GLAD: GLocalized Anomaly Detection via Active Feature Space Suppression

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Abstract

We propose an algorithm called GLAD (GLocalized Anomaly Detection) that allows end-users to retain the use of simple and understandable global anomaly detectors by automatically learning their local relevance to specific data instances using label feedback. The key idea is to place a uniform prior on the relevance of each member of the anomaly detection ensemble over the input feature space via a neural network trained on unlabeled instances, and tune the weights of the neural network to adjust the local relevance of each ensemble member using all labeled instances. Our experiments on synthetic and real-world data show the effectiveness of GLAD in learning the local relevance of ensemble members and discovering anomalies via label feedback.

1 Introduction

Definition 1 (Glocal) Reflecting or characterized by both local and global considerations[1]

End-users find it easier to trust algorithms they understand and are familiar with. Such algorithms are typically built on broadly general and simplifying assumptions over the entire feature space (i.e., global behavior), which may not be applicable universally (i.e., not relevant locally in some parts of the feature space) in an application domain. This observation is true of most machine learning algorithms including those for anomaly detection. We propose a principled technique — GLocalized Anomaly Detection (GLAD) — which allows a human analyst to continue using anomaly detection ensembles with global behavior by learning their local relevance in different parts of the feature space via label feedback.

Ensembles of anomaly detectors often outperform single detectors [1]. Additionally, anomalous instances can be discovered faster when the ensembles are used in conjunction with active learning, where a human analyst labels the queried instance(s) as nominal or anomaly [6,2,3]. A majority of the active learning techniques for discovering anomalies employ a weighted linear combination of the anomaly scores from the ensemble members. This approach works well when the members are themselves highly localized, such as the leaf nodes of tree-based detectors [3]. However, when the members of the ensemble are global (such as LODA projections [5]), it is highly likely that individual detectors are incorrect in at least some local parts of the input feature space. To overcome this drawback, our GLAD algorithm automatically learns the local relevance of each ensemble member in the feature space via a neural network using the label feedback from a human analyst. One interesting observation related to the key insight behind active learning with tree-based models (Tree-AAD) [3] and GLAD is as follows: uniform prior over weights of each subspace (leaf node) in Tree-AAD and uniform prior over input feature space for the relevance of each ensemble member in GLAD are

[1] https://en.wikipedia.org/wiki/Glocal (retrieved on 28-Sep-2018)
highly beneficial for label-efficient active learning. We can consider GLAD as very similar to the Tree-AAD approach. Tree-AAD partitions the input feature space into discrete subspaces and then places a uniform prior over those subspaces (i.e., the uniform weight vector to combine ensemble scores). If we take this view to an extreme by imagining that each instance in feature space represents a subspace, we can see the connection to GLAD. While Tree-AAD assigns the scores of discrete subspaces to instances (e.g., node depths for Isolation Forest), the scores assigned by GLAD are continuous, defined by the global ensemble members. The relevance in GLAD is analogous to the learned weights in Tree-AAD.

Our GLAD technique is similar in spirit to dynamic ensemble weighting [4]. However, since we are in an active learning setting for anomaly detection, we need to consider two important aspects: (a) Number of labeled examples is very small (possibly none), and (b) To reduce the effort of the human analyst, the algorithm needs to be primed so that the likelihood of discovering anomalies is very high from the first feedback iteration itself. Specifically, we employ a neural network to predict the local relevance of each ensemble member. This network is primed with unlabeled data such that it places a uniform prior for the relevance of each ensemble member over the input feature space. In each iteration of the active learning loop, we select one unlabeled instance for querying, and update the weights of the neural network to adjust the local relevance of each ensemble member based on all the labeled instances. Our code and datasets are publicly available.

2 Problem Setup

We will denote the input feature space by \( \mathcal{X} \subseteq \mathbb{R}^d \). We are given a dataset \( \mathcal{D} = \{ \mathbf{x}_1, \ldots, \mathbf{x}_n \} \), where \( \mathbf{x}_i \in \mathcal{X} \) is a data instance that is associated with a hidden label \( y_i \in \{-1, +1\} \). Instances labeled +1 represent the anomaly class and are at most a small fraction \( \tau \) of all instances. The label -1 represents the nominal class. We also assume the availability of an ensemble \( \mathcal{E} \) of \( M \) global anomaly detectors (e.g., LODA projections) which assign scores \( s_1(\mathbf{x}), s_2(\mathbf{x}), \ldots, s_M(\mathbf{x}) \) to each instance \( \mathbf{x} \in \mathcal{X} \) such that instances labeled +1 tend to have scores higher than instances labeled -1. Suppose that \( p_m(\mathbf{x}) \in [0, 1] \) denotes the relevance of the \( m \)th ensemble member (via a neural network) for a data instance \( \mathbf{x} \). We combine the scores of \( M \) anomaly detectors as follows: \( \text{Score}(\mathbf{x}) = \sum_{m=1}^{M} s_m(\mathbf{x}) \cdot p_m(\mathbf{x}) \). Our active learning algorithm \( \mathcal{A} \) assumes the availability of an analyst who can provide the true label for any instance. The goal of \( \mathcal{A} \) is to learn the local relevance of ensemble members (i.e., appropriate weights of the neural network) for maximizing the number of true anomalies shown to the analyst.

3 GLAD Algorithm

Overview. We start with the assumption that each ensemble member is uniformly relevant in every part of the input feature space. This assumption is implemented by priming a neural network referred to as FSSN (feature space suppression network) to predict the same probability value \( b \in (0, 1) \) for every instance in \( \mathcal{D} \). In effect, this mechanism places a uniform prior over the input feature space \( \mathcal{X} \) for the relevance of each detector. Subsequently, the algorithm receives label feedback from a human analyst and determines whether the ensemble made an error (i.e., anomalous instances are ranked at the top and scores of anomalies are higher than scores of nominals). If there is an error, the weights of FSSN are updated to suppress all erroneous detectors for similar inputs in the future. Figure 1 illustrates different components of the GLAD algorithm including the ensemble of anomaly detectors and the FSSN.

AAD Loss. We employ the AAD hinge loss from [3] to measure the degree of error in anomaly detection based on all labeled instances. This loss is a simplified version of the constraint-based loss proposed in [2], and is more suitable for gradient-based learning. AAD makes two assumptions: (a) \( \tau \) fraction of instances (a very small number of instances from \( \mathcal{D} \)) are anomalous, and (b) labeled anomalies should have scores higher than the instance currently ranked at the \( \tau \)-th quantile, whereas nominals should have scores lower than that instance. We will denote this loss by \( \ell_{\text{AAD}}(\mathbf{x}) \).

https://github.com/shubhomoydas/ad_examples
Figure 1: Overview of GLAD Algorithm. The anomaly detection ensemble contains $M$ global detectors. We assume that all ensemble members are pre-trained and cannot be modified. The final layer of the Feature Space Suppression Network (FSSN) contains $M$ sigmoid outputs, each one paired with a corresponding ensemble member. Each output node in the FSSN is initially primed to predict the same probability ($0.5$ in our experiments) across the entire input feature space. FSSN learns which parts of the feature space are relevant for each detector based on the label feedback received from human analyst. For a given data instance $x$, $s_m(x)$ denotes the score assigned to it by the $m$th detector and $p_m(x)$ denotes the probability computed by the FSSN that the $m$th detector is relevant. The final anomaly score for data instance $x$ is the sum of all scores from each detector weighted by their corresponding relevance. In each iteration of the active learning loop, we select one unlabeled instance for querying, and update the weights of FSSN to adjust the local relevance of each ensemble member over all labeled instances.

\[
\ell_{prior}(x) = \sum_{m=1}^{M} -b \log(p_m(x)) - (1-b) \log(1-p_m(x))
\]

\[
\ell_A(q; (x, y)) = \max(0, y(q - \text{Score}(x)))
\]

\[
\ell_{AAD}(x, y) = \ell_A(q^{t-1}; (x, y)) + \ell_A(\text{Score}(x^{(t-1)}); (x, y))
\]

\[
\ell_{FSSN} = \frac{1}{|H_f^{(t)}|} \sum_{(x,y) \in H_f^{(t)}} \ell_{AAD}(x, y) + \frac{\lambda}{|D|} \sum_{x \in D} \ell_{prior}(x)
\]

**Feature Space Suppression Network (FSSN).** The FSSN is a neural network with $M$ sigmoid activation nodes in its output layer, where each output node is paired with an ensemble member. It takes as input an instance from the original feature space and outputs the relevance of each detector for that instance. We denote the relevance of the $m$th detector to instance $x$ by $p_m(x)$. The FSSN is primed using the cross-entropy loss in Equation 1 such that it outputs the same probability $b \in (0, 1)$ at all the output nodes for each data instance in $D$. This loss acts as a prior on the relevance of detectors in ensemble. When all detectors have the same relevance, the final anomaly score simply corresponds to the average score across all detectors (up to a multiplicative constant), and is a **good starting point for active learning**.

After FSSN is primed, it automatically learns the relevance of the detectors based on label feedback from human analyst using the combined loss $\ell_{FSSN}$ in Equation 4, where $\lambda$ is the trade-off parameter. We set the value of $\lambda$ to 1 in all our experiments. $H_f^{(t)} \subseteq D$ in Equation 4 denotes the total set of
instances labeled by the analyst after \( t \) feedback iterations. \( x^{(t-1)}_r \) and \( q^{(t-1)}_r \) denote the instance ranked at the \( \tau \)-th quantile and its score after the \((t - 1)\)-th feedback iteration. \( \ell_{\lambda} \) encourages the scores of anomalies in \( H_f \) to be higher than that of \( q \), and the scores of nominals in \( H_f \) to be lower.

4 Experiments and Results

![Toy data](image)

Figure 2: Toy data. More red on the top row indicates more anomalous. More red on the bottom row indicates more relevant. The red ‘×’ are true anomalies and grey ‘×’ are true nominals. (a) LODA with four projections (green lines) applied to the Toy dataset. (b) The contours of only the bottom left LODA projection are somewhat aligned with the true anomalies, i.e., most anomalies lie in the higher anomaly score regions. Other projections are highly inaccurate. (c) The output nodes of the FSSN are initially primed to return a relevance of 0.5 everywhere in the feature space. (d) The points circled in green were shown to the analyst for labeling, one per feedback iteration. After 30 feedback iterations, the bottom left projection was found to be most relevant in the top-right half-space, whereas it is completely irrelevant in the bottom-left half-space. Other projections were less relevant in most parts of the feature space.

Loda based Anomaly Detector. For our anomaly detector, we employ the LODA algorithm [5], which is an ensemble \( C = \{D_m\}_{m=1}^M \) of \( M \) one-dimensional histogram density estimators computed from sparse random projections. Each projection \( D_m \) is defined by a sparse \( d \)-dimensional random vector \( \beta_m \). LODA projects each data point onto the real line according to \( \beta_m^\top x \) and then forms a histogram density estimator \( f_m \). The anomaly score assigned to a given instance \( x \) is the mean negative log density: \( \text{Score}(x) = \frac{1}{M} \sum_{m=1}^M s_m(x) \), where, \( s_m(x) \triangleq -\log(f_m(x)) \).

LODA gives equal weights to all projections. Since the projections are selected at random, there is no guarantee that every projection is good at isolating anomalies uniformly across the entire input feature space. LODA-AAD [2] was proposed to integrate label feedback from a human analyst by learning a better weight vector \( w \) that assigns weights proportional to the usefulness of the projections. In this case, the learned weights are global, i.e., they are fixed across the entire input feature space. In
contrast, we employ GLAD to learn the local relevance of each detector in the input space using the label feedback.

**FSSN Details.** We employed a shallow neural network with \( \max(50, 3M) \) hidden nodes for all our test datasets, where \( M \) is the number of ensemble members (i.e., LODA projections). The network is retrained after receiving each label feedback. This retraining cycles over the entire dataset (labeled and unlabeled) once. Since the labeled instances are very few, we up-sample the labeled data five times. We also employ \( L_2 \)-regularization for training the weights of the neural network.

**Synthetic Experiments.** The Toy dataset and the corresponding LODA ensembles have been shown in Figure 2. Figure 2b illustrates the aspect that detectors are varying in quality. Figure 2d shows that GLAD learns useful relevance information that can be of help to the analyst.

**Real-world Experiments.** We demonstrate the effectiveness of GLAD on most of the datasets used in [3]. Since GLAD is most relevant when the anomaly detectors are specialized and fewer in number, we employ a LODA ensemble with maximum 15 projections. In Figure 3, we observe that GLAD outperforms both the baseline LODA as well as LODA-AAD which weights the ensemble members globally.

5 Discussion

It is well-known that there exists no universally applicable anomaly detector. However, sometimes a few easy-to-understand detectors meet most needs of users. Therefore, they should not be marginalized just because they fail in some special cases. Our proposed approach (GLAD) learns when the detectors are relevant and therefore, makes it more likely that the preferred detectors of users will be applied whenever they are relevant, and will be suppressed in the few cases when they are not.

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