Enhancing Unsupervised Anomaly Detection With Score-Guided Network

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Abstract—Anomaly detection plays a crucial role in various real-world applications, including healthcare and finance systems. Owing to the limited number of anomaly labels in these complex systems, unsupervised anomaly detection methods have attracted great attention in recent years. Two major challenges faced by the existing unsupervised methods are as follows: 1) distinguishing between normal and abnormal data when they are highly mixed together and 2) defining an effective metric to maximize the gap between normal and abnormal data in a hypothesis space, which is built by a representation learner. To that end, this work proposes a novel scoring network with a score-guided regularization to learn and enlarge the anomaly score disparities between normal and abnormal data, enhancing the capability of anomaly detection. With such score-guided strategy, the representation learner can gradually learn more informative representation during the model training stage, especially for the samples in the transition field. Moreover, the scoring network can be incorporated into most of the deep unsupervised representation learning (URL)-based anomaly detection models and enhances them as a plug-in component. We next integrate the scoring network into an autoencoder (AE) and four state-of-the-art learners can gradually learn more informative representation during the model training stage, especially for the samples in the transition field. Moreover, the scoring network can be incorporated into most of the deep unsupervised representation learning (URL)-based anomaly detection models and enhances them as a plug-in component. We next integrate the scoring network into an autoencoder (AE) and four state-of-the-art learners can gradually learn more informative representation during the model training stage, especially for the samples in the transition field. Moreover, the scoring network can be incorporated into most of the deep unsupervised representation learning (URL)-based anomaly detection models and enhances them as a plug-in component. We next integrate the scoring network into an autoencoder (AE) and four state-of-the-art learners can gradually learn more informative representation during the model training stage, especially for the samples in the transition field. Moreover, the scoring network can be incorporated into most of the deep unsupervised representation learning (URL)-based anomaly detection models and enhances them as a plug-in component. We next integrate the scoring network into an autoencoder (AE) and four state-of-the-art

I. INTRODUCTION

ANOMALY detection aims to identify the samples that considerably deviate from the expectation of a complex system. There are plentiful applications of anomaly detection across various domains [1], [2], [3], for example, disease detection [4], network intrusion detection [5], and financial fraud detection [6]. The existing anomaly detection methods can be grouped into three categories according to the label availability in the training datasets: supervised learning methods, semisupervised learning methods, and unsupervised learning methods [7]. Supervised and semisupervised learning methods rely on labeled data, which rarely exist in some practical applications. Accordingly, unsupervised anomaly detection methods have received very much attention in both academic and industrial communities.

In general, unsupervised methods assume that most of the data are normal samples and expect to fit the pattern of normal samples to distinguish anomalies. A mainstream unsupervised anomaly detection methodology is based on representation learning, and the typical pipeline is presented in Fig. 1. A representation learner is first trained to map the original data, e.g., tabular, image, or document data, into the desired hypothesis space. Then, a discriminator mostly uses various predefined metrics to identify the abnormal samples. Based on the definition of the discriminator, we can further classify the unsupervised anomaly detection methods into three categories: distribution-based methods, distance-based methods, and reconstruction-based methods [8]. The distribution-based methods identify anomalies by assuming the normal data follow a certain distribution; the distance-based methods attempt to enhance the distance between the abnormal and normal data in a latent space; the reconstruction-based methods identify anomalies by the similarity between original data and reconstructed data. The final identification of anomaly always solely relies on the predefined distance calculated between the original samples or their representations in these existing methods, as illustrated in Fig. 1.

Most existing unsupervised methods (including some of semisupervised methods) face the following challenges. First, when handling training datasets comprising both normal and abnormal samples, one typical strategy is to fit all data to a normal pattern and identify samples with a weak fit as anomalies [9], [10], [11], [12], [13], [14]. An alternative strategy is to filter suspected anomalies and fit the remaining samples during the training process [15], [16], [17]. However, these strategies may not effectively deal with the anomaly contained situation, where we can utilize the information of suspected anomalies to enhance the model’s detection capability. Second, the manually selected metric to compute the anomaly scores will impact the performance and can hardly be “one-model-fits-all” [11], [15], [17]. Third, data distribution can be divided into three fields: obvious-normal
Fig. 1. Typical pipeline of URL-based anomaly detection method and the proposed scoring network. The scoring network can be embedded into existing methods without additional assumptions. Using the predefined metric as a self-supervised signal, the scoring network distinguishes the obvious-normal and obvious-abnormal samples and makes full use of them to strengthen the representation learner and to enlarge the score disparity between normal and abnormal samples, enhancing the discrimination ability of the original method.

Fig. 2. Toy example to illustrate the concepts of obvious-normal, obvious-abnormal, and transition fields.

field, transition field, and obvious-abnormal field, as shown in Fig. 2. The samples in obvious-normal or obvious-abnormal fields can be clearly distinguished as normal or abnormal data. However, the mixture of normal and abnormal data in the transition field hampers the identification of the abnormal samples.

To overcome these challenges, we propose a scoring network to promote the performance of anomaly identification via learning and enhancing the disparity between normal and abnormal data. As shown in Fig. 1, the scoring network can be incorporated into an existing deep unsupervised representation learning (URL)-based anomaly detection method and directly connected with the representation learner, which maps the original data into a hypothesis space. The scoring network utilizes the original predefined metric as a self-supervised signal to distinguish obvious-normal and obvious-abnormal samples and leverages these samples to guide the training of the representation learner to extract valuable information, which is more helpful for discrimination. Specifically, we introduce a score-guided regularization in the scoring network to gradually intensify the divergence between obvious-normal and obvious-abnormal samples during model training. We assign smaller scores to the obvious-normal data and larger scores to the obvious-abnormal data. Paying attention to the distinguishable samples accelerates the model’s convergence and enhances the capability of both the representation learner and the scoring network. This strategy leads to an incremental increase in score disparity between normal and abnormal data and facilitates the discrimination of nonobvious data in the transition field throughout the model training process. Moreover, the anomaly scores are calculated by the discrimination metric learned by the scoring network rather than the predefined one, enhancing the transferability of the original method. Without additional assumptions, this scoring network can be flexibly embedded into most existing anomaly detection models.

We further propose a novel instantiation, embedding the scoring network into an autoencoder (AE) framework, named score-guided AE (SG-AE). The AE reconstructs data instances and learns their representations in a latent space. Then, the scoring network assigns scores to these representations and attempts to maximize the disparity between the normal and abnormal samples. A sample with a higher anomaly score is more likely to be an anomaly. To explain how the scoring network works, we conduct simulation experiments to observe the changes in the score differences in the transition field. Also, we compare the performances of SG-AE with classic and state-of-the-art methods on seven tabular datasets. We also present the distributions of anomaly scores of normal and abnormal data and utilize t-SNE to reveal the anomaly detection performance in a 2-D space. Moreover, we extend the scoring network to three state-of-the-art models and explore the performance improvement of these score-guided models (SG-Models). We also examine the potential of using the scoring network on two document datasets and one image dataset. The main contributions of this work are summarized as follows.

1) We propose a scoring network with a score-guided regularization, which can directly learn the anomaly scores and be easily integrated into most URL-based models without imposing more assumptions. The scoring network utilizes the obvious data, distinguished by the self-supervised signal, to strengthen the representation learner and expand the learned scores disparity between normal and abnormal samples in the transition field, thus enhancing the anomaly detection ability.
2) We integrate the scoring network into an AE structure and introduce a simple but effective instantiation, SG-AE. SG-AE breaks the limitation of the AE on normal data input and achieves competitive performance on several datasets. We also incorporate the scoring network into four state-of-the-art models to examine the adaptability to different methods.

3) Extensive experiments on synthetic and real-world datasets demonstrate the effectiveness of the scoring network. The SG-AE outperforms the classic and state-of-the-art methods on tabular datasets, and the other SG-Models show performance improvements with the help of a scoring network. Moreover, our scoring network is robust to the anomaly rate by learning the disparity between normal and abnormal data, which is also demonstrated by the experiments.

II. RELATED WORK

In this section, we briefly review the related work in URL-based anomaly detection and revisit the use of regularization techniques in anomaly detection. Then, we compare our design with the existing methods.

A. URL Anomaly Detection

1) Distribution-Based Methods: Distribution-based methods assume that normal data follow a certain distribution in the original or latent space and anomalies deviate from the distribution [18], [19], [20]. The classic distribution-based methods, based on extreme-value analysis, consider the tail of a probability distribution as anomalies [21]. In recent years, deep learning brings more possibilities with more distribution hypotheses in the hidden space. For instance, deep autoencoding Gaussian mixture model (DAGMM) [11] assumes that the low-dimensional representations and reconstruction errors of normal data follow a Gaussian Mixture Model, and uses the probability value to distinguish between normal and abnormal data. Some one-class classification methods also fall into this category due to the consideration of manifold distribution. Deep SVDD [10] attempts to map the normal data into a hypersphere in a latent space and the abnormal data fall outside the hypersphere. DROCC [12] assumes that the normal data lie on a low-dimensional manifold and distinguishes data via Euclidean distance. It generates synthetic abnormal data to learn a robust boundary with a well-designed optimization algorithm. GOAD [13] maps data into a sphere feature space with random affine transformations, and anomalies are assumed to deviate from the center. Some methods, such as, outlier exposure [22], utilize extra information provided by auxiliary datasets to learn the normal distribution and detect the out-of-distribution samples. Note that although a number of generative methods assume various distributions in latent spaces, they finally determine anomalies based on the reconstruction errors. As such, we classify them into reconstruction-based methods.

2) Distance-Based Methods: Distance-based methods consider the positional relations or neighbor structures in the original or hidden space, assuming that anomalous samples stay far away from the normal ones [23], [24]. Nearest-neighbor-based methods, such as LOF [25] and DN2 [26], are typical of distance-based methods. Likewise, the tree-based methods, such as Isolation Forest (iForest) [27] and RRCT [28], can be regarded as distance-based methods, since they attempt to capture high-density fields that are reflected in the depth or complexity of the tree [8]. Deep learning technologies are advantageous tools to learn data representation, so that distance can be measured in a hypothesis space [29]. For example, random distance prediction (RDP) [16] builds deep neural networks to learn a certain random mapping, which can preserve the proximity information for data.

3) Reconstruction-Based Methods: Reconstruction-based methods train models to reconstruct data, with an assumption that the trained models learn the patterns of the major data and anomalies are unable to be well reconstructed. AE framework [30] is one fundamental architecture in reconstruction-based methods. Robust deep autoencoder (RDA) [15] is an early work to build an AE on corrupted data. It isolates noise and outliers with robust principal component analysis (RPCA) and thereafter trains an AE. Robust subspace recovery AE (RSRAE) [17] constructs an RSR layer within an AE with a well-designed loss. Cosine similarity between original and reconstructed data is used to identify the abnormal samples. CoRA [31] is a transductive semisupervised model, which modifies the AE framework with one encoder and two decoders. The two decoders distinguish normal data from abnormal data by reconstruction errors and then decode them separately. Generative models for anomaly detection can also be considered as reconstruction-based methods. VAE adopts reconstruction probability to identify anomalies [3], [32], [33], while GAN-based methods detect anomalies by the discriminator due to the inaccurate reconstruction by the generator [34], [35], [36].

B. Anomaly Detection With Regularization

Regularization is a widely used technique to alleviate the overfitting problem [37] and achieve adversarial robustness [38]. Many pieces of work utilize regularization to encourage AE to learn an informative low dimensional representation of input data [39], [40], [41], [42]. In the context of anomaly detection, regularization methods are introduced to enforce robustness against anomalies, encouraging the model to learn key underlying regularities [43]. Motivated by RPCA, RDA [15] adds sparsity penalty $\ell_1$ and group penalty $\ell_{2,1}$ into its RPCA-like loss function of AE to improve robustness. RSRAE [17] further incorporates a special regularizer into the embedding of the encoder to enforce anomaly robust linear structure. DAGMM [11] introduces $\ell_1$ penalty to constrain training. Some one-class classification methods also employ the regularization to better learn the boundary and improve performance. Ruff et al. [8] presented a unified view of anomaly detection methods and comprehensively summarized the methods using regularizations.

C. Comparison With the Existing Methods

Compared with the existing work, the proposed method has the following characteristics to tackle the challenges
mentioned in Section I. First, many existing unsupervised models are only fitting normal samples [9], [10], [11], [12], [13], [14]. Although some methods can deal with the contaminated data [15], [16], [17], they make efforts to retain the obvious-normal data and filter out the suspected abnormal data. Our method leverages both normal and abnormal samples in the datasets and attempts to enhance the detection capabilities in the transition field. Specifically, our score-guided regularization utilizes the obvious data to enlarge the score disparity between normal and abnormal data and guide the training of the representation learner and the scoring network. By doing so, the proposed scoring network can improve the ability of the representation learner and the robustness of the entire detection method. Second, the existing unsupervised models define anomaly scores with selected appropriate metrics, such as Euclidean distance for distance-based methods [10], [12], [29] or cosine similarity for reconstruction-based methods [15], [17], [34]. The anomaly scores are not directly optimized in an end-to-end fashion. DevNet [44] is the first weakly supervised method to achieve end-to-end anomaly score learning. However, DevNet guides model training with labels that are missing in unsupervised settings and treats the unknown anomalies as normal data. In contrast, our scoring network is devised to take the obvious-normal data first based on the reference scores and then gradually try to guide the nonobvious data in the transition field based on the information learned from obvious data.

In fact, we can use the predefined metric value as a self-supervised signal to guide the training of the scoring network. We suppose that the metric function has the ability to assign different reference scores to the obvious-normal and obvious-abnormal data. The scoring network assigns anomaly scores to data representations learned by the representation learner and guides anomaly score distribution based on the reference scores. Note that the reference scores are calculated by the predefined metric function to prejudge the normal and abnormal samples with obvious differences, while the anomaly scores are learned by the network and used to finally evaluate the abnormalities of all samples. The scoring network is expected to guide the anomaly score distribution of the obvious data first based on the reference scores and then gradually try to guide the nonobvious data in the transition field based on the information learned from obvious data.

To achieve this, we propose a scoring network with a score-guided regularization to learn and enlarge the anomaly score disparity and to enhance the capability of the representation learner, as shown in Fig. 1. Supposing \( z \) is the representation of a data sample in the latent space, the scoring network is devised to take \( z \) as input and outputs an anomaly score in an end-to-end manner. As expected to assign smaller anomaly scores to obvious-normal samples and larger scores to obvious-abnormal samples, the regularization function \( L_{SE} \) can be defined as follows:

\[
L_{SE}(f, s) = \begin{cases} 
|s|, & f < \epsilon_1 \\
\lambda_a \cdot \max(0, a - s), & f > \epsilon_2 
\end{cases}
\]

where the reference score \( f \) is calculated from the aforementioned discrimination function \( f(\cdot) \), \( s \) is the learned anomaly score, and \( \lambda_a \) is a weight hyperparameter to adjust the effect of score guidance for anomalies. \( \epsilon_1 \) and \( \epsilon_2 \) are thresholds to split the data space into obvious-normal and obvious-abnormal fields, as shown in Fig. 2. As the training progresses, the anomaly scores of obvious-normal samples are expected to be zero, and the scores of obvious-abnormal samples are expected to be larger than value \( a \). However, the selection of the two thresholds is difficult in unsupervised settings. Considering that most samples in a dataset are normal, we apply only one threshold \( \epsilon \) to divide the obvious-normal field and the suspected abnormal field. Then, the regularization function
$L_{SE}$ is revised as follows:

$$L_{SE}(f, s) = \begin{cases} |s - \mu_0|, & f < \epsilon \\ \lambda_p \cdot \max(0, a - s), & f \geq \epsilon. \end{cases} \tag{3}$$

We set a very small positive value $\mu_0$ approaching zero to be the target anomaly scores for the obvious-normal data, due to that the zero scores will force most weights of the scoring network to be 0. The threshold $\epsilon$ is a specific score value and difficult to choose; thus, we select a percentile, denoted as $\epsilon_p$, of the reference scores to find the corresponding $\epsilon$. For example, we can set $\epsilon_p = 70\%$ if we assume that $70\%$ of data are obvious-normal samples. Then, the samples with scores less than $0.7 \cdot f$ are regarded as obvious-normal ones and guided to obtain smaller scores. The other samples are considered as suspected abnormal ones and tend to get larger scores. In fact, $\epsilon_p$ does not require an accurate normal data ratio, which is unknown in the unsupervised scenario, because it is an approximate proportion to define the obvious-normal samples and can be much smaller than the true normal data ratio, which has been confirmed in the experiments and reflected in Fig. 7. We further discuss the hyperparameter selection for general datasets in Section V.

Note that some samples, especially in the transition field, may be judged as suspected abnormal data by the predefined metric, and their anomaly scores will be guided in the wrong direction in the early stage of training. However, there are also obvious-normal and obvious-abnormal samples that are effortless to identify. The SG-Model can leverage these obvious data to accelerate the convergence of the model and enhance the capability of the representation learner to extract more valuable information that more clearly reflects the abnormality of the data. With the gradually enhanced detection capability during the training process, the SG-Model can finally be expected to better distinguish these nonobvious data and assign them correct anomaly scores.

The score-guided regularization can be integrated with the existing URL methods. Let $L_{OE}$ be the loss function of an URL model, and the total loss function $L$ of the integrated model with score-guided regularization is

$$L = L_{OE} + \lambda_{SE} \cdot L_{SE} \tag{4}$$

where $\lambda_{SE}$ is a hyperparameter to adjust the effect of score-guided regularization. In other words, it affects the convergence speed of the $L_{SE}$ relative to the $L_{OE}$. $L_{OE}$ ensures the optimization of the representation learner, while $L_{SE}$ directly guides the training of the scoring network and indirectly promotes the representation learner to obtain differentiated representation. $\lambda_{SE}$ is usually less than 1 to ensure faster convergence of the representation learner than the scoring network. These two loss functions participate in the training of the model together.

The score-guided regularizer is easy to combine limited labels by using labels instead of reference scores for the labeled data. In this case, the regularizer does not rely entirely on labels to guide the anomaly scores, such as DevNet, due to the use of self-supervised signals.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig3.png}
\caption{Proposed SG-AE.}
\end{figure}

### B. Score-Guided Models

As mentioned above, we can integrate the scoring network into URL-based methods. The score-guided methods can be collectively called SG-Models. Here, we first propose SG-AE, an instantiation of applying scoring network to one reconstruction-based method, and then introduce a general form of SG-Models.

As illustrated in Fig. 3, SG-AE consists of a reconstructor and a score guider. Given a data sample $x$, the reconstructor first maps it to a representation $z$ in a latent space and then generate an estimation $\tilde{x}$. The score guider learns an anomaly score $s$ using $z$ as its input. In practice, we adopt an AE framework as our reconstructor and a fully connected network in the score guider. For tabular data, we also use fully connected networks in the AE. It is noteworthy that this AE network is easy to transfer to other data types. For example, we can utilize recurrent networks for sequence data and convolutional networks for image data [17], [44].

Let $E$ and $D$ denote the encoder and decoder in an AE, respectively. We denote the score networking as $S$ and, thus, have

$$z = E(x), \quad \tilde{x} = D(z), \quad s = S(z) \tag{5}$$

where $x$ is the input data, $\tilde{x}$ is the reconstructed counterpart of $x$, $z$ is the latent representation, and $s$ is the anomaly score.

The end-to-end network SG-AE can be represented as $M$

$$M(x) = S(E(x)). \tag{6}$$

We can obtain the parameters of $M$ by minimizing a loss function, which is a combination of two parts: the reconstruction loss and the score-guidance loss. For the AE, we use the $L_2$ loss to assess the reconstruction; thus, the $L_{OE}$ can be represented as follows:

$$L_{OE}(x, \tilde{x}) = \frac{1}{N} \sum_{i=1}^{N} \|x_i - \tilde{x}_i\|_2^2. \tag{7}$$

In the reconstruction-based settings, we also utilize the reconstruction error as a self-supervised signal; that is, we use $L_2$ as the self-signal function $f(\cdot)$. Thus, we can rewrite the
score-guided regularization in (3) as follows:
\[
L_{SE}(\|x_i - \hat{x}_i\|_2, s_i) = \begin{cases} 
|s - \mu_0|, & \|x_i - \hat{x}_i\|_2 < \epsilon \\
\lambda_a \cdot \max(0, a - s), & \|x_i - \hat{x}_i\|_2 \geq \epsilon. 
\end{cases}
\]

(8)

We finally define the overall loss function of SG-AE, an instantiation of (4), as the combination of the two loss items in (7) and (8), that is,
\[
L(x, \hat{x}, s) = \frac{1}{N} \sum_{i=1}^{N} \|x_i - \hat{x}_i\|_2 + \lambda_{SE} \cdot L_{SE}(\|x_i - \hat{x}_i\|_2, s_i).
\]

(9)

Our goal is to minimize the loss function (9). Lower reconstruction loss in (7) ensures better reconstructions \(\hat{x}\) and representations \(z\) of normal data. As the score-guidance loss decreases, the anomaly scores of normal data approach zero, and the scores of suspected abnormal data tend to \(a\); thus, the score disparities between normal and abnormal data continue to widen. A higher anomaly score of a sample indicates a higher possibility to be an anomaly. By observing the distribution of anomaly scores, one can distinguish between normal and abnormal samples.

In addition to SG-AE with reconstruction-based assumption, the scoring network can also be applied to other URL methods, such as distance-based methods and distribution-based methods. Here, we discuss a general form of combining the scoring network with URL methods. Let \(R\) be a representation learner in an URL method. With the discrimination metric \(f(\cdot)\), the general form of an unsupervised method is
\[
M_{URL}(x) = f(R(x)).
\]

(10)

Combined with the scoring network \(S\), the general form of SG-Models is
\[
M_{SG}(x) = S(R(x)).
\]

(11)

The metric value from \(f(\cdot)\) in SG-Models is only used as a self-supervised signal to assist model training and does not participate in the calculation of anomaly score. By optimizing the total loss function, (4), the score-guided regularization can encourage SG-Models to learn and guide the anomaly scores and also help the representation learner of the original model to learn better data representations. To better understand the transferability, we extend the scoring network to four state-of-the-art models and evaluate the performance in the experiments.

C. SG-Models Algorithm

We illustrate the training process of SG-Models in Algorithm 1. An SG-Model \(M_{SG}\) consists of an existing URL model \(M_{URL}\) and the scoring network \(S\). The \(M_{URL}\) has a representation learner \(R\), a predefined metric function \(f(\cdot)\), and its original loss function \(L_{OE}\). The metric value calculated by \(f(\cdot)\) is denoted as \(f\). The parameters of \(M_{SG}\) are initialized randomly and optimized in the training iteration [Steps 2–12] with the minimization of the loss in (4). Specifically, the data representation \(z\) is learned by the representation learner \(R\), through \(z = R(x)\) in Step 5). Then, the scoring network learns the anomaly scores \(s\) through \(s = S(z)\) in Step 6).

In Step 7), we calculate \(L_{OE}\) and the self-supervised signal \(f\) from \(M_{URL}\). Then, Step 8) calculates \(L_{SE}\) with the loss function (3). After that, we get the total loss in Step 9), and Step 10) takes the backpropagation algorithm and updates the network parameters. With the guidance from the loss function (4), data representation and anomaly score distribution are optimized during training, and finally, we obtain a well-trained SG-Model.

In terms of testing, the trained SG-Model \(M_{SG}\) directly calculates the anomaly scores \(s\) given samples \(x\); that is, \(s = M_{SG}(x) = S(R(x))\). The predefined metric function \(f(\cdot)\) is not used in testing. The anomaly scores reflect the possibility of being anomalies. A sample with a higher anomaly score means that it has a greater possibility of being abnormal.

Algorithm 1: Training an SG-Model

**Input:** Training set \(\{x_i\}_N, x_i \in \mathbb{R}^D\)

**Output:** An SG-Model \(M_{SG}\): An optimized anomaly detection network

1. Randomly initialize the network parameters of \(M_{URL}, S\)
2. for each epoch do
3. Divide input data into batches
4. for each batch do
5. \(z \leftarrow z = R(x)\)
6. \(s \leftarrow s = S(z)\)
7. \(L_{OE}, f \leftarrow M_{URL}\)
8. \(L_{SE} \leftarrow L_{SE}(f, s)\)
9. \(L \leftarrow L = L_{OE} + L_{SE}\)
10. Backpropagate and update the parameters of \(M_{URL}, S\)
11. end for
12. end for
13. return An optimized SG-Model

IV. EXPERIMENTS

In this section, we empirically evaluate the effectiveness and robustness of the SG-Models on both synthetic and real-world datasets.

A. Simulation Experiments

The score-guided regularization is designed to intensify the differentiation between normal and abnormal samples during the training process. To verify that, we conduct simulation experiments to observe the change in anomaly scores during the model training. We compare our SG-AE model with AE [30] and RDP [16] in three artificial datasets.

1) Data Generation: As illustrated in Fig. 4, we generate a 1-D dataset and two 2-D datasets. The normal data are shown in blue, while the abnormal data are in red. We utilize different equations to generate datasets of different complexities. For the 1-D scenario, we sample data points from Gaussian distribution \(N(\mu, \sigma^2)\) in geometric coordinates. To generate samples in 2-D scenarios, we control two variables in polar coordinates and then transform them into geometric coordinates. One
Fig. 4. Simulation experiments in three synthetic datasets. \((R_0\sim R_3)\) represent fields with different ratio of anomaly data. For SG-AE, the score difference between normal and abnormal data in each field gradually expands with the training process.

Variable follows a Gaussian distribution, and the other follows a uniform distribution. The normal and abnormal data are sampled with different mean \(\mu\) and the same variance \(\sigma^2\). The detailed equations are shown in Fig. 4.

2) Settings: The training and testing sets are independently generated, each with 10,000 data samples. The ratio of abnormal to normal data is one to nine. In the testing sets, we use three thresholds to divide each dataset into four parts \((R_0\sim R_3)\), as shown in Fig. 4. For a normal distribution, the more off-center a sample is, the less likely it is to appear, and the more likely it is to be an anomaly. Therefore, we could use the \(3\sigma\) rule to select the thresholds, that is, \(\{\mu + \sigma, \mu + 2\sigma, \mu + 3\sigma\}\). Most of the data in \(R_0\) are normal, namely, obvious normal. Similarly, \(R_3\) is regarded as obvious abnormal; \(R_1\) and
$R_2$ are two transition fields. In each field, we calculate the difference between the average anomaly scores of abnormal data and normal data. That is,

$$S_i = \frac{1}{N_{a}} \sum_{j=1}^{N_{a}} s_j - \frac{1}{N_{n}} \sum_{k=1}^{N_{n}} s_k, \quad i \in \{0, 1, 2, 3\} \quad (12)$$

where $S_i$ is the score difference in $R_i$, $N_{a}$ and $N_{n}$ are the numbers of abnormal and normal samples in $R_i$, and $s_j$ is the anomaly score of a sample. Note that the scores of these models are calculated in different ways; thus, we mainly compare the trends of the score differences during training, which reflect the capability of the model to learn the disparities between normal and abnormal data. We also use the area under receiver operating characteristic curve (AUC-ROC) to evaluate the model performances. In terms of model settings, AE and SG-AE share the same Adam optimizer, learning rate, and fully connected networks. The layer sizes are set as 20 for the 1-D dataset and (64, 20) for the 2-D datasets. The scoring network in SG-AE is also a fully connected network with layer size (20, 1). The RDP keeps the originally proposed settings. The batch size and the training epoch are 1024 and 100, respectively.

3) Results Analysis: As shown in Fig. 4, for AE, the score differences decrease during training, suggesting that AE attempts to reconstruct the abnormal data. The continuous decrease of score differences $S_1$ and $S_2$ means that AE starts to fail in distinguishing the normal and abnormal data in the transition field. For RDP, it uses a boosting process to filter anomalies, and the iteration size is set as 8; thus, the curves of score difference are jagged, and the total epochs are 800. The changes of $S_1$ and $S_2$ are not obvious. For SG-AE, the score difference in each field is increasing during training, suggesting that the model reacts differently to normal and abnormal data. Specifically, the abnormal data are guided to obtain a larger anomaly score, while the normal data to a smaller anomaly score. More important, as expected, the increase of $S_1$ and $S_2$ indicates the improvement of the detection ability of the model in the transition field. Moreover, the SG-AE achieves the best AUC-ROC performances in the three datasets. The results demonstrate the effectiveness of the scoring network.

B. Evaluation Experiments

1) Datasets Description: As shown in Table I, we use seven publicly available tabular datasets in our experiments. Two datasets are in the healthcare domain, e.g., diagnosis of breast cancer (breast) [45] and diabetic detection (diabetic) [46]. Another two datasets are related to the attack in cybersecurity, e.g., intrusion [47] and attack [48]. Market includes data of potential subscribers in bank marketing [49]. Creditcard is a credit-card fraud dataset. Donor is a valuable project selection dataset. Details of these two datasets can be found in [44]. The notations in Table I are defined as follows: $N_{\text{orig}}$ is the original size of the dataset. $D_{\text{num}}$ and $D_{\text{cat}}$ are dimensions of numerical and categorical features. $R_{\text{dup}}$ and $R_{\text{miss}}$ are the rates of duplicate and missing data. $N$ and $D$ are the size and dimension after preprocessing. $N_{\text{noise}}$ is the number of injected noise, and $R_{\text{anomaly}}$ is the rate of anomalies.

Data Preprocessing: We first preprocess the datasets by removing duplicated samples or samples with missing features. For example, 73.22% of duplicates are found on intrusion, and 12.02% of missing data are found on donor. Next, we encode the categorical features with one-hot encoding and standardize each numerical feature. In addition, following [44], we inject noises into the training data to improve the robustness. Specifically, we randomly select 1% of normal data and swap 5% features of these data. Finally, the training, validation, and testing sets are randomly divided into 6/2/2. Note that some datasets have a part of features that leak anomaly labels. To keep consistency in real applications, we drop one feature in attack and five features in donor to avoid using this supervised-like information.

2) Benchmarks and Settings: We compare SG-AE with eight benchmarks: two statistical learning methods, iForest [27] and ECOD [50], and six deep learning methods, RDA [15], DAGMM [11], RDP [16], RSRAE [17], GOAD [13], and ICLAD [14]. We use the originally proposed model structures for iForest, DAGMM, RDP, GOAD, ECOD, and ICLAD. As for RDA, RSRAE, and SG-AE, we use the same fully connected layer settings in the AE framework to maintain consistency.

In terms of hyperparameter settings, these two statistical learning methods, iForest and ECOD, do not require hyperparameters. The deep learning models are sensitive to their hyperparameters in different datasets. To fairly compare the upper bound of performance, we conduct hyperparameter searching to obtain optimal results, starting from the recommended hyperparameters. The mainly tuned hyperparameters of deep baselines are described as follows.

1) RDA isolates suspected anomalies and fits cleaned samples. It has a $\lambda$ to adjust the proportion of isolated samples and a hyperparameter to control the step interval to update the isolation.
2) DAGMM uses Gaussian mixture model to fit data representation. It has two $\lambda$ to adjust loss weights and a hyperparameter to decide the component number of Gaussian mixture model.
3) RSRAE utilizes an RSR layer to remove anomalies in the hidden space. It is tuned with two loss weights $\lambda$ and the intrinsic dimension of latent space.
4) RDP adopts a training strategy of multiple iterations, filtering suspected anomalies, and retraining the model at each iteration. It is tuned with a loss weight $\lambda$, the iteration number, and the latent dimension.

| Data | Before Preprocessing | After Preprocessing |
|------|----------------------|---------------------|
| Attack | 357873 | 39 | 3 | 0.00 | 0.00 | 7595 | 81 | 542 | 25.24 |
| Breast | 462563 | 16 | 0 | 17.83 | 0.00 | 102122 | 14 | 2243 | 2.42 |
| Creditcard | 284507 | 30 | 0 | 0.38 | 0.00 | 285441 | 30 | 1716 | 0.17 |
| Diabetic | 101786 | 12 | 31 | 0.00 | 0.00 | 365755 | 15 | 522 | 12.10 |
| Donor | 665094 | 6 | 16 | 0.04 | 12.02 | 367893 | 79 | 3317 | 6.28 |
| Intrusion | 505900 | 38 | 3 | 73.22 | 0.00 | 216420 | 119 | 820 | 37.23 |
| Market | 45311 | 7 | 9 | 0.00 | 0.00 | 45451 | 31 | 241 | 11.70 |
5) GOAD learns a spherical distribution for data representation. It is tuned with a loss weight $\lambda$ and two-dimension-related hyperparameters.

6) ICLAD maximizes the mutual information between one sample and its masked counterpart. It is tuned with three hyperparameters, including the kernel size, the hidden dimension, and the temperature constant in its loss.

SG-AE is tuned with two $\lambda$ and $\epsilon_p$, while $a$ is set to 6. We set batch size as 1024, the training epochs as 100, and the Adam optimizer with a learning rate of 0.0001. We select the well-trained models in the validation sets. The PyTorch implementation code is publicly released at https://github.com/urbanmobility/SGM, and we also implement the code with MindSpore released at https://github.com/urbanmobility/SGM_mindspore.

3) Performance Evaluation: We use the AUC-ROC and the area under precision–recall curve (AUC-PR) to evaluate the performance of reference methods. Higher AUC values suggest better performance. The results are averaged over ten independent runs, in which the datasets are regenerated randomly, to report stable performance and are shown in Table II. The best performance in each dataset is highlighted in bold text, and the second-best one is underlined.

Among these baselines, we can see RDP and ECOD achieve the best and second-best performances in terms of AUC-ROC. DAGMM, GOAD, and ICLAD attempt to fit all training data without handling suspected anomalies; thus, their performances are easily degraded by noise and data pollution. On the contrary, RDP gradually filters out the suspected anomalies and fits the rest of the data during training, while ECOD uses empirical cumulative distribution functions to estimate the anomaly probability of each sample. These strategies to deal with data contamination contribute to the relatively better performances of RDP and ECOD. While RDA and RSRAE also use filtering strategies, they are not as effective as RDP due to their less reliable filtering techniques. In contrast, SG-AE utilizes an active strategy, called the score-guidance strategy, to handle contaminated samples. Unlike these passive strategies used in baselines, our approach actively utilizes the samples with high abnormal probabilities to guide model optimization, thereby enhancing both the capability of the representation learner and the score disparity. This is the main reason why SG-AE outperforms these baselines in all datasets.

Compared with the results in [16], the performance difference is mainly caused by the construction of the datasets. For example, we obtained 22 features from the data sources in donor, but [16] takes only ten features without detailed prepossessing steps. However, we can have a convincing comparison result in creditcard, a standard dataset preprocessed in the original data source. On this dataset, iForest and RDP perform similarly in our work and [16].

Fig. 5 presents the score distribution of SG-AE. We can see that the anomaly score distributions of normal data (blue bars) and abnormal data (red bars) are notably separated on most datasets. For numerical comparison between the typical methods, we use the KS test to reflect the distribution distance between normal and abnormal scores. KS test is a statistical hypothesis test that checks whether two samples differ in distributions [51]. A higher KS index indicates a larger score difference. As shown in Table III, the average values of the KS of SG-AE on the seven datasets are 0.539, surpassing the 0.355 of AE, 0.372 of AE, 0.336 of RDA, 0.415 of RDP, 0.227 of GOAD, 0.398 of ECOD, and 0.362 of ICLAD. This suggests that our scoring network successfully enhanced the disparity between the normal and abnormal data. A larger KS index correlates with a better performance shown in Table II, especially on the bcsc, creditcard, and intrusion datasets. Taken together, these results demonstrate the effectiveness of the score guidance design.

To intuitively understand the anomaly detection results, we utilize t-SNE for dimensionality reduction and visualize the seven datasets in 2-D space, as shown in Fig. 6. Data samples are colored with their true labels or anomaly scores generated by our SG-AE, RDP, and ECOD. RDP and ECOD perform the best two among the baselines. The light color indicates these samples cannot be easily distinguished as normal or abnormal data. One can select different thresholds to identify the abnormal samples, according to the datasets and needs. In Fig. 6, we observe that t-SNE can well segregate the anomalies in the 2-D space on half of the datasets, and SG-AE presents more similar segregation to the ground truth (GT) than RDP and ECOD, especially on attack, bcsc, and intrusion. These results are consistent with the results in Table II, reflecting the anomaly detection capabilities of SG-AE. We also notice that the anomalies are not segregated well on diabetic and donor, indicating the challenge of anomaly detection.

4) Comparison With Variants: In SG-AE, we introduce the score-guidance strategy to assign anomaly scores with the reconstruction error as a self-supervised signal. To examine the effect of the learnable anomaly score, we remove the scoring network and use the reconstruction error as the anomaly score, keeping the regularizer in (9). That means regularizer is used to guide the reconstruction error. This variant of SG-AE is named SG-AE $\text{recon}$. We also test AE, the original AE without the score-guided loss and the scoring network.
The anomaly scores appear to have a normal or log-normal distribution in our SG-AE. The outputs of the scoring network are altered to mean and standard deviation of scores, denoted by $\mu$ and $\sigma$. We utilize KL divergence to measure the distribution difference; thus, the score-guided regularization (8) can be written as follows:

$$L_{SE}(x, \tilde{x}, \mu, \sigma) = \begin{cases} \text{KL}(D(\mu, \sigma), D(0, 1)), & ||x - \tilde{x}||_2 < \epsilon \\ \lambda_a \cdot \max(0, a - \mu), & ||x - \tilde{x}||_2 \geq \epsilon. \end{cases}$$

Table III compares the performance of the original SG-AE and its variants. The original SG-AE performs best on five datasets, SG-AE$_{normal}$ and SG-AE$_{lognormal}$ have similar performances, which are slightly worse than SG-AE$_{original}$ in most cases. SG-AE$_{econ}$ achieves the best performances on diabetic and donor. However, the performance of SG-AE$_{econ}$ has large variances across datasets, which is caused by the conflict of these two loss functions. The reconstruction loss tends to reduce the reconstruction error, but the score guidance loss attempts to enlarge the reconstruction error for anomalies. This conflict brings challenges to the update of network states. The results of SG-AE$_{original}$, SG-AE$_{normal}$, and SG-AE$_{lognormal}$ are significantly better than AE, which demonstrates the effectiveness of the scoring network.

5) **Sensitivity of Parameters:** In this part, we examine the sensitivity of SG-AE to different parameters. For convenience, we divide the four parameters into two groups, $\epsilon_p$ and $a$ in group 1, and $\lambda_{SE}$ and $\lambda_a$ in group 2. We first test group 1 by fixing $\lambda_{SE} = 0.01$ and $\lambda_a = 18$ and then test group 2 with fixed $\epsilon_p$ and $a$.

Fig. 7 reports the AUC-ROC values of the two-step testing on three datasets, attack, creditcard, and market. The darker colors suggest better performance. We note that state-of-the-art results can be achieved without complicated and time-consuming hyperparameter searching. In addition, we find that the following hold. First, $\epsilon_p$ and $\lambda_a$ have relatively greater impact on model performances than $a$ and $\lambda_{SE}$. Second, although datasets attack (25.24%), creditcard (0.17%), and market (11.70%) have different anomaly rates, SG-AE can achieve optimal performances with threshold $\epsilon_p$ smaller than 80%, suggesting that our score-guidance strategy does not require the exact anomaly rate and can be effective in unsupervised scenarios. Moreover, we can utilize the variations of the score distribution under different $\epsilon_p$ values to approximately observe the true anomaly rate. Third, the hyperparameter $a$ determines the target for the guided scores of abnormal samples, and the performances of SG-AE change lightly when $a > 5$. The results reflect that a too-large $a$ only extends the distribution of scores without further performance improvements. In addition, the performances also remain stable with variations of $\lambda_{SE}$, indicating that we do not need to pay efforts to tune these two parameters. Fourth, $\lambda_a$ adjusts the loss effect of the suspected abnormal part, and a larger $\lambda_a$ is preferred, revealing the difficulty of distinguishing those nonobvious normal samples in the transition fields. In summary, although the scoring network introduces four parameters, the SG-Model is not much sensitive to these parameters. When the scoring network transfers to a new model or an SG-Model applies to a new dataset, $\epsilon_p$ and $\lambda_a$ are the core parameters to tune, and the score distribution will help the tuning process.

6) **Robustness to Different Anomaly Rates:** As we intend to learn the disparity between the normal and abnormal data using a scoring network, we can expect that the performance of SG-AE would be robust to the ratio of the abnormal data. To validate this expectation, we reorganize the two datasets with high anomaly rates, attack and intrsion, and compare SG-AE with iForest, AE, RDP, and ECOD on these datasets with different anomaly rates. Specifically, we randomly drop anomaly samples in the training set, adjusting the anomaly rate to [5%, 10%, 15%, 20%, 25%] on attack.
Fig. 6. t-SNE visualization analysis. The three rows refer to the GT and results of RDP, ECOD, and SG-AE, respectively. Red represents abnormal, while blue represents normal. The darker color indicates a larger probability of being normal or abnormal.

TABLE IV

| Dataset       | SG-AE (original) | SG-AE (regular) | SG-AE (noisy) | AE     | SG-AE (original) | SG-AE (regular) | SG-AE (noisy) | AE     |
|---------------|------------------|-----------------|----------------|-------|------------------|-----------------|----------------|-------|
| Attack        | 0.83 ± 0.009     | 0.77 ± 0.06     | 0.75 ± 0.09    | 0.63 ± 0.11 | 0.56 ± 0.037     | 0.59 ± 0.024     | 0.63 ± 0.072 | 0.41 ± 0.079 | 0.43 ± 0.016 |
| Bsc           | 0.92 ± 0.008     | 0.87 ± 0.06     | 0.89 ± 0.06    | 0.62 ± 0.28 | 0.87 ± 0.101     | 0.81 ± 0.064     | 0.78 ± 0.050 | 0.75 ± 0.078 | 0.22 ± 0.281 |
| Creditcard    | 0.96 ± 0.004     | 0.94 ± 0.17     | 0.92 ± 0.07    | 0.71 ± 0.13 | 0.90 ± 0.013     | 0.29 ± 0.072     | 0.13 ± 0.060 | 0.12 ± 0.046 | 0.06 ± 0.197 |
| Diabetic      | 0.52 ± 0.007     | 0.54 ± 0.015    | 0.54 ± 0.013   | 0.55 ± 0.077 | 0.53 ± 0.007     | 0.14 ± 0.004     | 0.13 ± 0.009 | 0.15 ± 0.005 | 0.15 ± 0.043 |
| Donor         | 0.54 ± 0.004     | 0.53 ± 0.006    | 0.56 ± 0.006   | 0.55 ± 0.063 | 0.46 ± 0.045     | 0.07 ± 0.002     | 0.07 ± 0.002 | 0.07 ± 0.011 | 0.06 ± 0.007 |
| Intrusion     | 0.96 ± 0.016     | 0.71 ± 0.077    | 0.69 ± 0.037   | 0.74 ± 0.112 | 0.54 ± 0.036     | 0.90 ± 0.035     | 0.54 ± 0.055 | 0.54 ± 0.024 | 0.75 ± 0.042 |
| Market        | 0.70 ± 0.025     | 0.64 ± 0.018    | 0.64 ± 0.013   | 0.60 ± 0.076 | 0.67 ± 0.008     | 0.27 ± 0.030     | 0.19 ± 0.009 | 0.18 ± 0.006 | 0.19 ± 0.007 |

Fig. 7. AUC-ROC values for SG-AE with various sets of parameters on three datasets, attack, creditcard, and market. We first fix $\lambda_{SE} = 0.01$ and $\lambda_a = 18$ for each dataset and train the SG-AE with different values of $\epsilon_p$ and $a$. Then, we fix $\epsilon_p$ and $a$ and train the SG-AE with different values of $\lambda_{SE}$ and $\lambda_a$.

and [5%, 10%, 15%, 20%, 25%, 30%, 35%] on intrusion. The validation and testing sets keep the original anomaly rate.

Fig. 8 presents the comparison results in different anomaly rates. Obviously, SG-AE achieves a more stable performance than other competing models, while AE has the fastest AUC-ROC performance degradation on both datasets. The strong sensitivity of AE to the anomaly rate is mainly due to its intention to reconstruct all input data, while a large fraction of abnormal data hinders the training of the reconstruction model. We also observe that the AUC-ROC values of iForest and...
GOAD’s representation learner is relatively simple, which also constrains the potential for optimization. In summary, these experimental results not only demonstrate the effectiveness of the scoring network design but also reflect that the scoring network can be incorporated into different unsupervised anomaly detection models.

C. Extension to SOTA Models

To examine the transferability of the scoring network to other models, we evaluate the performances of four extended models in the seven tabular datasets.

1) Settings: We extend the scoring network to four state-of-the-art models: DAGMM, RDA, RSRAE, and GOAD. The extended models are named score-guided DAGMM (SG-DAGMM), score-guided RDA (SG-RDA), score-guided RSRAE (SG-RSRAE), and score-guided GOAD (SG-GOAD). For the input of the scoring network, SG-DAGMM takes the same input as the compression network in DAGMM, SG-RDA takes the output of the encoder, SG-RSRAE takes the output of the RSR layer, and SG-GOAD takes the output of the representation learner. Here, the datasets are configured the same as the experiments of SG-AE. We also search parameters to adapt the SG-Models to these datasets. Specifically, SG-RDA is tuned with its original $\lambda$ and $\lambda_{SE}$, SG-DAGMM and SG-RSRAE are tuned with their two original $\lambda$ and $\lambda_{SE}$, and SG-GOAD is tuned with $\lambda_{SE}$ and $\lambda_a$.

2) Performance Evaluation: The results of AUC-ROC and AUC-PR are shown in Table V. Compared with the performances of the original models, as shown in Table II, these SG-Models achieve varying degrees of improvement in most datasets. Specifically, the averaged improvements of SG-AE, SG-RDA, SG-RSRAE, SG-DAGMM, and SG-GOAD on AUC-ROC than the original models on the seven datasets are 20.5%, 15.1%, 14.1%, 10.6%, and 2.3%, while the averaged improvements on AUC-PR are 45.2%, 27.7%, 63.6%, 170.2%, and 6.9%. These results suggest that the score-guidance strategy can better handle the contaminated data. In addition, SG-AE and SG-DAGMM obtain more obvious performance improvements, and SG-DAGMM even surpasses SG-AE on some datasets. This is mainly because the scoring network enables them to deal with anomaly contamination and generates better data representation. Although GOAD has demonstrated some improvements in performance, these improvements are relatively modest compared with other baseline methods. This can be attributed to two factors. First, GOAD’s initial performance is already strong, thereby limiting the potential for further improvement. Second, the structure of GOAD’s representation learner is relatively simple, which also constrains the potential for optimization. In summary, these experimental results not only demonstrate the effectiveness of the scoring network design but also reflect that the scoring network can be incorporated into different unsupervised anomaly detection models.

D. Extension to Document and Image Tasks

To examine the transferability to different tasks, we compare SG-AE with iForest, DAGMM, RDA, RSRAE, and RDP on document and image datasets.

1) Settings: For the document task, we utilize datasets, news and reuters [17]. News involves newsgroup documents with 20 different labels, and reuters contains five text categories. Following the preprocessing steps in [17], news and reuters are randomly split into 360 documents per class, and the documents are embedded into vectors of size 10,000 and 26,147, respectively. In each round of testing, we choose one class as normal data in turns and randomly select abnormal samples from other classes. By collecting different numbers of abnormal data, we compare the SG-AE with baselines in the document datasets with varying anomaly rates [5%, 10%, 15%, 20%, 25%]. For image task, we take mnist dataset as an example [15]. Mnist consists of 5124 instances, with the anomaly rate of 5.2%. The normal data are the image of digit “4,” and the abnormal data are other digits. For each task, we average the AUC-ROC and AUC-PR values over ten independent runs. The training and testing sets are 8/2. The layer sizes of the AE framework are [1024, 256, 64, 20] in document tasks and [128, 64, 32] in the image task. The batch size is set as 32, and other settings are consistent with the previous experiments. We also conduct hyperparameter searching to achieve nearly optimal results.

2) Performance Evaluation: Fig. 9 illustrates the results for document datasets. SG-AE achieves the best performance in reuters. In 20news, SG-AE performs slightly weaker than RSRAE and RDA at a smaller anomaly rate but performs better at a larger anomaly rate. This might be due to the different granularity when handling anomalies. Specifically, RSRAE and RDA filter abnormal parts for each sample at the feature level, which is effective for datasets with large feature
correlations (such as document or image datasets). SG-AE simply guides the sample distribution at the data level. In fact, the feature-level and the data-level strategies are not in conflict. The combination of these two strategies can be further studied in the future. The results for the image dataset are shown in Table VI. Similar to the document datasets, SG-AE has competitive results on AUC-ROC but performs weaker than RSRAE in terms of AUC-PR. Therefore, we further evaluate SG-RSRAE, achieving performance improvements of 1% on AUC-ROC and 19% on AUC-PR. These results confirm the effectiveness of the score-guidance strategy in different tasks.

V. DISCUSSION ON HYPERPARAMETER SELECTION

Hyperparameter selection is a common challenge for unsupervised deep learning methods, especially when we do not have a validation dataset. Our proposed method contains four hyperparameters. They are obvious-normal percentile \( \epsilon_p \), target anomaly score \( a \), and two loss weights \( \lambda_{SE} \) and \( \lambda_a \), which commonly appear in multitask learning. The hyperparameter \( \epsilon_p \) is highly related to the anomaly ratio of a specific dataset, while the rest can be set to fixed values, because the method is not so sensitive to them, as discussed in the experiment. In the real-world scenario, experts can easily set \( \epsilon_p \) according to their experience in the task. If we turn to a new dataset without knowing the concept of abnormal samples, we suggest to use the standardized reference scores \( f \) to determine \( \epsilon_p \), which is formulated as follows:

\[
\epsilon_p = \frac{N(\hat{f} < \text{std}(\hat{f}))}{N(f)} \cdot \epsilon = \frac{\text{f-mean}(f)}{\text{std}(f)} \tag{14}
\]

where \( f \) is the reference score introduced in Section III-A, mean(\( \epsilon \)) and \( \text{std}(\epsilon) \) calculate the mean and standard deviation of all \( \epsilon \), and \( N(\epsilon) \) counts the number of \( \epsilon \). The hyperparameter \( \epsilon_p \) is updated with (14) every training epoch.

We conduct experiments to evaluate the effectiveness of (14) on five tabular datasets. The hyperparameters \( a, \lambda_{SE} \), and \( \lambda_a \) are set to fixed values of 10, 0.01, and 20. The SG-AEs with fixed \( \epsilon_p = 90 \) and \( \epsilon_p = 80 \) are denoted as SG-AE90 and SG-AE80. The SG-AE with (14) to determine \( \epsilon_p \) is denoted as SG-AE_{p}. Besides, we propose a variant SG-AE_{p, tuned}, which is based on SG-AE_{p} but uses tanh() to constrain the anomaly scores to (−1, 1). This variant discards the hyperparameter \( \epsilon_p \) and the target anomaly score is 1. We also include the tuned SG-AE, denoted as SG-AE_{tuned}, and ECOD [50] in comparison.

The results are the average of ten independent runs and are shown in Table VII, where the best and the second-best results are highlighted in bold and underline, respectively. First, compared with ECOD, SG-AE_{90} performs better on \text{bsec} and \text{market} but worse on the other three datasets. When \( \epsilon_p \) turns to 80, SG-AE_{80} achieves significant performance improvements on \text{attack} and \text{intrusion}, because \( \epsilon_p = 80 \) is closer to the true normal ratios of these two datasets. This indicates that \( \epsilon_p \) has a huge impact on performance, especially when it is much smaller than the true normal ratio. Second, SG-AE_{p} obtains the second-best results on three datasets and outperforms ECOD on four datasets in AUC-ROC, which demonstrates the effectiveness of the proposed (14). It is because the automatically set \( \epsilon_p \) utilizes the distribution of

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**TABLE V**

| AUC-ROC and AUC-PR (\text{Mean \pm Std}) of SG-SOTA Models. (*) Indicates the Performance Improvement of SG-SOTA Models Over the Original Models.

| Datasets | SG-AE | SG-RDA | SG-RSRAE | SG-DAGMM | SG-GOOD |
|----------|-------|--------|----------|-----------|---------|
| Attack   | 0.833±0.009 (48.5%)  | 0.816±0.016 (32.7%) | 0.771±0.064 (13.2%) | 0.783±0.044 (2.8%) | 0.785±0.010 (7.5%) |
| Bsec     | 0.912±0.008 (3.9%)   | 0.905±0.004 (3.8%)  | 0.868±0.043 (3.3%)  | 0.785±0.117 (16.8%) | 0.898±0.012 (1.8%) |
| Creditcard | 0.946±0.004 (6.8%)  | 0.940±0.010 (2.2%)  | 0.930±0.019 (-1.3%) | 0.915±0.021 (8.9%)  | 0.941±0.015 (0.2%) |
| Diabetic | 0.548±0.007 (2.4%)   | 0.561±0.027 (43.3%) | 0.345±0.012 (14.3%) | 0.581±0.066 (13.0%) | 0.514±0.016 (-1.9%) |
| Donor    | 0.541±0.004 (11.3%)  | 0.540±0.007 (3.3%)  | 0.597±0.059 (23.3%) | 0.558±0.049 (9.4%)  | 0.508±0.013 (2.6%) |
| Intrusion| 0.908±0.016 (59.5%)  | 0.899±0.019 (46.4%) | 0.808±0.144 (9.0%)  | 0.917±0.003 (13.5%) | 0.916±0.017 (2.0%) |
| Market   | 0.750±0.025 (10.8%)  | 0.747±0.033 (10.8%) | 0.733±0.030 (38.6%) | 0.694±0.003 (9.1%)  | 0.737±0.018 (3.9%) |

**TABLE VI**

| AUC-ROC and AUC-PR Values on the Mnist Dataset.

| Datasets | SG-AE | SG-RDA | SG-RSRAE |
|----------|-------|--------|----------|
| ifForest | 0.873±0.014 | 0.372±0.036 |
| DAGMM    | 0.758±0.040 | 0.235±0.036 |
| RDP      | 0.888±0.024 | 0.475±0.005 |
| RDA      | 0.912±0.010 | 0.356±0.038 |
| RSRAE    | 0.939±0.007 | 0.615±0.026 |
| SG-AE    | 0.939±0.005 | 0.563±0.015 |
| SG-RSRAE | 0.951±0.010 | 0.736±0.062 |

**TABLE VII**

| AUC-ROC | Attack | Bsec | Creditcard | Intrusion | Market |
|---------|-------|------|------------|-----------|-------|
| ECOD    | 0.770 | 0.749 | 0.934 | 0.903 | 0.676 |
| SG-AE_{90} | 0.547 | 0.855 | 0.936 | 0.564 | 0.741 |
| SG-AE_{80} | 0.831 | 0.832 | 0.916 | 0.845 | 0.729 |
| SG-AE_{p} | 0.819 | 0.877 | 0.946 | 0.866 | 0.741 |
| SG-AE_{p, tuned} | 0.827 | 0.833 | 0.939 | 0.841 | 0.666 |
| SG-AE_{90} | 0.833 | 0.912 | 0.964 | 0.906 | 0.750 |

| AUC-PR | Attack | Bsec | Creditcard | Intrusion | Market |
|--------|-------|------|------------|-----------|-------|
| ECOD   | 0.457 | 0.075 | 0.161 | 0.762 | 0.215 |
| SG-AE_{90} | 0.283 | 0.294 | 0.054 | 0.429 | 0.244 |
| SG-AE_{p} | 0.569 | 0.321 | 0.071 | 0.729 | 0.229 |
| SG-AE_{p, tuned} | 0.538 | 0.475 | 0.085 | 0.745 | 0.240 |
| SG-AE_{90} | 0.564 | 0.369 | 0.061 | 0.702 | 0.200 |
| SG-AE_{p, tuned} | 0.596 | 0.816 | 0.291 | 0.904 | 0.270 |

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the reference scores on the dataset. This strategy is adaptable to different datasets and has fewer wrong assignments than manually setting an unmatched $\epsilon_p$. Third, SG-AE$_{ep}$ performs worse than SG-AE$_{ep}$ overall, because constraining the score to $(-1, 1)$ requires the model to be more sensitive to numerical differences, making it more difficult to distinguish anomalies. Fourth, SG-AE$_{tuned}$ performs best on the five datasets, indicating that flexible hyperparameter settings contribute to a higher level of performance. In summary, we can use (14) to automatically set $\epsilon_p$ with fixed three other hyperparameters, when we apply this method to a brand new dataset. If we have a validation dataset, we can tune the model to achieve better performances.

VI. Conclusion and Future Work

Targeting the unsupervised anomaly detection task, this work introduced an effective scoring network with score-guided regularization. The proposed scoring network can be integrated into existing deep URL-based anomaly detection methods and enhances their anomaly detection capabilities. Specifically, the scoring network utilizes the original discrimination metric as a self-supervised signal to prejudge the obvious-normal samples and leverage these samples to strengthen the representation learner and enlarge the score disparity between obvious-normal and suspected abnormal samples. Moreover, the scoring network learns the discrimination metric according to the dataset and directly outputs the anomaly scores, enhancing the transferability of the original method. We next proposed a representative instantiation of incorporating the scoring network into an AE framework, namely, SG-AE. We first conducted experiments on synthetic datasets to examine the effectiveness of the score-guidance strategy. The results show that the anomaly score disparity between normal and abnormal data continues to expand during training, especially in the transition field. Then comprehensive experiments are conducted on seven tabular datasets, suggesting that the proposed SG-AE is competitive with the state-of-the-art methods in terms of both AUC values and the Kolmogorov–Smirnov statistical index. We also analyzed the sensitivity of the introduced parameters in our scoring network and found that different datasets can share similar configurations. In addition, as the scoring network can learn the disparity between normal and abnormal data, we expect that SG-AE can work well even with a large fraction of anomaly data. To validate this expectation, we then tested the SG-AE on two datasets with varying anomaly rates, indicating that SG-AE is more robust to the anomaly rate than the other three baselines. In order to present the transferability of the scoring network on different URL-based methods, we then applied the scoring network to four state-of-the-art methods, and the experimental results approve the performance improvement. Moreover, we applied the scoring network to two document datasets and one image dataset to present the transferability to different anomaly detection tasks. Experimental results show that SG-Models are comparable to the state-of-the-art methods, especially for datasets with large anomaly rates. Finally, we further discussed the hyperparameter selection and proposed a method to automatically set $\epsilon_p$, which is highly related to datasets. We also conducted experiments to demonstrate its effectiveness.

There are several improvements and potential extensions that merit further study. First, adjusting the $\lambda$ parameters to balance the effects of several loss function terms is challenging when applying the scoring network to a method with multiple loss functions. Potential solutions could be utilizing the multiobjective optimization techniques [52], [53], which attempt to balance the trade-offs between several objectives. Hyperparameter tuning techniques [54], [55], which map hyperparameters into loss functions and optimize them during training, are also worthy of consideration to deal with the problem of too many hyperparameters. Second, the score-guided strategy deserves to be further applied to convolutional frameworks or sequential frameworks to evaluate the performance changes in various anomaly detection tasks with image, time series, or graph datasets.

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