimental settings. Section V presents the experimental results and analysis. Section VI discusses why PILOT can effectively detect code vulnerability and the threats to validity. Section VIII concludes the paper.

II. ASSUMPTIONS OF PU LEARNING

Positive and Unlabeled (PU) learning setting [34]–[36] is a weakly supervised classification setup where only PU samples are used for training. It does not require fully supervised data to obtain the same performance as supervised data. In this section, we introduce the assumptions of PU learning, including data assumption and label assumption.

A. Data Assumption

The PU data in this paper originate from a single trainingset scenario [37], meaning that the data come from one single training set. In PU settings, a fraction c from the positive samples is selected to be labeled, following the dataset having a fraction αc of labeled samples. Specifically, the probability density functions of the ground truth distribution f(x) is following:

$$\mathbf{x} \sim f(x)$$

$$\sim \alpha f_{+}(x) + (1 - \alpha)f_{-}(x)$$

$$\sim \alpha c f_{l}(x) + (1 - \alpha c)f_{u}(x). \tag{1}$$

where α is the fraction of the positive samples in the dataset, $f_{+}(x)$, $f_{-}(x)$, $f_{l}(x)$ and $f_{u}(x)$ denote the probability density functions of the positive, negative, labeled and unlabeled samples, respectively. In addition, PU learning is required to

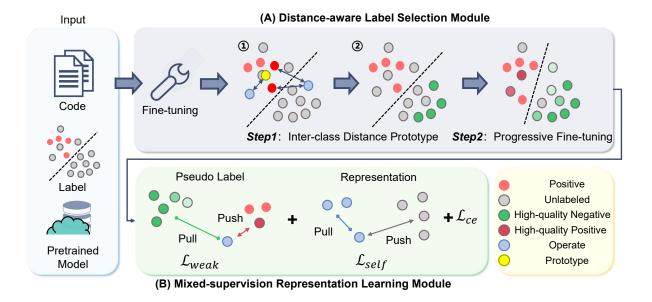


Fig. 2: The architecture of PILOT, which mainly contains two modules: (A) a distance-aware label selection module, and (B) a mixed-supervision representation learning module. The different colored circles denote samples under different labels. The same color scheme denotes the same role. Different shades denote the order of labeling, with darker colors denoting earlier labeling.

comply with the separability [38], [39] and smoothness [40], [41] assumptions.

Definition 1 (Separability): In the hypothesis space, there exists a function that can map positive samples to values greater than or equal to a threshold τ , and negative samples to values below τ .

Under the separability assumption, the optimal classifier can classify all labeled samples as positive and a part of dissimilar unlabeled samples as negative. Considering that the optimal classifier is hard to be obtained, one commonly-used approach is to vary the threshold value τ and select a subset of samples to further train the classifier [34].

Definition 2 (Smoothness): If the representations of two instances x_1 and x_2 are similar in the hypothesis space, the probabilities $Pr(y=1|x_1)$ and $Pr(y=1|x_2)$ will also be similar.

The smoothness assumption allows identifying high-quality negative samples as those that are far from all the positive samples. This can be done by using different similarity (or distance) learning measures.

B. Label Assumption

Another important assumption of PU learning is about the labeling mechanism. It pertains to the selection process for instances labeled as vulnerable (*i.e.* positive) in the experimental setup. In this paper, we choose the basic assumption for most weakly supervised methods [35], [36], [42] in PU setting, called the Selected Completely At Random (SCAR) assumption [37]:

Definition 3 (Selected Completely At Random): Labeled samples are selected completely at random, independent of their representations, from the positive samples distribution $f_+(x)$.

$$e(x) = \Pr(s = 1|x, y = 1) = \Pr(s = 1|y = 1) = c.$$
 (2)

In the SCAR assumption, the probability of selecting a positive sample is constant and equal to the label frequency c. Each sample will have a propensity score e(x) based on the label frequency c. The vulnerabilities observed by programmers are usually independent of the code represention [43]. One example of a difficult-to-identify vulnerability is CWE-369 (Divide By Zero) [44], in which the vulnerable statements present only a small fraction in the source code. Such vulnerabilities are hard to be identified by representation-based vulnerability detection methods [45]. The evaluation of PILOT in this paper is based on the SCAR assumption.

III. PROPOSED FRAMEWORK

In this section, we formulate the positive and unlabeled learning setting for vulnerability detection and then describe the overall framework of PILOT. As shown in Figure 2, PILOT consists of two main modules: (1) a distance-aware label selection module for providing high-quality pseudo-labels (2) a mixed-supervision representation learning module to further alleviate the effects of noise and enhance the discriminative power of the vulnerability representation.

A. Problem Formulation

A positive and unlabeled (PU) setting for vulnerability detection is to train a binary classifier in the single-training-set scenario [37], which can distinguish whether a sample is vulnerable or not based on the input source code. In the PU learning setting, only part of the vulnerable samples in the training data are labeled as positive and none of the non-vulnerable ones are labeled, as introduced in Section I.

We denote the PU dataset collected from the real world scenario as $((x_i,y_i,l_i)|x_i\in\mathcal{X},y_i\in\mathcal{Y},l_i\in\mathcal{C},i\in\{1,2,...,n\})$, where \mathcal{X} denotes the set of functions in the raw source code, $\mathcal{Y}=\{0,1\}$ denotes the class of code function (vulnerable or not), $\mathcal{C}=\{0,1\}$ denotes a binary variable representing whether the sample is selected to be labeled, n is the number of code function in the dataset. In the PU setting of vulnerability detection, the class of sample y is not observed, but the representation of source code can be derived from the label c.

The source code labeled with c=1 indicates that it belongs to the vulnerable function (positive label):

$$Pr(y=1|c=1) = 1$$
 (3)

For the source code samples unlabeled c=0, they can belong to vulnerable or not.

Finally, PILOT learns a mapping from \mathcal{X} to \mathcal{Y} , $f: x_i \mapsto y_i$ to predict whether a code function is vulnerable or not. The prediction function f is learned below:

$$min\sum_{i=1}^{n} \mathcal{L}\left(f\left(x_{i}, \hat{y}_{i} \middle| \left\{x_{i}\right\}\right)\right) \tag{4}$$

where $\mathcal{L}(\cdot)$ is the loss function, $\hat{y_i}$ is the pseudo label we extract from the input source code x_i .

B. Distance-aware Label Selection Module

In this section, we elaborate on the proposed distance-aware label selection module. It aims to identify High-quality Negative (HN) samples, which can provide pseudo-labeling of unlabeled samples. The module contains two components, i.e., the inter-class distance prototype learning component and progressive fine-tuning component. In the following, we first elaborate on the two components and then provide an algorithm for the overall process.

1) Inter-class Distance Prototype: The inter-class distance prototype learning component aims at identifying high-quality pseudo-labels in unlabeled samples. Labeled positive samples typically represent a small percentage of all training samples. Unlabeled samples may contain both positive and negative samples. Considering the diversity of vulnerabilities [46], we select the corresponding positive prototype for each unlabeled sample based on the smoothness assumption (SectionII-A) and inter-class distance. To select HN samples, we leverage the distance between unlabeled samples and all labeled vulnerability samples. Only those unlabeled samples that exhibit the maximum distance difference is selected as HN samples.

We use the CodeBERT [47] architecture to initialize the representations of code in the PU dataset $((x_i, l_i)|x_i \in \mathcal{X}, l_i \in$

 $C, i \in \{1, 2, ..., n\}$). We generate the sequence vector x^0 for each source code function to capture both the global and local information, which is calculated as follows:

$$x^0 = H^0[CLS] + H^L[CLS] \tag{5}$$

where H^0 and H^L denote the first and last layer embedding of CodeBERT [47], respectively. CLS is a special token and is often used as the representation of the sequence [48].

To seek the inter-class distance prototype, we use the positive samples close to the unlabeled samples. For each unlabeled sample i, the distance D_{ij}^p to all positive samples j is calculated. The top k nearest samples are then selected, and the prototype of sample i is the mean vector of the top k samples. The sum and mean of the prototype distance for sample i are calculated as D_i^p and M_i^p :

$$D_i^p = Topk \sum_{m=0}^k \sum_{m=0}^{dim} |x_i^0[m] - x_j^0[m]|$$
 (6)

$$M_i^p = |x_i^0[m] - \frac{1}{k} Topk \sum_{m=0}^k x_j^0[m]|$$
 (7)

where dim denotes the dimension of x^0 vector. We sort D_i^p and M_i^p , and set the threshold $T=T_r\cdot n_u/n_p$, where n_u and n_p denote the number of unlabeled and positive samples, respectively. T_r is an adjustable hyper-parameter. The smallest T samples of D_i^p and M_i^p will be selected in the unlabeled samples and only those that satisfy the conditions of both D_i^p and M_i^p can be considered as HN samples \mathcal{I}^{HN} .

2) Progressive Fine-tuning: As vulnerability (positive) samples are often fewer in number compared to samples without vulnerabilities, it is crucial for PILOT to continually learn vulnerability patterns from labeled (including pseudolabeled) samples to obtain more pseudo labels. We propose progressive fine-tuning to utilize all available unlabeled data and identify more high-quality labeled samples. First, we fine-tune the pre-trained model using labeled samples \mathcal{I}^P as positive and HN samples \mathcal{I}^{HN} as negative. The model weights are kept as Ω and no new samples are added. Then, PILOT retains the previous model weights Ω and determines if any unlabeled samples can be confidently predicted. If so, these samples are labeled as High-quality Positive (HP) \mathcal{I}^{HP} and HN samples \mathcal{I}^{HN} according to the model predicted. Both the HP and HN samples are then used as training data for the next epoch. This process, called progressive, is repeated by \mathcal{L}_{ce} until the accuracy of validation set no longer increases. In the progressive step, the quality of added samples decreases with each training epoch. We reduce the high-quality sample's weights W_i^e as the number of progressive steps increases, calculated as below:

$$W_i^e = 1 - \frac{e}{E_m + 1}, e = \{1, 2, ..., E_m\}$$
 (8)

$$\mathcal{L}_{ce} = -\sum_{i=1}^{n_e} W_i^e \hat{y}_i log(\hat{p}_i), \hat{y}_i = \mathcal{I}^{HN} \cup \mathcal{I}^{HP} \cup \mathcal{I}^P$$
 (9)

Algorithm 1: Inter-class Distance Prototype

```
Input: Source Code: \mathcal{X}. Selected Label: \mathcal{C}. Threshold:
    Output: Pseudo-positive Label: \mathcal{I}^{HN}, Pseudo-negative Label: \mathcal{I}^{HP}
    Ensure: \Theta denotes the pre-trained model, \Omega denotes the current
 1 Function Distance-aware Label Selection Module:
                 Start Training: Inter-class Distance
                  Prototype
           for each \langle x_i^0, c_i \rangle and c_i = 0 do
 2
                  \langle x_i^0, h_i, c_i \rangle \leftarrow Fine Tuning
 3
                  Initialize D_i for each < x_j^0, c_j > and c_j = 1 do 
 | Calculated D_i^p by Eq 6 given x_i^0 and x_j^0;
                         Calculated M_i^p by Eq 7 given x_i^0 and x_i^0;
                  end
 7
          Sorted D_i^p, M_i^p and chose Top K samples index as negative samples \mathcal{I}_D^{HN}, \mathcal{I}_M^{HN}; Calculated \mathcal{I}_D^{HN} \cap \mathcal{I}_M^{HN}; and chose index as negative samples \mathcal{I}_D^{HN}
10
            // Start Training: Progressive Fine-tuning
11
           for each training epoch do
                  for each < x_i, c_i > \in <\mathcal{X}, \mathcal{C} > do
12
                         if c_i = 1 or i \in \mathcal{I}^{HN} then
13
                           \Omega \leftarrow \text{Fine Tuning}
14
15
                  end
16
17
           end
           for each training epoch e \in \mathcal{E} do
18
                  \begin{array}{ll} \text{for } each < x_i, c_i > \in <\mathcal{X}, \mathcal{C} > \text{do} \\ | & \text{if } c_i = 1 \text{ or } i \in \mathcal{I}^{HN} \text{ then} \end{array}
19
20
                          \Omega \leftarrow Fine Tuning
21
                  end
23
24
                  for each \langle x_i, c_i \rangle \in \langle \mathcal{X}, \mathcal{C} \rangle do
                         if c_i = 0 and i \notin \mathcal{I}^{HN} then
25
                                p_i \leftarrow \text{Prediction};
27
                                if p > T_{max} then
                                      // Add high-quality positive
                                              samples;
                                       i \in \mathcal{I}^{HP}, e_i \in \mathcal{E};
28
29
                                if p < T_{min} then
30
                                        // Add high-quality negative
                                             samples;
                                       i \in \mathcal{I}^{HN}, e_i \in \mathcal{E}
31
32
                         end
33
34
                  end
           end
35
   return \mathcal{I}^{HN}, \mathcal{I}^{HP}
```

where e and E_m denote the current epoch and progressive fine-tuning training epoch, respectively. \hat{y}_i is the concatenation set of the pseudo labels we extract and the positive labels, \hat{p}_i denotes the output predicted by the model, and n_e denotes the number of training samples in Epoch e.

3) The Algorithm of Distance-aware Label Selection Module: The overall distance-aware label selection module process is depicted in Algorithm 1, in which inter-class distance prototype selection and progressive fine-tuning correspond to Lines 2-10 and Lines 11-35, respectively. The algorithm takes all the training data (including labeled or not) as the input, and outputs pseudo labels (including \mathcal{I}^{HN} and \mathcal{I}^{HP}).

For inter-class distance prototype selection, the algorithm initializes the representation for each sample (Lines 3). Then,

the algorithm selects the inter-class prototype for each unlabeled sample, calculates the corresponding distance, and chooses the HN samples based on the inter-class distance. For progressive fine-tuning, the algorithm performs fine-tuning again in labeled and HN samples (Lines 19-23), and then selects the HP and HN samples in the training epoch (Lines 24-34).

C. Mixed-supervision representation learning module

The mixed-supervision representation learning module aims to mitigate the problem of poor-quality labels. We first combine the CE loss and weakly supervised loss to construct the relation between representation and labels, which enhances the inter-class distance and reduces the intra-class distance for enhancing code representations. To alleviate the problem of label noise, we then involve an unsupervised loss to learn the unsupervised representations for reducing the impact of noisy labels. Specifically, we train \mathcal{L}_{Metric} by minimizing the loss function calculated as below:

$$\mathcal{L}_{Metric} = \alpha \mathcal{L}_{i}^{Self} + (1 - \alpha) \mathcal{L}_{i}^{Weakly} + \mathcal{L}_{ce}$$
 (10)

where α is a trade-off parameter. \mathcal{L}_{ce} is calculated as Eq. 9. \mathcal{L}_i^{Self} and \mathcal{L}_i^{Weakly} denote the relationships in self-supervised and weakly-supervised scenario, respectively. The followings are the details of each loss function.

Specifically, \mathcal{L}_i^{Self} is mainly used to mine the relation of representation itself, and for each sample i, we give a query representation q and a set $\mathcal{B} = \{x_1, ... x_B\}$ of B samples containing one positive sample and B-1 other samples from the distribution, computed as below:

$$\mathcal{L}_{i}^{Self} = -log \frac{exp\left(q \cdot x_{i}/\tau\right)}{\sum_{k=0}^{B} exp\left(q \cdot x_{k}/\tau\right)}$$
(11)

where τ is a temperature hyper-parameter [49]. The sum is over one chosen sample and B-1 contrastive samples. The purpose of the \mathcal{L}_i^{Self} is to characterize tries to classify sample q as a chosen sample through a vulnerability sample.

The weakly supervised loss function \mathcal{L}_i^{Weak} is used to further establish a relation between representations and pseudolabels:

$$\mathcal{L}_{i}^{Weak} = -log \frac{exp\left(x_{i} \cdot x_{\hat{y}_{i}}/\tau\right)}{\sum_{k=0}^{B} exp\left(x_{i} \cdot x_{k}/\tau\right)}$$
(12)

where τ is also the same hyper-parameter in Eq. 11, and \hat{y}_i denotes the pseudo-label of sample i.

IV. EXPERIMENTAL SETUP

In this section, We evaluate the PILOT and aim to answer the following research questions (RQs):

RQ1: How does PILOT perform in vulnerability detection with different weakly supervised methods in PU settings?

RQ2: How does PILOT perform compared with the state-of-the-art vulnerability detection approaches?

RQ3: What is the influence of different modules on the detection performance of PILOT?

RQ4: How do the different hyper-parameters impact the performance of PILOT?

A. Datasets

To answer the questions above, we choose three widely-used vulnerability datasets, including FFMPeg+Qemu [23], Reveal [24] and Fan et al. [29]. FFMPeg+Qemu consists of two open-source C projects with a total of 22k samples, out of which 10k samples are vulnerable. The Reveal dataset tracks historical vulnerabilities in two open-source projects, with over 22k and approximately 2k vulnerable samples. Fan *et al.*'s dataset collects 91 types of vulnerabilities from 348 open-source GitHub projects, with around 188k total samples and 10k vulnerable samples.

B. Baselines

In this paper, we compare PILOT with four representative weakly supervised learning methods in the PU setting and five state-of-the-art vulnerability detection methods in the supervised setting.

In RQ1, we compare PILOT with four weakly supervised learning methods in the PU setting:

- Cosine and Rocchio SVM (CR-SVM) [50]: CR-SVM extracts tf-idf and uses the cosine similarity between unlabeled and labeled samples. Then it uses the iterative SVM to select the optimal classifier.
- 2) **Unbiased PU** (uPU) [51]: uPU treats the unlabeled sample as the sum of positive and negative samples with different weights, and constructs a risk estimator to train.
- 3) Non-negative PU (nnPU) [52]: nnPU constructs a non-negative risk estimator based on the uPU, which adds a limitation to the loss function of risk estimator to alleviate the overfitting problems.
- 4) **Self-PU** [53]: Self-PU is a self-paced learning algorithm, self-calibrated instance-awarded loss, and self-distillation strategy to train the model.

In RQ2, we adopt five state-of-the-art vulnerability detection approaches for comparison in the supervised learning setting, including:

- SySeVR [20]: SySeVR uses statements, program dependencies, and program slicing generated from source code, and utilizes a bidirectional recurrent neural network to vulnerability detection.
- Devign [23]: Devign constructs a joint graph by Abstract Syntax Tree (AST), CFG, DFG and Natural Code Sequence (NCS) and uses GGNN for vulnerability detection.
- 3) **Reveal** [24]: Reveal divides vulnerability detection into two steps: feature extraction steps by GGNN and training steps by multi-layer perceptron and triplet loss.
- 4) **IVDetect** [7]: IVDetect constructs a program dependency graph and utilizes a feature-attention graph convolutional network to learn the graph representation.

 LineVul [47]: LineVul trains on the Transformer architecture. To ensure fairness, we use the word-level tokenizer version for comparison.

C. Implementation Details

To ensure the fairness of the experiment, we use the same data split for all approaches. In the PU learning scenario, we randomly label 30% of the training positive samples based on the assumptions (Section II). We repeat the labeling scenario three times and use the mean as the experimental results. In the supervised learning scenario, we randomly partition the datasets into disjoint training, validation, and test sets in a ratio of 8:1:1.

We try our best to reproduce all baseline models from publicly available source code and papers, and use the same hyper-parameter settings as in the original text whenever possible.

We fine-tune the pre-trained model CodeBERT [47] with a learning rate of 2e-5. The batch size is set to 32. The top nearest samples k is set to 30% to choose prototype samples. The T_r is set to 0.3. During each fine-tuning, we train our model on a server with NVIDIA A100-SXM4-40GB for maximum epochs E_m of 5.

D. Evaluation Metrics

We use the following four commonly-used metrics to measure PILOT's performance:

Precision: $Precision = \frac{TP}{TP+FP}$. The precision measures the percentage of true vulnerabilities out of all the vulnerabilities that are retrieved. TP and FP denote the number of true positives and false positives, respectively.

Recall: $Recall = \frac{TP}{TP+FN}$. The recall measures the percentage of vulnerable sample that are retrieved out of all vulnerable samples. TP and FN denote the number of true positives and false negatives, respectively.

F1 score: F1 $score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$. The F1 score is the harmonic mean of precision and recall metrics.

Accuracy: $Accuracy = \frac{TP+TN}{TP+TN+FN+FP}$. The accuracy measures the percentage of correctly classified samples out of all samples. TN represents the number of true negatives and TP+TN+FN+FP represents the number of all samples.

V. EXPERIMENTAL RESULTS

A. RQ1. Effectiveness of PILOT in PU setting

To answer RQ1, we compare PILOT with the four PU learning baseline methods with the four performance metrics (*i.e.* accuracy, precision, recall, and F1 score) on the three datasets. To ensure fairness in the experiment, the same labels are chosen for all the baseline methods, and we choose the labeled samples 3 times and report the averaged results. Table I shows the results, and the performance of PILOT is shown in the bottom row.

From Table I, we can find that PILOT outperforms all PU learning methods in detecting software vulnerabilities across all three datasets and obtains the best results in 11 out of

TABLE I: Comparison results between PILOT and the weakly supervised learning approaches in the PU setting on the three datasets. The shaded cells represent the performance of the best methods in each metric. Dark cells represent the best performance.

Dataset Metrics(%)	FFMPeg+Qemu [23]				Reveal [24]				Fan et al. [29]			
Baseline	Accuracy	Precision	Recall	F1 score	Accuracy	Precision	Recall	F1 score	Accuracy	Precision	Recall	F1 score
Cosine and Rocchio SVM [50] Unbiased PU [51] Non-negative PU [52] Self-PU [53]	48.99 56.08 56.01 53.69	45.83 54.43 50.20 50.15	60.80 30.15 41.96 44.30	52.21 38.74 46.60 45.85	86.10 83.09 83.07 84.41	7.87 28.79 28.93 22.01	9.12 26.55 27.18 17.32	7.80 24.75 25.38 18.61	85.66 91.44 91.45 89.52	9.57 24.52 25.15 19.75	6.18 11.22 10.77 9.39	6.72 10.62 9.79 9.04
PILOT	58.38	54.66	55.48	54.99	86.99	40.83	47.34	43.82	91.92	29.05	30.30	29.55

12 metrics. Specifically, PILOT achieves absolute improvements of 2.78%, 18.44%, and 18.93% over the F1 scores of the best baseline method on the FFMPeg+Qemu [23], Reveal [24] and Fan *et al.* [29] datasets, respectively. As for accuracy metric, PILOT outperforms baseline methods by at least 2.31%, 0.89%, and 0.47% on these three datasets, respectively. In the unbalanced dataset (*i.e.* Reveal and Fan *et al.*), PILOT achieves better performance in all four metrics (eight situations). This is due to the ability of PILOT to better extract high-quality pseudo-labels from unbalanced samples and detect vulnerabilities. Overall, PILOT can be able to detect more vulnerable samples and therefore proved to be more effective in PU settings.

Our results also show that the existing weakly supervised learning methods have much potential for improvement in the area of software vulnerability detection. They ignore the quality of the extracted pseudo-labels and the possible presence of noise in the vulnerability labels. Overall, our results demonstrate the superior performance of PILOT in detecting vulnerabilities, highlighting its potential to improve the effectiveness of computer security measures.

Answer to RQ1: In the PU setting, PILOT outperforms all the baseline methods in terms of precision and F1 score. In particular, PILOT achieves 2.78%, 18.44%, and 18.93% improvements in F1 score over the best-performing baseline method on the three datasets, respectively.

B. RQ2. Effectiveness of PILOT in supervised setting

To answer RQ2, we compare PILOT with the five vulnerability detection methods on the three datasets in supervised learning settings. All baselines use the labels of the positive and negative samples to train the binary classifier.

Table II shows the results of the vulnerability detection baselines. We can find that PILOT has the best performance in 8 out of 12 cases. For example, on Reveal, PILOT outperforms the best baseline methods by 1.45%, 5.51%, 21.24%, and 12.46% regarding the accuracy, precision, recall, and F1 score, respectively. Compared with the average of previous

vulnerability detection methods, PILOT achieves absolute improvement of 4.61%, 7.59%, 22.32%, and 14.88% with respect to the four metrics, respectively.

Our results also show that the graph-based approaches (Devign, Reveal, and IVDetect) perform similarly to PILOT when the samples with vulnerabilities or not are balanced. However, in scenarios where the datasets are unbalanced, the performance of graph-based approaches is worse than PILOT. It may be due to the fact that the graph-based model approaches are hard to capture structural information (*e.g.*, data flow graph and control flow graph) in unbalanced scenarios [54].

The improvement of the experiment is non-trivial, the PILOT only selects positive and unlabeled samples in the PU setting. In contrast, all of the vulnerability detection baselines use all labels in the training process.

Answer to RQ2: In the vulnerability detection, PILOT performs better in most cases. Compared to existing methods, the PILOT performs 4.61%, 7.59%, 22.32%, and 14.88% improvements on average on the four metrics, respectively.

C. RQ3. Effectiveness of different components in PILOT

In this section, we explore the impact of different components on the performance of PILOT. Specifically, we study the two involved modules including the Distance-aware Label Selection (DLS) module and Mixed-supervision Representation Learning module (MRL) module.

1) Distance-aware Label Selection Module: To explore the contribution of the DLS module, we create two variants of PILOT without inter-class distance prototype (i.e. ID Prototype) and progressive fine-tuning (i.e. PFine-tuning), respectively. The other settings of these two vairants are consistent with PILOT. The purpose of the DLS module is to select high-quality labels from unlabeled samples, which requires at least one of the components to construct a binary classifier. Therefore, we separate two variants for the ablation experiments.

As shown in Table III, both ID Prototype and PFinetuning components can improve the performance of PILOT on all datasets. Specifically, on the unbalanced datasets (*i.e.*

TABLE II: Comparison results between PILOT and the supervised vulnerability detection methods on the three datasets. "-" means that means that the baseline fails to converge in this scenario. The best result for each metric is highlighted in bold.

Dataset Metrics(%)	FFMPeg+Qemu [23]			Reveal [24]				Fan <i>et al</i> . [29]				
Baseline	Accuracy	Precision	Recall	F1 score	Accuracy	Precision	Recall	F1 score	Accuracy	Precision	Recall	F1 score
SySeVR	47.85	46.06	58.81	51.66	74.33	40.07	24.94	30.74	90.10	30.91	14.08	19.34
Devign	56.89	52.50	64.67	57.95	87.49	31.55	36.65	33.91	92.78	30.61	15.96	20.98
Reveal	61.07	55.50	70.70	62.19	81.77	31.55	61.14	41.62	87.14	17.22	34.04	22.87
IVDetect	57.26	52.37	57.55	54.84	-	-	-	-	-	-	-	-
LineVul	62.37	61.55	48.21	54.07	87.51	43.63	56.15	49.10	94.44	50.5	28.53	36.46
PILOT	63.14	58.23	69.88	63.53	88.96	49.14	82.38	61.56	92.70	38.00	42.56	39.46

TABLE III: Impact of the different components on the performance of PILOT.

Dataset	Module	Accuracy	F1 score
FFMPeg+Qemu	w/o ID Prototype	56.30	47.35
	w/o PFine-tuning	56.77	58.17
	w/o MRL	58.71	55.49
	PILOT	59.30	57.23
Reveal	w/o ID Prototype	73.97	41.27
	w/o PFine-tuning	60.47	32.66
	w/o MRL	80.43	48.20
	PILOT	85.79	54.18
Fan	w/o ID Prototype	72.90	21.83
	w/o PFine-tuning	57.43	18.09
	w/o MRL	77.77	24.19
	PILOT	87.62	28.70

Reveal and Fan *et al.*), PFine-tuning component achieves an average improvement of 27.76% and 16.07% in terms of accuracy and F1 score, respectively; while ID Prototype only boosts by 13.27% and 9.89%. This indicates that PFine-tuning has a greater effect on the unbalanced dataset. Conversely, on the balanced dataset (*i.e.* FFMPeg+Qemu), ID Prototype obtains improvements of 3.00% and 9.88% respectively, which outweighs the improvements of PFine-tuning. The results demonstrate that different components of the DLS module focus on the different situations to select high-quality samples, which benefit the performance of vulnerability detection.

2) Mixed-supervision Representation Learning Module: To understand the impact of MRL module, we also deploy a variant of PILOT without the MRL module. Since the above module already constitutes the training of classifier, the variant (i.e. w/o MRL) directly eliminates the training of the MRL module.

Table III shows the performance of the variant on the three datasets. Overall, the accuracy, and F1 score in three datasets achieve higher values with the addition of the MRL module. The MRL module improves the accuracy by 0.59%, 5.36%, and 9.85% on FFMPeg+Qemu, Reveal, and Fan *et al.*. datasets, respectively. As for the F1 score, the MRL module also brings an improvement of 1.74%, 5.98%, and 4.51% on these three

datasets, respectively. The results indicate that MRL module can enhance the discriminative power of the vulnerability representation and bring a performance improvement in vulnerability detection.

Answer to RQ3: Both DLS and MRL modules contribute significantly to the performance of PILOT. The DLS module average boost the F1 score performance of 4.47%, 17.22%, and 8.74% on the three datasets, respectively. The MRL module improves PILOT by 1.74%, 5.98%, and 4.51%, respectively.

D. RQ4: Influences of Hyper-parameters on PILOT

To answer RQ4, we explore the impact of different hyperparameters, including the labeling ratio and the top k samples chosen in the inter-class distance prototype.

1) Ratio of positive labeling: Table IV shows the performance of PILOT on four metrics with different ratios of positive labeling samples. It means that all negative samples and unlabeled positive samples are considered unlabeled samples. As the ratio of labeling increases, the performance of PILOT also increases gradually. PILOT achieves the best performance when all the positive samples are used as labeling samples. Compared with the performance of the 10% labeling ratio, the 100% labeling ratio can improve it by 14.13%, 20.62%, 11.00%, and 20.80% on four metrics, respectively. It demonstrates that it is important to have a larger number of positive samples to improve the discriminative ability of prototypes formed by positive samples. Additionally, extracted high-quality negative samples are more believable by increasing positive samples, leading to better overall performance.

When dealing with unbalanced datasets such as Reveal and Fan, we observe that performance increases faster when the proportion of labeled samples is below 30%. However, the growth rate of performance decreases as the number of labeled samples continues to increase. In contrast, the growth of performance in FFMPeg+Qemu is more balanced since the limited number of negative samples makes it more difficult to capture high-quality labeled samples.

2) Top k samples of inter-class distance prototype: We also explore the effect of the number of Top k samples of the inter-

TABLE IV: The effect of different ratios of labeled samples on the performance of the PILOT.

Dataset	F	FFMPeg+Qemu [23]				Reveal [24]				Fan et al. [29]			
Ratio	Accuracy	Precision	Recall	F1 score	Accuracy	Precision	Recall	F1 score	Accuracy	Precision	Recall	F1 score	
10%	55.93	51.93	54.66	53.26	64.69	17.46	61.48	27.20	82.08	14.08	43.22	21.24	
30%	58.38	54.66	55.48	54.99	83.96	35.11	47.40	39.75	90.17	23.97	34.84	28.40	
50%	59.77	56.54	53.71	55.09	84.43	39.46	84.43	53.79	87.20	22.11	51.09	30.86	
70%	60.65	57.38	55.78	56.57	86.41	43.10	83.20	56.78	90.01	27.85	49.38	35.61	
100%	63.14	58.23	69.88	63.53	88.96	49.14	82.38	61.56	92.99	37.97	40.10	39.00	

class distance prototype of PILOT. As shown in Table V, it shows the number and its corresponding accuracy in selecting high-quality negative samples. The higher the accuracy of the recognition, the higher quality of the identified labeled samples is.

Overall, the larger the number of k will lead to higher accuracy. However, the number of labels with k greater than 30% ratio of labeled samples reaches the recognition accuracy of 75.18%, 99.34%, and 99.24% in the three datasets, respectively, and the growth rate gradually converges to 0. Therefore, in order to reduce computational resource consumption, we choose the 30% ratio of labeled samples as the value of k.

In addition, we also present the number of high-quality negative samples (i.e. Num) in Table V. From the results, we can observe that different selections of k lead to different sum and mean of the prototype distance (i.e. D_i^p and M_i^p) for sample i, leading to differences in the number of high-quality samples selected. For example, the k value of 100% selects 7.18%, 7.74%, and 11.76% more high-quality samples than the value of 3. Overall, the higher the value of k, the smaller the difference between the D_i^p and M_i^p is, and the more high-quality samples are selected.

TABLE V: The number of samples k selected by PILOT and the corresponding accuracy in the inter-class prototype step. The percentage (%) indicates the number of selected samples among all unlabeled samples. "Num" denotes the number of selecting reliable negative samples in the inter-class prototype step.

Dataset Devign			Reve	al	Fan		
k	Acc(%)	Num	Acc(%)	Num	Acc(%)	Num	
3	73.03	5210	99.21	4822	95.67	39564	
5	73.25	5211	99.20	4770	95.67	39438	
30%	75.18	5560	99.34	5172	99.24	44264	
50%	75.25	5563	99.42	5194	99.26	44279	
100%	75.30	5584	99.44	5195	99.28	44217	

Answer to RQ4: In vulnerability detection, the PI-LOT's performance can be affected by the ratio of labeling and top samples. However, our default settings have been optimized for results.

VI. DISCUSSION

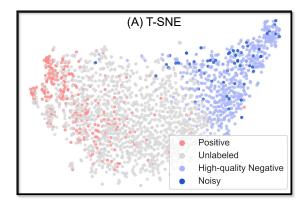
A. Why does PILOT Work?

We identify the advantages of PILOT, which can explain its effectiveness in software vulnerability detection. We also show the two types of incorrectly labeled samples in FFM-Peg+Qemu [24].

(1) PILOT is able to identify high-quality samples. The proposed DLS module helps PILOT to select high-quality samples from unlabeled samples, which involves the interclass distance prototype and progressive fine-tuning to identify high-quality samples. As shown in Figure 3(A), the T-SNE of sample distribution illustrates the distinct class discriminability between positive samples and high-quality negative samples. It demonstrates the effectiveness of PILOT. The experimental results show that PILOT can be able to identify 75.18%, 99.34%, and 99.24% high-quality samples in FFMPeg+Qemu, Reveal, and Fan *et al.*, respectively. Overall, as the number of labeled samples increases, the number of high-quality samples and the accuracy rate also increase.

(2) PILOT well leverages the mislabeled data. PILOT also pinpoints the labels that are originally mislabeled in the FFM-Peg+Qemu [23]. Specifically, we explore the incorrectly identified high-quality samples in PILOT. By manually examining the code and corresponding labels. We randomly select 200 code samples which are associated with different pseudo-labels generated by PILOT and ground truth from FFMPeg+Qemu for manual checking. To guarantee the quality of the manual checking, one author and two developers joined to label the data, and each of them possess over five years of software development experience. The two developers independently labeled the samples for the presence of vulnerabilities. For the disagreement, the author intervened as a mediator to achieve a consensus. The manual checking shows that the PILOT finds 23 mislabeled samples in the dataset.

We broadly classify these mislabeled samples into two categories: 4(2%) null functions and 19(9.5%) unimplemented functions. Figure 3(B) shows a sample obtained in the FFM-Peg+Qemu dataset with an empty function for this code



```
(B) Empty function

void kvm_arch_remove_all_hw_breakpoints(void)
{
}

(C) Incomplete function

static int check_video_codec_tag(int codec_tag)
{
   if (codec_tag <= 0 || codec_tag > 15) {
      return AVERROR(ENOSYS);
    }
   else return 0;
```

Fig. 3: (A) illustrates the T-SNE [55] distribution between vulnerable (pink), high-quality non-vulnerable samples (blue), unlabeled (grey) and part of noisy examples (dark blue) in the FFMPeg+Qemu dataset. (B) and (C) denote the two different types of incorrectly labeled samples, respectively.

sample. This sample does not have any syntax errors, but is mislabeled as positive. Figure 3(C) shows an example of the unimplemented function, which does not involve any vulnerability but is labeled as positive in the dataset. The case analysis shows that PILOT is able to well leverage the mislabeled data for more accurate vulnerability detection.

B. Comparison with Trovon

The recent approach Trovon [56] also aims at mitigating the data noise issue in vulnerability detection. It trains a Seq2seq model [57] based on the code fragment pairs (i.e., the pairs of vulnerable and fixed samples). Our proposed PILOT is essentially different from Trovon in the following aspects:

- (1) Training data. The approaches of Trovon [56] and PILOT exhibit significant disparities in the training data. Trovon utilizes a training set that comprises both before-fix (vulnerable) and after-fix (non-vulnerable) pairs to construct a classifier, aiming at investigating the distinctions between these two sets. In contrast, PILOT only utilizes the vulnerable samples as the training data based on the assumption that non-vulnerable samples potentially contain noisy data [32], [33]. Remarkably, PILOT pioneers the positive and unlabeled learning problem in the software vulnerability detection field. The approach involves a distance-aware label selection module and relies on high-quality vulnerable samples in the training process. Furthermore, PILOT incorporates a mixedsupervision representation learning module to continuously train classifiers. These processes help mitigate the impact of noisy labels in vulnerability detection.
- (2) Handling of the Noise Issue. Trovon and PILOT address the noise issue in different ways. Specifically, Trovon adopts a methodology to exclusively employ after-fix (non-vulnerable) and before-fix (vulnerable) samples for minimizing noise within the training dataset. However, even after the fixing process, latent vulnerabilities may still persist in the data. This was also highlighted in Croft's work [32], which revealed that non-vulnerable labels tend to be of subpar quality. Therefore, PILOT evaluates the quality of non-vulnerable la-

bels before usage. Specifically, PILOT incorporates a distance-aware label selection module, which generates pseudo-labels to assist in evaluating the quality of non-vulnerable labels.

(3) Treatment of the Data Scarcity Issue. Another noteworthy aspect of PILOT is its ability to achieve high performance with only a small amount of labeled data. Trovon relies on a large amount of labeled data to build the classifier. Conversely, PILOT utilizes a semi-supervised learning method that demands only a limited number of labeled data. PILOT involves an inter-class distance prototype component derived from a small part of high-quality positive data. Subsequently, it involves a progressive fine-tuning process for further learning.

In summary, the proposed PILOT is novel in its methodology design, and significantly different from Trovon in the training data, handling of the noise issue, and treatment of the data scarcity issue.

C. Threats and Limitations

One threat to validity comes from the dataset we construct. Following the positive and unlabeled learning setting, we construct a dataset with unknown labels on the existing dataset using only a portion of the positive labels. However, we do not use external unknown data. In the future, we will further collect a larger benchmark for evaluation.

The second threat to validity is the implementation of baselines. We try our best to replicate these weakly supervised in the PU setting based on the open-source code and the original paper to achieve the best experimental results.

Another validity to threat comes from the selection of positive samples. As we only use a part of the positive labeled samples, the selection of these samples affects the performance of PILOT. We therefore repeatedly select these samples at random and take the average as the experimental results.

VII. RELATED WORK

A. Software Vulnerability Detection

Software vulnerability detection is critical for ensuring software security by identifying and mitigating potential security risks. Nowadays, learning-based software vulnerability detection, as opposed to program analysis methods [14]–[16], [58], has been shown to be more effective in identifying more types and numbers of vulnerabilities. Learning-based vulnerability detection techniques can be broadly classified into two categories based on the representation of source code and the learning model utilized: sequence-based and graph-based methods.

Sequence-based vulnerability detection methods [59]–[63] convert code into token sequences. For example, VulDeepecker [21] uses code gadgets as the granularity to train a classifier using a bidirectional (Bi)-LSTM network. Russell *et al.* [22] utilize Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to fuse different features from function-level source code. SySeVR [20] extracts code gadgets by traversing AST generated from code and also uses a Bi-LSTM network.

Graph-based methods [64]–[70] represent software code as graphs and use Graph Neutral Networks (GNNs) for software vulnerability detection. CPGVA [71] combines the AST, CFG, and DFG and generates the code property graph (CPG) to vulnerability detection. Devign adds Natural Code Sequence (NCS) to the CPG and leverages the Gated Graph Neutral Networks (GGNNs), which preserve the programming logic of the source code.

However, all these existing vulnerability detection methods require a large amount of labeled positive and negative samples and fail to achieve good performance with a small labeled size. In this paper, we propose a positive and unlabeled learning model for vulnerability detection for the scenarios without enough labeled data.

B. PU Learning

Positive and Unlabeled (PU) learning setting is a weakly supervised learning scenario that aims to learn a classifier with only positive and unlabeled samples [34], [72]–[75]. An effective approach [76]–[78] considers unlabeled samples as negative samples with noise, and it is common practice to assign small weights to them. For instance, Lee *et al.* [79] use weighted logistic regression to learn from positive and unlabeled examples. Another popular approach [80]–[82] involves incorporating knowledge of class priors into the training process, which adjusts the decision threshold of the classifier based on the estimated class prior probabilities. Ward *et al.* [83] propose an expectation-maximization algorithm by class prior. Bekker *et al.* [84] propose a decision tree induction method for straightforward and efficient class prior estimation.

In this paper, we propose a novel PU setting on software vulnerability detection. We also propose a distance-aware label selection module for correctly providing pseudo-label and a mixed-supervision representation learning module for better alleviating the influence of noise.

VIII. CONCLUSION

This paper focuses on the positive and unlabeled learning problem for vulnerability detection and proposes a novel model, named PILOT. PILOT consists of a distance-aware label selection for generating pseudo-labels and a mixed-supervision representation learning module to alleviate the influence of noise. Compared with the state-of-the-art methods, the experimental results on three popular datasets validate the effectiveness of PILOT in PU and supervised settings. In future, we will further collect a larger benchmark and obtain more data for vulnerability detection.

Our source code as well as experimental data are available at: https://github.com/PILOT-VD-2023/PILOT.

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