DEEPFIB: SELF-IMPUTATION FOR TIME SERIES ANOMALY DETECTION

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ABSTRACT

Time series (TS) anomaly detection (AD) plays an essential role in various applications, e.g., fraud detection in finance and healthcare monitoring. Due to the inherently unpredictable and highly varied nature of anomalies and the lack of anomaly labels in historical data, the AD problem is typically formulated as an unsupervised learning problem. The performance of existing solutions is often not satisfactory, especially in data-scarce scenarios. To tackle this problem, we propose a novel self-supervised learning technique for AD in time series, namely DeepFIB. We model the problem as a Fill In the Blank game by masking some elements in the TS and imputing them with the rest. Considering the two common anomaly shapes (point- or sequence-outliers) in TS data, we implement two masking strategies with many self-generated training samples. The corresponding self-imputation networks can extract more robust temporal relations than existing AD solutions and effectively facilitate identifying the two types of anomalies. For continuous outliers, we also propose an anomaly localization algorithm that dramatically reduces AD errors. Experiments on various real-world TS datasets demonstrate that DeepFIB outperforms state-of-the-art methods by a large margin, achieving up to 65.2% relative improvement in F1-score.

1 INTRODUCTION

Anomaly detection (AD) in time series (TS) data has numerous applications across various domains. Examples include fault and damage detection in industry (Hundman et al., 2018), intrusion detection in cybersecurity (Feng & Tian, 2021), and fraud detection in finance (Zheng et al., 2018) or healthcare (Zhou et al., 2019), to name a few.

Generally speaking, an anomaly/outlier is an observation that deviates considerably from some concept of normality (Ruff et al., 2021). The somewhat “vague” definition itself tells the challenges of the AD problem arising from the rare and unpredictable nature of anomalies. With the lack of anomaly labels in historical data, most AD approaches try to learn the expected values of time-series data in an unsupervised manner (Blazquez-Garcia et al., 2021). Various techniques use different means (e.g., distance-based methods (Angiulli & Pizzuti, 2002), predictive methods (Holt, 2004; Yu et al., 2016; Deng & Hooi, 2021); or reconstruction-based methods (Shyu et al., 2003; Malhotra et al., 2016; Zhang et al., 2019; Shen et al., 2021)) to obtain this expected value, and then compute how far it is from the actual observation to decide whether or not it is an anomaly.

While existing solutions have shown superior performance on some time series AD tasks, they are still far from satisfactory. For example, for the six ECG datasets in (Keogh et al., 2005), the average F1-score of state-of-the-art solutions (Kieu et al., 2019; Shen et al., 2021) with model ensembles are barely over 40%. Other than the TS data” complexity issues, one primary reason is that the available data is often scarce while deep learning algorithms are notoriously data-hungry.

Recently, self-supervised learning (SSL) that enlarges the training dataset without manual labels has attracted lots of attention, and it has achieved great success in representation learning in computer vision (Zhang et al., 2016; Pathak et al., 2016; Chen et al., 2020), natural language processing (Devlin et al., 2019), and graph learning (Hu et al., 2020) areas. There are also a few SSL techniques for time series analysis proposed in the literature. Most of them (Falck et al., 2020; Saeed et al., 2021; Fan et al., 2020) craft contrastive TS examples for classification tasks. (Deldari et al., 2021) also leverages contrastive learning for change point detection in time series.

1.1 Motivation

The motivation of DeepFIB stems from the following observations. First, in many practical scenarios, the amount of labeled data is limited or even non-existent. In these cases, an effective AD solution should be able to extract more robust temporal relations with existing training samples through self-supervised learning. Second, for time series data, the two major anomaly types, point-outliers and sequence-outliers, can be regarded as the “Fill In the Blank” game. By imitating the way human self-imputes missing values while completing the blanks in a sentence, we extend this idea to the TS domain and propose DeepFIB, a self-supervised learning technique that innovatively addresses both anomaly shapes. Finally, a self-supervised approach can be readily extended to incorporate other self-training methods such as anomaly localization, which is a crucial feature for practical applications.

The contributions of this paper are threefold:

1. A novel self-supervised learning framework named DeepFIB for TS anomaly detection.
2. A simple yet effective self-imputation game to model the anomaly detection problem.
3. An anomaly localization algorithm for continuous outliers.

We evaluate DeepFIB on various real-world TS datasets and demonstrate its effectiveness in identifying both point- and sequence-outliers. Compared to state-of-the-art methods, DeepFIB achieves a significant improvement in F1-score, up to 65.2%.

1.2 Paper Outline

The rest of the paper is organized as follows. Section 2 provides an overview of related work. The proposed methodology is detailed in Section 3. Experimental results are presented in Section 4. Finally, we conclude our work in Section 5.
While interesting, the above SSL techniques do not apply to the AD task because detecting anomalies in time series requires fine-grained models at the element level. In this work, inspired by the context encoder for visual feature learning (Pathak et al., 2016) and the BERT model for language representation learning (Devlin et al., 2019), we propose a novel self-supervised learning technique for time series anomaly detection, namely DeepFIB. To be specific, we model the problem as a Fill In the Blank game by masking some elements in the TS and imputing them with other elements. This is achieved by revising the TS forecasting model SCINet (Liu et al., 2021) for the TS imputation task, in which the masked elements are regarded as missing values for imputation. Such self-imputation strategies facilitate generating a large amount of training samples for temporal relation extraction. As anomalies in time series manifest themselves as either discrete points or subsequences (see Fig. 1), correspondingly, we propose two kinds of masking strategies and use them to generate two pre-trained models. They are biased towards recovering from point-wise anomalies (DeepFIB-p model for point outliers) and sequence-wise anomalies (DeepFIB-s model for continuous outliers), respectively. To the best of our knowledge, this is the first SSL work for time series anomaly detection.

Generally speaking, AD solutions have difficulty detecting sequence-wise anomalies because it is hard to tell the real outliers from their neighboring normal elements due to their interplay. To tackle this problem, we propose a novel anomaly localization algorithm to locate the precise start and end positions of continuous outliers. As a post-processing step, we conduct a local search after determining the existence of sequence-wise anomalies within a timing window with our DeepFIB-s model. By doing so, the detection accuracy for continuous outliers is significantly improved.

We conduct experiments on several commonly-used time series benchmarks, and results show that DeepFIB consistently outperforms state-of-the-art solutions. In particular, the average F1-score of DeepFIB for the six ECG datasets is more than 62%, achieving nearly 50% relative improvement.

2 RELATED WORK

In this section, we mainly discuss recent deep learning-based time series AD approaches. A comprehensive survey on the traditional techniques can be found in (Gupta et al., 2014).

Existing anomaly detection approaches can be broadly categorized into three types (see Fig. 2): (i) Density-based methods consider the normal instances compact in the latent space and identify anomalies with one-class classifiers or likelihood measurements (Su et al., 2019; Shen & Kwok, 2020; Feng & Tian, 2021). (ii) Reconstruction-based methods use recurrent auto-encoders (RAE) (Malhotra et al., 2016; Yoo et al., 2021; Kieu et al., 2019; Shen et al., 2021; Zhang et al., 2019) or deep generative models such as recurrent VAEs (Park et al., 2018) or GANs (Li et al., 2019; Zhou et al., 2019) for reconstruction. The reconstruction errors are used as anomaly scores. (iii) Prediction-based methods rely on predictive models (Bontemps et al., 2016; Deng & Hooi, 2021; Chen et al., 2021) and use the prediction errors as anomaly scores.
While the above methods have been successfully used in many real-world applications, practical AD tasks still have lots of room for improvement, especially in data-scarce scenarios. Unlike existing AD approaches, the proposed mask-and-impute method in DeepFIB exploits the unique property of TS data that missing values can be effectively imputed (Fang & Wang, 2020). By constructing many training samples via self-imputation, DeepFIB extracts robust temporal relations of TS data and improves AD accuracy dramatically. Moreover, for the more challenging sequence-wise anomalies, most prior work assumes a user-defined fixed-length for anomaly subsequences (Cook et al., 2020) or simplifies the problem by stating all the continuous outliers have been correctly detected as long as one of the points is detected (Su et al., 2019; Shen & Kwok, 2020). In DeepFIB, we lift these assumptions and try to locate the exact location of sequence-wise anomalies.

3 METHOD

In this section, we first introduce the overall self-imputation framework in DeepFIB and then discuss the separate AD models for detecting point- and sequence-wise anomalies with different mask-and-impute strategies, namely DeepFIB-p and DeepFIB-s, respectively. Next, we describe the TS imputation method used in DeepFIB, based on an existing TS forecasting approach SCINet (Liu et al., 2021). Finally, we present our anomaly localization algorithm for continuous outliers.

3.1 SELF-IMPUTATION FOR ANOMALY DETECTION

Given a set of multivariate time series wherein \( X_s = \{x_1, x_2, \ldots, x_{T_s}\} \in \mathbb{R}^{d \times T_s} \) (\( T_s \) is the length of the \( s \)th time series \( X_s \)), the objective of the AD task is to find all anomalous points \( x_t \in \mathbb{R}^d \) (\( d \) is the number of variates) and anomalous subsequences \( X_{t,\tau} = \{x_{t-\tau+1}, \ldots, x_t\} \).

The critical issue to solve the above problem is obtaining an expected value for each element in the TS, which requires a large amount of training data to learn from, especially for deep learning-based solutions. However, time-series data are often scarce, significantly restricting the effectiveness of learning-based AD solutions.

DeepFIB is a simple yet effective SSL technique to tackle the above problem. We model this problem as a Fill In the Blank game by randomly masking some elements in the TS and imputing them with the rest. Such self-imputation strategies generate many training samples from every time series and hence dramatically improve temporal learning capabilities.

In particular, we propose to train two self-imputation models (Fig. 3), biased towards point- and sequence-wise anomalies in the TS data, respectively.

- **DeepFIB-p model** targets point outliers, as shown in Fig. 3(a), in which we mask discrete elements and rely on the local temporal relations extracted from neighboring elements for reconstruction. For each time series \( X_s \), we generate \( M \) training samples by masking it \( M \) times with randomly-selected yet non-overlapping \( \frac{d \times T_s}{M} \) elements.
DeepFIB-s model targets continuous outliers, as shown in Fig. 3(b), in which we mask continuous elements and rely on predictive models for reconstruction. For each time series $X_s$, we evenly divide it into $N$ non-overlapping sub-sequences as $\{X_{s,i}^{d \times T_s}, i \in [0, N - 1] \}$ and generate $N$ training samples by masking one of them each time.

During training, for each time series $X_s$, we obtain a set of non-overlapped imputed data with the above model and integrate them together results in a reconstructed time series $\hat{X}_s$ (i.e., $\hat{X}_s$-p for DeepFIB-p model and $\hat{X}_s$-s for DeepFIB-s model). The training loss for both models are defined as the reconstruction errors between the input time series and the reconstructed one:

$$L = \frac{1}{T_s} \sum_{t=1}^{T_s} \|x_t - \hat{x}_t\|$$ (1)

where $x_t$ is the original input value at time step $t$ and the $\hat{x}_t$ denotes the reconstructed value from the corresponding model, and $\|\cdot\|$ is the L1-norm of a vector.

During testing, to detect point outliers with the DeepFIB-p model, we simply use the residual error as the anomaly score, defined as $e_t = \sum_{i=0}^{d} |\hat{x}_t^i - x_t^i|$, and when $e_t$ is larger than a threshold value $\lambda_p$, time step $t$ is regarded as an outlier. In contrast, for continuous outliers, we use dynamic time warping (DTW) (Sakoe & Chiba, 1978) distance metrics as our anomaly scoring mechanism, which measures the similarity between the input time series $X_s$ and reconstructed sequence $\hat{X}$.

### 3.2 Time Series Imputation in DeepFIB

While the time-series data imputation problem has been investigated for decades (Fang & Wang, 2020), there are still lots of rooms for improvement and various deep learning models are proposed recently (Cao et al., 2018; Liu et al., 2019; Luo et al., 2019).

SCINet (Liu et al., 2021) (Fig. 4) is an encoder-decoder architecture motivated by the unique characteristics of time series data. It incorporates a series of SCI-Blocks that conduct down-sampled convolutions and interactive learning to capture temporal features at various resolutions and effectively blend them in a hierarchical manner. Considering the highly-effective temporal relation extraction capability of SCINet when compared to other sequence models, we propose to revise it for the TS imputation task. More details about SCINet can be found in (Liu et al., 2021).

To impute the missing elements from the two masking strategies with DeepFIB-p and DeepFIB-s models, we simply change the supervisions for the decoder part accordingly. For point imputation, we use the original input sequence as the supervision of our DeepFIB-p model, making it a reconstruction structure. By doing so, the model concentrates more on the local temporal relations inside the timing window for imputing discrete missing data, as shown in Fig. 5(a). As for continuous imputation, we propose to change SCINet as a bidirectional forecasting structure in our DeepFIB-s model, with the masked sub-sequence as supervision. As shown in Fig. 5(b), the two sub-models, namely F-SCINet and B-SCINet, are used to conduct forecasting in the forward and backward directions, respectively. By doing so, the model can aggregate the temporal features from both directions and learn a robust long-term temporal relations for imputing continuous missing data.
3.3 ANOMALY LOCALIZATION ALGORITHM

During inference, we use a sliding window with stride \( \mu \) to walk through the time series and find anomalies in each window. For sequence-wise anomalies, without knowing their positions a priori, we could mask some normal elements in the window and use those unmasked outliers for prediction (see Fig. 5(b)), thereby leading to mispredictions. To tackle this problem, we propose to conduct a local search for the precise locations of the sequence-wise anomalies.

As shown in Fig. 6, the Active window are the current input sequence to the DeepFIB-s model with length \( \omega (\omega \geq \mu) \), i.e., \( X_t = \{x_t, x_{t+1}, ..., x_{t+\omega-1}\} \) at time step \( t \). When the DTW distance between the original time series in the Active window and the imputed sequence is above the threshold \( \lambda_s \), a sequence-wise anomaly is detected in the current window, and the localization mechanism is triggered. As the sliding window is moving along the data stream with stride \( \mu \), if no outliers are detected in the previous window, the start position of the sequence-wise anomaly can only exist at the end of \( X_t \) in the window \( \{x_{t-\mu+1}, ..., x_{t+\omega-1}, x_{t+\omega-1}\} \) with length \( \mu \). Consequently, by gradually shifting the Active window backward to include one more element in the Buffer window (see Fig. 6) at a time and calculating the corresponding DTW distances as \( \epsilon_1, ..., \epsilon_i, ..., \epsilon_\mu \), we can find the maximum \( i \) with \( \epsilon_i < \lambda_s \), indicating the following element after the Active window starting with \( i \) is the start of the anomaly subsequence. The Anomaly flag is then activated from this position. Similarly, to determine the ending position of the anomaly subsequence, we keep sliding the Active windows until we find a window with DTW distance smaller than \( \lambda_s \), indicating that the ending position is within \( \{x_{t-\mu}, ..., x_{t-2}, x_{t-1}\} \). Again, we shift the Active window backwardly one-by-one to include one element of the above window at a time and calculate the corresponding DTW distance, until we find the ending position with its DTW distance larger than \( \lambda_s \).
4 EXPERIMENTS

In this section, we conduct extensive experiments to answer the following two questions: Whether DeepFIB outperforms state-of-the-art AD methods (Q1)? How does each component of DeepFIB affect its performance (Q2)?

Table 1: Datasets used in experiments

| Datasets   | #Dim | #Train | #Test | Anomaly  |
|------------|------|--------|-------|----------|
| 2d-gesture | 2    | 8590   | 2420  | 24.63%   |
| Power demand | 1    | 18145  | 14786 | 11.44%   |
| (A)chfdb_ch101_275 | 2   | 2888   | 1772  | 14.61%   |
| (B)chfdb_ch13_35590 | 2  | 2439   | 1287  | 12.35%   |
| (C)chfdb_ch15 | 2    | 10863  | 3548  | 4.45%    |
| (D)ltstdb_20221_43 | 2   | 2610   | 1121  | 11.51%   |
| (E)ltstdb_20321_240 | 2  | 2011   | 1447  | 9.61%    |
| (F)mitdb_100_180 | 2    | 2943   | 2255  | 8.38%    |
| Credit Card | 3    | 142403 | 142404 | 0.173%  |

Experiments are conducted on a number of commonly-used benchmark TS datasets, namely 2d-gesture, Power demand, ECG and Credit Card, ranging from human abnormal behavior detection, power monitoring, healthcare and fraud detection in finance (see Table 1). As the anomalies in 2d-gesture, Power demand, and ECG are mainly sequence outliers, we apply the DeepFIB-s model on these datasets. In contrast, the Credit Card dataset only contains point outliers, and hence we use DeepFIB-p model on it.

To make a fair comparison with existing models, we use the standard evaluation metrics on the corresponding datasets. For 2d-gesture, Power demand and Credit Card, we use precision, recall, and F1-score following (Shen & Kwok, 2020). For ECG datasets, we use the AUROC (area under the ROC curve), AUPRC (area under the precision-recall curve) and F1-score, following (Shen et al., 2021). To detect anomalies, we use the maximum anomaly score in each sub-models over the validation dataset to set the threshold.

More details on experimental settings, additional experimental results and discussions (e.g., hyperparameter analysis) are presented in the supplementary materials.

4.1 Q1: COMPARISON WITH STATE-OF-THE-ART METHODS

Table 2: Comparison of anomaly detection performance (as %), on 2d-gesture and Power demand datasets. The best results are in bold and the second best results are underlined.

| Methods    | 2d-gesture | Power demand |
|------------|------------|--------------|
|            | precision  | recall       | F1-score | precision  | recall       | F1-score |
| DAGMM      | 25.66      | 47.42        | 38.91    | 34.37      | 41.72        | 37.69    |
| EncDec-AD  | 24.88      | 100.0        | 39.85    | 13.98      | 54.20        | 22.22    |
| LSTM-VAR   | 36.62      | 67.72        | 47.54    | 8.00       | 56.66        | 14.03    |
| MADGAN     | 29.41      | 76.4         | 42.47    | 13.20      | 60.57        | 27.67    |
| AOGAN      | 75.83      | 46.50        | 51.55    | 20.28      | 44.41        | 28.85    |
| BeatGAN    | 56.11      | 45.33        | 49.74    | 8.04       | 76.58        | 14.56    |
| OmniAnomaly| 27.70      | 79.67        | 41.11    | 8.55       | 78.73        | 15.42    |
| MSCRED     | 61.26      | 59.11        | 60.17    | 35.80      | 34.32        | 42.50    |
| THOC       | 54.78      | 75.00        | 63.31    | 61.50      | 36.34        | 45.68    |
| DeepFIB    | 93.90 ± 0.35 | 60.77 ± 0.24 | 73.79 ± 0.19 | 52.21 ± 0.31 | 99.99 ± 0.01 | 68.60 ± 0.15 |

- The results of other baselines in the table are extracted from (Shen & Kwok, 2020)

2d-gesture and Power demand: The results in Table 2 show that the proposed DeepFIB-s achieves 16.55% and 50.18% F1-score improvements on 2d-gesture and Power demand, respectively, compared with the second best methods.

For 2d-gesture, the available training data is limited and the temporal relations contained in the data are complex (body jitter), making it difficult to obtain a discriminative representation in AD models. DAGMM (Zong et al., 2018) shows low performance since it does not consider the temporal
information of the time-series data at all. As for the AD solutions based on generative models (EncDecAD (Malhotra et al., 2016), LSTM-VAE (Park et al., 2018), MAD-GAN (Li et al., 2019), AnoGAN (Schlegl et al., 2017), BeatGAN (Zhou et al., 2019), OmniAnomaly (Su et al., 2019)), they usually require a large amount of training data, limiting their performance in data-scarce scenario. Compared to the above methods, the encoder-decoder architecture MSCRED (Zhang et al., 2019) is relatively easier to train and its AD performance is considerably higher. Moreover, the recent THOC (Shen & Kwok, 2020) work further improves AD performance by fusing the multi-scale temporal information to capture the complex temporal dynamics.

The proposed DeepFIB-s model outperforms all the above baseline methods since the proposed self-imputation technique allows the model to learn more robust temporal relations from much more self-generated training samples. Notably, we also observe that the precision of the DeepFIB-s dominates the other baselines. We attribute it to the anomaly localization algorithm that can locate the anomaly’s precise start and end positions, significantly reducing the false positive rate.

![Figure 7](image_url)

For Power demand dataset, (a) shows two cycles of normal data (0-1200 frame) wherein each cycle contains 5 peaks. (b) shows two cycles with anomaly with missing peaks highlighted using red arrows. The waveform of original data (light blue) is overlaid on the prediction result (light red). Lower color bars show the ground truth (GT) label and our detection result (Result).

For Power demand, the data contains many contextual anomaly subsequences (see Fig. 7). It is quite challenging for existing AD approaches to learn such context information by extracting temporal features from the entire time series as a whole. In contrast, the proposed sequence-wise masking strategy facilitates learning different kinds of temporal patterns, which is much more effective in detecting such contextual anomalies. As shown in Table 2, the recall of our DeepFIB-s model almost reaches 100%, indicating all anomalies have been detected. The precision is not the best, and we argue that some of the false positives are in fact resulted from the poorly labeled test set (see our supplementary material).

**ECG(A-F):** Compared with (A),(B),(C) datasets, (D),(E),(F) are clearly noisy, which affect the performance of the anomaly detectors significantly. Nevertheless, Table 3 shows that DeepFIB-s achieves an average 46.3% F1-score improvement among all datasets and an impressive 65.2% improvement for ECG(F) dataset. There are mainly two reasons: (1) the data is scarce (See Table 1). Existing AD methods are unable to learn robust temporal relations under such circumstances. In contrast, the self-imputation training strategy together with the bidirectional forecasting mechanism used in our DeepFIB-s model can well address this issue; (2) the proposed DTW anomaly score is more effective in detecting the anomaly sequence than the previous point-wise residual scoring (see Section 4.2.1). Notably, the AUPRC of DeepFIB in ECG(E) is slightly lower than RAMED (Shen et al., 2021), and we attribute to the fact that some unlabeled sub-sequences are too similar to labeled anomalies in the raw data.

**Credit Card:** Due to the nature of this application, this dataset is stochastic and the temporal relation is not significant. Therefore, as shown in Table 4, traditional AD solutions without modeling the underlying temporal dependency achieve fair performance, e.g., OCSVM (Ma & Perkins, 2003), ISO

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1. Contextual anomalies are observations or sequences that deviate from the expected patterns within the time series however if taken in isolation they are within the range of values expected for that signal (Cook et al., 2020).
### Table 3: Comparison of anomaly detection performance (as %), on ECG datasets.

| Metrics | Methods          | A   | B   | C   | D   | E   | F   | Average |
|---------|------------------|-----|-----|-----|-----|-----|-----|---------|
|        | AUROC            |     |     |     |     |     |     |         |
|        | RAE              | 64.95 | 75.24 | 68.27 | 60.71 | 77.92 | 44.68 | 65.29  |
|        | RRN              | 69.50 | 72.07 | 68.49 | 47.05 | 78.81 | 47.87 | 65.97  |
|        | BeatGAN-p        | 95.81 | 75.14 | 59.09 | 29.33 | 84.98 | 44.19 | 68.74  |
|        | RAE-ensemble     | 68.26 | 77.63 | 70.55 | 64.64 | 83.14 | 39.66 | 67.31  |
|        | RAMED            | 72.58 | 76.82 | 76.79 | 69.44 | 83.36 | 55.64 | 73.27  |
|        | DeepFIB-p        | 87.00 ± 0.85 | 84.40 ± 1.23 | 94.05 ± 0.73 | 72.55 ± 0.54 | 84.81 ± 0.62 | 63.23 ± 0.12 | 81.11  |
|        | AUROC            |     |     |     |     |     |     |         |
|        | RAE              | 51.84 | 40.32 | 31.22 | 15.34 | 34.17 | 7.36  | 28.48  |
|        | RRN              | 54.90 | 43.13 | 33.49 | 11.83 | 37.68 | 7.93  | 31.46  |
|        | BeatGAN-p        | 52.50 | 44.94 | 19.01 | 14.84 | 34.46 | 7.06  | 28.90  |
|        | RAE-ensemble     | 56.23 | 54.21 | 49.90 | 18.84 | 38.48 | 7.25  | 27.42  |
|        | RAMED            | 56.23 | 54.21 | 49.90 | 18.84 | 38.48 | 7.25  | 27.42  |
|        | DeepFIB-p        | 58.18 ± 0.63 | 75.48 ± 0.56 | 14.47 ± 0.67 | 23.14 ± 0.45 | 58.27 ± 0.12 | 13.16 ± 0.23 | 51.45  |
|        | F1               |     |     |     |     |     |     |         |
|        | RAE              | 52.51 | 49.03 | 32.79 | 25.43 | 33.63 | 15.47 | 38.41  |
|        | RRN              | 56.08 | 43.48 | 38.30 | 20.94 | 44.37 | 15.47 | 36.39  |
|        | BeatGAN-p        | 53.93 | 45.18 | 27.99 | 23.67 | 47.02 | 16.68 | 35.81  |
|        | RAE-ensemble     | 56.44 | 52.40 | 45.68 | 27.75 | 44.98 | 15.47 | 42.62  |
|        | RAMED            | 54.27 | 51.03 | 34.45 | 20.87 | 32.23 | 20.63 | 40.58  |
|        | DeepFIB-p        | 80.90 ± 0.63 | 78.06 ± 0.82 | 76.37 ± 0.13 | 44.71 ± 0.19 | 58.90 ± 0.26 | 34.08 ± 0.73 | 62.35  |

* The results of other baselines in the table are referred from [Shen et al., 2021].

Forest [Liu et al., 2008]. Besides, the AR (Rousseeuw & Leroy, 1987) with a small window size (e.g., 3, 5) can also identify the local change point without considering longer temporal relations. However, the large recall and small precision values show its high false positive rates. The prediction-based method, LSTM-RNN (Bontemps et al., 2016) tries to learn a robust temporal relation from the data, which is infeasible for this dataset. In contrast, the reconstruction-based method, RAE (recurrent auto-encoder) (Malhotra et al., 2016) performs better since it can estimate the outliers based on the local contextual information. The proposed DeepFIB-p model outperforms all baseline methods, because it can better extract local correlations with the proposed self-imputation strategy. At the same time, compared to our results on other datasets, the relative 26.3% improvement over the second best solution (AR) is less impressive and the F1-score with our DeepFIB-p model is still less than 25%. We attribute it to both the dataset complexity and the lack of temporal relations in this dataset.

### Table 4: Comparison of anomaly detection performance (as %), on Credit Card dataset.

| Methods | Credit Card |
|---------|-------------|
|         | precision  | recall | F1-score |
| AR      | 11.30      | 65.20  | 19.20    |
| ISO Forest | 9.80      | 56.90  | 16.80    |
| OCSVM   | 1.70       | 62.00  | 18.30    |
| LSTM-RNN | 0.40      | 11.00  | 0.70     |
| RAE     | 16.90      | 21.52  | 18.89    |
| DeepFIB-p | 16.52 ± 0.31 | 46.57 ± 0.41 | 24.25 ± 0.37 |
| RAE*    | 13.93 ± 0.12 | 53.36 ± 0.21 | 22.07 ± 0.36 |
| DeepFIB-p* | 16.55 ± 0.22 | 21.08 ± 0.12 | 18.50 ± 0.21 |

### 4.2 Q2: Ablation Study

In this section, we first evaluate the impact of various components in our DeepFIB-s and DeepFIB-p models. Next, we replace the SCINet with other sequence models to evaluate its impact.

#### 4.2.1 Component Analysis

**DeepFIB-p**: To demonstrate the impact of the proposed mask-and-impute mechanism in point outlier detection. We add two baseline methods: (1) DeepFIB-p”, wherein we remove the self-imputation strategy; (2) RAE”, we implement the same mask-and-impute strategy and apply it to the baseline method RAE. In Table 4, the performance improvement and degradation of the corresponding variants compared to DeepFIB-p and RAE clearly demonstrate the effectiveness of the proposed self-imputation strategy for point outlier detection.
DeepFIB-s: To investigate the impact of different modules of DeepFIB-s, we compare two variants of the DeepFIB-s on five datasets. The details of the variants are described as below: For \textit{w/o. localization}, we remove the anomaly localization algorithm from our DeepFIB-s model. The \textit{w/o. localization \& DTW} further removes the DTW scoring mechanism, and the anomalies are determined based on point-wise residual errors. As shown in Fig. 8, all these components are essential for achieving high anomaly detection accuracy. At the same time, the proposed self-imputation training strategy is still the main contributor to the performance of our DeepFIB-s model, as the results of \textit{w/o. localization \& DTW} are still much better than those of the 2nd best solution. Besides, the performance gain of the DTW anomaly scoring indicates that the point-wise outlier estimation is not suitable for evaluating sequence-wise anomalies.

4.2.2 Impact of SCINet

In our DeepFIB framework, we revise SCINet for time series imputation. To show its impact, we replace it with other sequence models in DeepFIB-s. As we can see in Table 5, compared with TCN (Bai et al., 2018) and LSTM (Hochreiter & Schmidhuber, 1997), using SCINet indeed brings significant improvements on F1-sc, which clearly shows its strong temporal relation extraction capability and the effectiveness of the revised architecture for TS imputation. At the same time, compared to the previous SOTA methods (2nd best) for the corresponding dataset, with the same mask-and-impute strategy, we can still achieve remarkable performance without using SCINet, indicating the effectiveness of the proposed self-imputation concept itself.

Table 5: The comparison of different sequence models. 2nd best denotes the previous SOTA methods in each datasets (THOC in 2d-gesture and RAE-ensemble in ECG(A)).

| Methods | ECG(A) | 2d-gesture |
|---------|--------|------------|
| SCINet  | 80.90 ± 0.63 | 73.79 ± 0.19 |
| TCN     | 69.86 ± 0.22 | 69.55 ± 0.28 |
| LSTM    | 64.16 ± 0.21 | 66.83 ± 0.35 |
| 2nd best| 56.42 | 63.31 |

5 Conclusion

In this paper, we propose a novel self-imputation framework DeepFIB for time series anomaly detection. Considering the two types of common anomalies in TS data, we implement two mask-and-impute models biased towards them, which facilitate extracting more robust temporal relations than existing AD solutions. Moreover, for sequence-wise anomalies, we propose a novel anomaly localization algorithm that dramatically improves AD detection accuracy. Experiments on various real-world TS datasets demonstrate that DeepFIB outperforms state-of-the-art AD approaches by a large margin, achieving up to more than 65% relative improvement in F1-score.
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