C-GATS: Conditional Generation of Anomalous Time Series

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Abstract

Sparsity of the data needed to learn about anomalies is often a key challenge faced when training deep supervised models for the task of Anomaly Detection (AD). Generating synthetic data by applying pre-determined transformations that conform to a set of known invariances has shown to improve performance of such deep models. In this work we present C-GATS to show that one can *learn* a much larger invariance space using the available sparse data by training a conditional generative model to do Data Augmentation (DA) for anomalous Time Series (TS) in a model-agnostic way. Particularly, we factorize an anomalous TS sequence into 3 attributes— *normal sub-sequence*, *anomalous sub-sequence*, and *position of the anomaly* and model each of them separately. This factorization helps exploit samples from the *dominant* class i.e normal TS to train a generative model for the *sparse* class i.e anomalous TS. We provide an exhaustive study to showcase that C-GATS not only learns to generate different types of anomalies (eg: point anomalies and level-shift) but those generated anomalies improve performance of multiple SOTA TS AD models on a set of popular public TS AD benchmark datasets.

1 Introduction

Deep models have been successful at achieving exceptional performance on a wide variety of machine learning tasks, ranging from vision and natural languages understanding to TS forecasting and anomaly detection [24]. The models have millions or even billions of parameters, allowing them to learn and represent complex functions, features and transformation automatically from data. However, learning the values of these parameters requires a large data-set. Gathering real world labelled training data is usually non-trivial and a costly task. As a result, the performance of deep algorithms is limited in data sparse tasks such as segmentation or AD [37].

A well studied way to handle this problem is by generating synthetic data that belongs to the original data distribution [28, 9, 10, 18, 34, 15]. We categorize these methods into two broad categories- (i) when invariances are known *apriori*; (ii) when invariances are *learned* from the original data distribution. The traditional Data Augmentation (DA) techniques like scaling, translations, rotations and their variants fall in the former category [13, 43, 40, 19] while the generative approaches like Generative Adversarial Networks (GANs), Variational Auto Encoders (VAEs) and their variants fall in the latter category. Although considered best practices for a long time [30], the former class of methods are shown to have limitations such as incapability of exploring a large invariance space [1]

NeurIPS 2022 Workshop on Synthetic Data for Empowering ML Research.

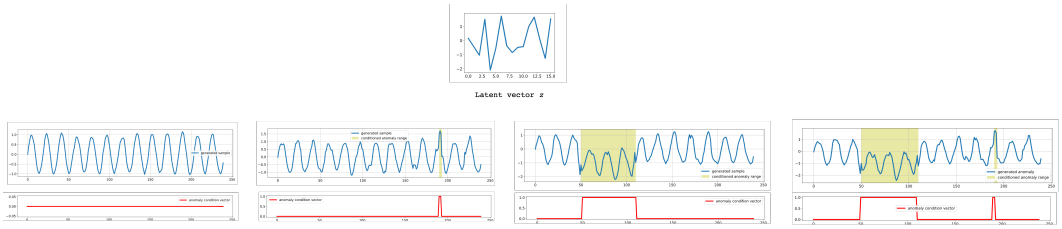

Figure 1: For a fixed latent z sampled from a standard gaussian, we vary the conditional vector $Y^A \in \mathbb{R}^T$ (in red) and generate the anomalous TS, $X^A \in \mathbb{R}^T$. Without any additional information about the type of anomaly, `C-GATS` uses the conditional vector to infer the type of anomaly from the training data. For example, lengthier anomalies are level-shift and the shorter ones are point anomalies. `C-GATS` is able to learn useful invariances hidden in the data.

and requiring domain knowledge to design augmentation schemes [18]. Hence, in this paper we build upon the latter class of methods.

Some recent works [14, 39, 8] have shown the value of using generative models for TS data but only on TS classification task. No work has been done to explore the same for more complicated TS task of AD, the only exception being [6, 7] where the problem of AD was again framed as a binary classification task. We consider the task of univariate TS AD in its original form [37] where given a TS sample $X_i \in \mathbb{R}^T$, goal is output a corresponding label $Y_i \in \{0,1\}^T$ where 0 denotes normal value and 1 denotes anomaly at each timestamp. In this task a well-known problem is the class imbalance between the TS samples that are normal, i.e without any anomalies v/s the ones that contain anomalies, which prevents us from training deep AD models in a supervised manner [5, 17].

We argue that generating synthetic anomalous TS samples for AD is non-trivial as compared to other tasks like classification due to 3 key reasons– **(a)** ***temporal labels***: the labels are no longer scalar and vary temporally for a given TS sample; **(b)** ***data imbalance***: the number of TS samples in the dataset that contain anomalies are sparse; **(c)** ***data scarcity***: for a given TS sample the number of data points that are anomalous are sparse. We show an example of (a) in supp figure 5 where either the DA method itself introduces new anomalies in the data or it corrupts the anomalous samples leading to contradicting labels. On the other hand, off-the-shelf deep generative models like vanilla GANs and VAEs fail to learn a good distribution of anomalous TS due to reasons (b) and (c). We show this in our experiments (Section 4). Conditional variants of these generative models [32] show some improvement by learning class dependent latent distributions, however when applied directly in our setting, face the *curse of dimensionality* [12] as the number of classes in TS AD task grow exponentially with the length of TS samples. A thorough survey of related work is provided in supp section 6.1.

To address these issues, we propose `C-GATS`, a conditional generative model trained in a semi-supervised manner to produce synthetic TS that contain anomalies. The main contribution of this paper is that these synthetic anomalies are—

- ***effective***: they improve performance of several SOTA TS AD models on downstream task of AD.
- ***diverse***: `C-GATS` learns to generates different types of anomalies present in the dataset (eg: point, level-shift).
- ***label-preserving***: they conform to the label used to condition `C-GATS` during generation.
- ***model agnostic***: they are independent of the downstream AD model.
- ***domain agnostic***: we show `C-GATS` can be trained on TS dataset from multiple domains.

2 Problem Definition

Consider a setting where $X^A \in \mathbb{R}^T$ is a univariate TS of length T with anomaly. We represent $X^N \in \mathbb{R}^T$ as a univariate TS of length T without any anomaly. $Y^A \in \{0,1\}^T$ is the corresponding binary label vector for X^A and $Y^N \in \{0\}^T$ is the label vector for X^N. We thus have a dataset $\mathcal{D}$ which comprises of m number of anomalous pairs (X^A, Y^A) and n number of normal pairs

(X^N, Y^N) such that $m << n$. Our goal is to learn a model that can produce anomalous TS with labels, i.e, learn a density $\hat{p}(X^A, Y^A)$ that best approximates $p(X^A, Y^A)$.

3 Proposed Algorithm

A standard way of learning the joint distribution (X^A, Y^A) is by trying to learn the conditional $p(X^A|Y^A)$ typically modeled using a CVAE [32]. This works well when the number of unique classes are relatively fewer, eg: MNIST [25] but doesn't scale as number of classes increase, i.e the condition vector becomes high dimensional [12]. In our setting, there are 2^T unique classes as $Y^A \in \mathbb{R}^T$ and a vanilla CVAE fails to learn a good distribution w.r.t each class due to the well-known problem in generative models called mode-collapse [33]. An example of this is seen in Figure 6.a where a vanilla CVAE fails to reconstruct an anomalous TS.

Note that in multi-class generative problems with class imbalance in vision domain, where for eg. the dominant class is *'dog'* and sparse class is *'ship'*— the two classes do not share underlying structural similarity. Hence, trying to generate samples of *'ship'* by exploiting samples from *'dog'* is possible, [4] but limited. However, in our setting the normal and anomalous TS share significant structural similarity that can be exploited. More formally, we study anomalous TS X^A where we can factorize them as shown in Eq. 1 where x^A is a sub-sequence of X^A that contains the anomalous data points, x^N is the normal sub-sequence such that $x^A \cup x^N \equiv X^A$, and Y^A is the corresponding binary label vector.

$$p(X^A) = \underbrace{p(x^N)}_{\substack{\text{modeled} \\ \text{using } p(X^N)}} \cdot \underbrace{p(x^A)}_{\substack{\text{modeled using} \\ p(X^A|X^N,Y^A)}} \cdot \underbrace{p(Y^A)}_{\substack{\text{modeled} \\ \text{using } P(Y^A)}} \tag{1}$$

To learn this factorized generative model, we model the following distributions–

$$\text{Anomaly Label model: } Y^A \sim p(Y^A) \tag{2}$$

$$\text{Sample Occlusion model: } \tilde{X} \sim p(\tilde{X}|X^N, Y^A) \tag{3}$$

$$\text{Foundation model: } \begin{cases} \text{Enc}_\theta : z \sim q_\theta(z|\tilde{X}) \\ \text{Dec}_\psi : X^N \sim p_\psi(X^N|z) \end{cases} \tag{4}$$

$$\begin{array}{l}\text{Anomaly} \\ \text{Generation Model:}\end{array} \begin{cases} \text{Enc}_{\theta^*} : z \sim q_{\theta^*}(z|\tilde{X}) \\ \text{Dec}_\phi : X^A \sim p_\phi(X^A|z, Y^A) \end{cases} \tag{5}$$

We start by decomposing the problem into two sub-problems— (i) learning a latent space of the normal sequences; (ii) learning to insert anomalies in latent space. **Stage 1:** We model the first sub-problem using an unconditional VAE (Eq. 4) with an important modification. Instead of learning a vanilla variational encoder $p_\psi(z|X^N)$, we learn $p_\psi(z|\tilde{X})$ where $\tilde{X} \in \mathbb{R}^T$ is the occluded version of a normal sequence X^N. Here occlusion refers to removing a set of values from the given TS and replacing with zeros [26]. Instead of occluding values randomly, we occlude values that follow $p(Y^A)$. More specifically, we sample a $Y^A \sim p(Y^A)$ and replace the values in $X^N \sim \mathcal{D}$ with zeros that correspond to timestamps that are labeled as 1 in Y^A. This is the *sample occlusion model* in Eq. 3 that gives us $\tilde{X}$. We then train the VAE's encoder and decoder jointly on the paired samples of $(X^N, \tilde{X})$ to maximize the following evidence lower bound (ELBO),

$$\log p(X^N) \ \geq \mathbb{E}_{q_\theta(z|\tilde{X})}[\log p_\psi(X^N|z)] - KL(q_\theta(z|\tilde{X}) \,||\, p(z)) \tag{6}$$

We use this ELBO objective to write a differentiable loss function below to train θ and ψ jointly—

$$\mathcal{L}(\theta, \psi) = -KL(q_\theta(z|\tilde{X}_i)||p(z)) + \frac{1}{n}\sum_{i=1}^{n} \log p_\psi(X_i^N|z_i) \tag{7}$$

Both θ and ψ are implemented using a 2-layer neural network with 32 and 64 units respectively and trained using ADAM optimizer [21] with an initial learning rate of 10^{-3}. Similar to [22] we assume $p(z)$ as multivariate Gaussian with a diagonal covariance $\mathcal{N}(z; \mu_z, \sigma_z^2 I)$. We are interested in the posterior $q_{\theta^*}(z|\tilde{X})$ which learned by above objective can produce a latent representation from an occluded version of a TS sample. This learned posterior will serve as our foundation model to the

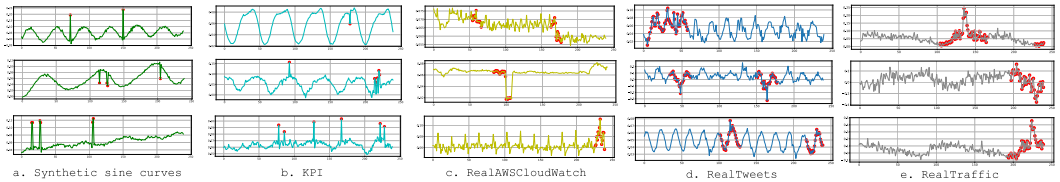

Figure 2: Labelled anomalous time series generated by C-GATS for different datasets showing generality, diversity and consistency of the method.

next stage of training. See pseudo code in Algorithm 1. **Stage 2:** We perform the same occlusion on anomalous samples where we replace the anomalous data points in X^A with zeros to obtain $\tilde{X} \sim p(\tilde{X}|X^A, Y^A)$. Note that post-occlusion the samples obtained from both normal and anomalous sequences belong to the same distribution, i.e $p(\tilde{X}|X^N, Y^A) \approx p(\tilde{X}|X^A, Y^A)$. This allows us to run inference using occluded *anomalous* sequences on a posterior learned on occluded *normal* sequences. We now make use of the anomalous training samples (X^A, Y^A) to train a generator $X^A \sim p_\phi(X^A|z, Y^A)$ conditioned on the labels Y^A where z is obtained from the learned posterior. Note that the posterior model θ^* is frozen and does not receive gradient updates during this stage of training. We model ϕ using a similar 2-layer LSTM decoder architecture as that of ψ. The condition vector Y^A, which is a binary label corresponding to each timestamp is applied temporally. We found that we must apply this condition at the very last layer of the decoder network to prevent the condition vector from interfering with the reconstruction process of the base signal and restrict it to contribute only in the anomaly insertion process in the high level feature space. This helps in achieving consistency in the generated samples. We show the qualitative and quantitative advantage of this approach in our ablation study in Supp. section 6.7. Training is done in a supervised fashion where ϕ is forced to generate an anomalous sequence by inserting anomalies in the latent space where the position and type of anomaly is controlled by the label on which the model is conditioned upon (see Algorithm 2). More specifically, we obtain ϕ^* by minimizing the below objective —

$$\min_{\phi} \sum_{i=1}^{m} -\log p(X_i^A|z_i, Y_i^A; \phi) \quad \text{where } z \sim q_{\theta^*}(z|\tilde{X}) \text{ and } \tilde{X} \sim p(\tilde{X}|X^A, Y^A) \tag{8}$$

Once trained, the decoder ϕ^* can be used to generate synthetic anomalous TS samples (X^A, Y^A) where Y^A is provided by the user which implicitly controls the attributes of anomaly such as position, duration or type. z is either sampled directly from a normal distribution or from a latent distribution produced by θ^* when given an occluded version of any normal or anomalous TS from same distribution. The overall architecture of C-GATS is shown in Figure 4 in Supplementary.

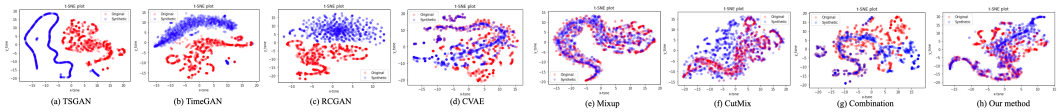

Figure 3: t-SNE visualization on Synthetic Sines dataset. Each plot denotes the visualization of a different TS generation/augmentation method. Red denotes original anomalous TS, and blue denotes the generated anomalous TS.

4 Experiments

We compare C-GATS with 7 different TS generation/augmentation methods— Mixup [43], CutMix [40], RCGAN [14] and a combination of classical methods like Scaling, Jittering, Permutation and TimeWarp [19] on 6 different public TS datasets using 8 different TS AD algorithms. Following [37], we emphasize that AD is both a quantitative and qualitative study. Hence, we observe the following desiderata as outlined in Section 1— (a) *diversity*; (b) *label-preserving*; (c) *effectiveness*; (d) *model-agnostic*; and (e) *domain-agnostic*. First two are analyzed qualitatively and the next three quantitatively.

Datasets We use 6 different datasets to run quantitative assessments of C-GATS. These datasets are common in most recent AD papers, and have (a) variety of attributes like noise, periodicity, trend, non-stationarity; (b) different types of anomalies like point anomalies, level-shift, change-point, etc; (c) are collected from different domains like machine telemetry, traffic data. This justifies our claim of domain-agnostic nature of C-GATS. Details of each dataset is described in Supp. section 6.2.

4.1 Qualitative Analysis

We apply t-SNE [35] on both the generated and real anomalous TS on the Synthetic Sines dataset to visualize the overlap between the two distributions in Figure 3, as in [31]. 3(h) shows a good overlap between the real anomalous TS and that generated by C-GATS. Furthermore, we visualize the raw generated samples by C-GATS in Figure 2. The red dots denote the inserted anomalies. In Synthetic Sines and KPI datasets, these are point anomalies while in RealAWSCloudWatch they correspond to change points. This provide support to the claim that C-GATS is able to generate *diverse* anomalies across dataset from different domains.

Next we qualitatively assess the *label-preserving* nature of C-GATS, i.e, if C-GATS is able to generate anomalies in position dictated by the conditioned label vector. We use Synthetic Sines dataset where we insert two different types of anomalies— point anomalies and level-shift anomalies randomly in the dataset and train C-GATS on it. Once trained, we use the decoder ϕ^* to generate anomalous samples X^A by passing as input a noise vector z sampled from a normal distribution along with a conditional vector Y^A as shown in Figure 1. C-GATS not only successfully inserts anomalies in the conditioned positions but also attributes the *type* of anomaly to the conditioned label vector, i.e, long anomalous period means level-shift, short anomalous period means point anomalies.

Table 1: Performance of different AD algorithms in different augmentation settings on *Synthetic Sines dataset*

AD Algorithm	TRTR			T(R+S)TR			TRTS			TSTR		
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
RobustTAD	0.76	0.73	0.74	0.76	0.75	0.75	0.74	0.70	0.71	0.77	0.75	0.75
SR-CNN	0.75	0.70	0.73	0.76	0.71	0.74	0.67	0.65	0.65	0.77	0.73	0.75
NCAD	0.80	0.74	0.77	0.81	0.78	0.79	0.75	0.70	0.71	0.80	0.76	0.77

Table 2: Performance of different AD algorithms in different augmentation settings on *KPI Dataset*

AD Algorithm	TRTR			T(R+S)TR			TRTS			TSTR		
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
RobustTAD	0.57	0.53	0.55	0.69	0.66	0.67	0.50	0.45	0.48	0.65	0.64	0.64
SR-CNN	0.55	0.51	0.54	0.61	0.55	0.58	0.47	0.43	0.44	0.60	0.55	0.57
NCAD	0.60	0.68	0.64	0.70	0.69	0.69	0.51	0.54	0.52	0.65	0.73	0.68

Table 3: Deep TS AD algorithms performance across different datasets

Algorithm	**Dataset**	**w/o Aug.**	**Mixup** *(alpha=0.2)*	**CutMix**	**Combination** *(Scaling, Jitter, Permute,TimeWarp)*	**RCGAN**	**C-GATS**
RobustTAD	Synthetic Sines	0.74 $\pm$0.005	0.74 $\pm$0.007	0.27 $\pm$0.003	0.75 $\pm$0.006	0.23 $\pm$0.002	**0.75 $\pm$0.004**
	KPI	0.55 $\pm$0.011	0.56 $\pm$0.008	0.23 $\pm$0.010	0.59 $\pm$0.003	0.19 $\pm$0.009	**0.67 $\pm$0.003**
	RealTweets	0.54 $\pm$0.021	0.53 $\pm$0.011	0.32 $\pm$0.026	0.57 $\pm$0.009	0.18 $\pm$0.041	**0.57 $\pm$0.010**
	RealTraffic	0.67 $\pm$0.026	0.68 $\pm$0.029	0.37 $\pm$0.020	0.69 $\pm$0.012	0.27 $\pm$0.071	**0.73 $\pm$0.015**
	RealAWSCloudWatch	0.34 $\pm$0.262	0.34 $\pm$0.089	0.06 $\pm$0.344	**0.36 $\pm$0.218**	0.04 $\pm$0.181	0.34 $\pm$0.192
	ArtificialWithAnomaly	0.36 $\pm$0.275	0.38 $\pm$0.118	0.33 $\pm$0.229	0.38 $\pm$0.136	0.05 $\pm$0.099	**0.41 $\pm$0.107**
SR-CNN	Synthetic Sines	0.73 $\pm$0.009	0.72 $\pm$0.002	0.18 $\pm$0.009	0.74 $\pm$0.001	0.16 $\pm$0.010	**0.74 $\pm$0.003**
	KPI	0.54 $\pm$0.008	0.55 $\pm$0.005	0.19 $\pm$0.009	0.56 $\pm$0.003	0.17 $\pm$0.011	**0.58 $\pm$0.007**
	RealTweets	0.46 $\pm$0.027	0.45 $\pm$0.019	0.24 $\pm$0.033	0.51 $\pm$0.009	0.19 $\pm$0.008	**0.53 $\pm$0.009**
	RealTraffic	0.64 $\pm$0.021	0.65 $\pm$0.017	0.33 $\pm$0.019	0.65 $\pm$0.028	0.26 $\pm$0.035	**0.66 $\pm$0.020**
	RealAWSCloudWatch	0.25 $\pm$0.319	0.25 $\pm$0.283	0.04 $\pm$0.081	**0.28 $\pm$0.193**	0.01 $\pm$0.198	0.27 $\pm$0.199
	ArtificialWithAnomaly	0.28 $\pm$0.019	0.30 $\pm$0.174	0.24 $\pm$0.111	0.32 $\pm$0.081	0.12 $\pm$0.059	**0.34 $\pm$0.011**
NCAD	Synthetic Sines	0.77 $\pm$0.008	0.76 $\pm$0.001	0.30 $\pm$0.003	0.78 $\pm$0.019	0.27 $\pm$0.071	**0.79 $\pm$0.001**
	KPI	0.64 $\pm$0.006	0.66 $\pm$0.003	0.24 $\pm$0.009	0.67 $\pm$0.010	0.21 $\pm$0.004	**0.69 $\pm$0.001**
	RealTweets	0.57 $\pm$0.019	0.55 $\pm$0.014	0.32 $\pm$0.028	0.58 $\pm$0.010	0.20 $\pm$0.085	**0.61 $\pm$0.009**
	RealTraffic	0.69 $\pm$0.029	0.69 $\pm$0.033	0.43 $\pm$0.098	0.71 $\pm$0.051	0.28 $\pm$0.171	**0.71 $\pm$0.019**
	RealAWSCloudWatch	0.35 $\pm$0.219	0.34 $\pm$0.118	0.11 $\pm$0.092	**0.37 $\pm$0.071**	0.07 $\pm$0.215	0.35 $\pm$0.111
	ArtificialWithAnomaly	0.39 $\pm$0.101	0.42 $\pm$0.213	0.36 $\pm$0.128	0.42 $\pm$0.098	0.13 $\pm$0.023	**0.45 $\pm$0.091**

4.2 Quantitative Analysis

Evaluation Frameworks We select 3 supervised NN-based, and 5 baseline TS anomaly detection (AD) algorithms to benchmark the improvement in anomaly detection quality using `C-GATS`. Details about these baseline algorithms are provided in Supp. section 6.6. We pick 7 different DA techniques to compare against C-GATS and details are in section 6.5. We adopt 4 evaluation frameworks [14], namely– TRTR (Train on real, Test on real), TSTR (Train on synthetic, Test on real), TRTS (Train on real, Test on synthetic) and T(R+S)TR (Train on real+synthetic, Test on real). We split each of the 6 datasets into a 80:20 train:test ratio. We use the 80% train set to train `C-GATS` and generate equal no. of synthetic samples as there are in the train set. More details about these frameworks are provided in Supp. section 6.3. For results, we report the average point-based precision, recall and F1 scores and justify the choice of these metrics in Supp. section 6.4.

Benchmark Results Tables 1-2 along with tables 5-8 in the supplementary show the performance of three neural-net based AD algorithms in different evaluation frameworks for each of 6 datasets. **(1)** We compare the TRTR and T(R+S)TR frameworks to see if augmenting the training data with `C-GATS` generated anomalous samples further improves the AD performance? On the simulated dataset where the training set is large and diverse (Synthetic Sines) the improvement is minimal ($< 2\%$) but on a more realistic dataset (KPI) the improvement is higher, $\sim 18\%$ increase in F1 score. **(2)** TSTR results help identify if generated samples actually lead to a useful AD model. We see that on both simulated and real-world datasets, the performance is equivalent and in some cases better than TRTR case. This indicates that the generated samples are not only realistic but also consistent with their corresponding ground truth labels leading to a comparable performance on real test sets. **(3)** In TRTS setting we see that the performance of AD models decline as compared to TRTR. This means if trained on real-world samples and tested on generated anomalous samples the detection quality declines. One could argue that this could mean the generates samples are corrupt/incorrect. But since TSTR leads to a higher performance than TRTR, we can safely conclude that the generated samples are not only good quality and correctly labelled but also much more diverse than the real dataset. **(4)** Table 3 shows the mean and standard deviation of F1 scores across 5 runs for each setting. The column of w/o Aug. simply represents the numbers from TRTR framework while all the other augmentation methods are evaluted in T(R+S)TR framework. We observe that— **(a)** Classic vision based augmentation strategies like CutMix [40] or Mixup [43] are not as effective when compared to an ensemble of traditional TS augmentation methods like scaling, jittering, permutation or TimeWarp on anomalous data. This is because the former approaches sometimes lead to corrupt anomalous samples with incorrect ground truth labels (see Figure 6 in Supp.) causing poor AD performance. **(b)** Complex GAN-based method like RCGAN [14] lead to unstable training and fail to learn sparse anomalous signal in the long complex TS. This leads to generation of unrealistic anomalous sequences and hence poor AD performance. **(c)** `C-GATS` outperforms all these augmentation methods for anomalous TS data on 5 out 6 datasets. However, when training set is small (eg: RealAWSCloudWatch dataset), `C-GATS` fails to learn good realistic patterns and hence in those cases an ensemble of classical DA methods outperforms `C-GATS`. **(d)** The algorithms Case 1-3, One-liner A and B serve as robust baselines to avoid creating an illusion of improvement in detection quality when using the DA method, as these baselines remain largely unaffected by augmentation strategies. We notice that some of these baselines, e.g. One-liner A and B have comparable, and in some cases, even better performance than some of the deep AD algorithms with augmentations (See Table 9 in Supp.). This echoes the claims made in [37] that deep learning might not always be the right solution to problem in TS AD domain. We further add that complex DA strategies do not boost the detection quality significantly in cases when the anomalies are trivial to detect.

5 Conclusion & Future Work

We present a simple semi-supervised approach to generate synthetic anomalous TS data with labels, and demonstrate that the generated samples exhibit properties similar to the anomalies in real dataset. What is unique is that our model is able to learn and embed invariances present in the real data into synthetic data without any extra supervision, leading to generation of more diverse anomalous samples as compared to traditional DA approaches. In Supp section 6.8 we discuss how this idea can be further extended to achieve not just diverse but more complex set of synthetic anomalies.

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