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Anomaly detection in streaming data using autoencoders

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Declaration of Authorship

I hereby certify that this thesis has been composed by me and is based on my own work, unless stated otherwise. No other person's work has been used without due acknowledgement in this thesis. All references and verbatim extracts have been quoted, and all sources of information have been specifically acknowledged.

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Contents

List of Figures

List of Tables

Abstract

The amount and variety of data stream generated from applications of different domain grows steadily and are valuable for big data research. One of the most important core component is the anomaly detection for streaming data, which has attracted attention and investigation in plenty of application areas, for example, the sensor data anomaly detection, predictive maintenance, event detection. Those efforts could potentially avoid large amount of financial costs in the manufacture. However, different from traditional anomaly detection tasks, anomaly detection in streaming data is especially difficult due to that data arrives over time with latent distribution changes, so that a single static model doesn't fit streaming data all the time. An anomaly could become normal along with data changing in the stream, it is necessary to maintain a dynamic system that deals with this problem. In this paper, we propose a novel LSTMs-Autoencoder anomaly detection architecture specially designed for streaming data. This is a mini-batch based streaming processing approach. We experimented with streaming datasets containing different kinds of anomalies as well as distribution changes, and the results suggest that our model can sufficiently detect anomaly in data stream and update model timely to fit the latest data property.

Chapter 1

Introduction

Anomaly detection is an core component of data mining, and widely used in the manufacturing industry, e-commerce, internet applications etc. It could avoid or reduce lose in many scenarios like machine health monitoring, credit card fraud detecting and spam email recognition, and could also be used as a preprocessing step to remove anomalies for datasets in many machine learning tasks. There are already plenty of anomaly detection techniques proposed in previous literatures, that solve this problem from variety perspectives, e.g. distance-based methods, clustering analysis, density-based methods etc.

There is no lack of anomaly detection approaches that perform good with respect to different kinds of data, however, majority of them are batch model, which means, all data should be available in advance. This becomes a shortcoming under today's big data background. With the rapid development of hardware in the last decade, the situation of data acquisition and analysis has significantly been changed. Specifically, the IoT application. Assume that we collect data from sensors attached to IoT devices, the data comes continuously and everlasting. In the beginning, no static full set of data is available for model initialization. Besides, during data analysis, we should always consider the volume and velocity of data, which means, on one hand, with traditional batch classifiers, the infinity data stream will lead to out of memory, on the other hand, streaming data usually comes in a high speed that leaving the system few processing time, the model should work with only single look at each data point in the stream. In addition, the statistical property of data may also change over time, which is formally called 'concept drift'. The model should always learn new knowledge from the stream and update its identification of anomaly automatically, while anomalies could be temporally. After a data distribution change, an anomaly possibly becomes normal in the new data environment. To this end, an anomaly detection system for streaming data should be able to 1) be initialized with only a small subset, 2) process streaming data and make prediction in real-time, 3) adapt data evolution over time.

Nowadays, LSTMs-based autoencoders are used for time series anomaly detection in order to capture the temporal information between data points. For example, Malhotra et al.

introduced an autoencoder based anomaly detection approaches in [1],[2], and achieved good performance in multiple time series dataset. However, in those approaches, they still assume that the whole datasets are available beforehand and work on static data. Also, they didn't consider the aforementioned online learning difficulties. Hence, we enhanced this kind of LSTMs-Autoencoder based static anomaly detection approaches with the online learning ability by implementing incremental model updating strategies with streaming data.

In this paper, we introduce a novel and robust incremental LSTMs-Autoencoder anomaly detection model, which designed specifically for time series data in a streaming fashion using Long Short-Term memory (LSTM) units, with also online learning ability for model updating. For each accumulated mini-batch of streaming data, the autoencoder reconstructs it with previous knowledge learned from normal data. Anomaly data (never used for training) is expected to cause significant larger reconstruction error than normal data. In addition, the model is able to update itself when detected data distribution changes.

Todo: Summary of experiment results. . .

The rest of this paper is organized as follow. In **??**, we collected previous works on anomaly detection and their shortcomings. We also refer some works on incremental neural network. In chapter 3, define the problem formally. In chapter 4, we propose our method for streaming data anomaly detection and discuss the advantage over previous works. In chapter 5, we describe the datasets used for experiments and the experimental set-up. In chapter 6, we present our experimental results. And in chapter 7, we summarize the work and discuss of success and deficiency.

Chapter 2

Related works

In this section, we present a survey on previous works in anomaly detection with classical machine learning models and with autoencoders, as well as studies of neural network updating along with streaming data.

2.1 Batch model

2.1.1 Classical machine learning based approaches

As an important component of data mining and machine learning, anomaly detection has been investigated using plenty efficient models. When talking about anomaly detection, the most intuitive solution may be detection of outliers from a dense cluster, or to find those data points that have obvious different property as their neighbors and so on. Considering the lack of label and extremely imbalanced dataset, unsupervised approaches are more widely used in practice, for example Local Outlier Factor (LOF).

In anomaly detection, the LOF is a common density-based approach. LOF shares some concepts with DBSCAN such as 'core distance' and 'reachability distance', in order to estimate local density. Here, points with substantially lower local density than their neighbors are considered as anomalies. LOF shows competitive performance in many anomaly detection tasks, especially when dealing with data with unevenly density distribution. However, when getting a numerical factor from LOF model, it is actually hard to define a threshold automatically for the judgement of anomaly.

Because normally the anomaly appears rarely in the dataset, and occurs usually in novel ways, it is expensive for labeling and hard to learn all kinds of anomalies in the training phase, so unsupervised models are commonly used. There are still a batch of semi-supervised or one-class anomaly detection models. The intuitive difference between anomaly detection and binary classification problem is the obvious few negative class data (anomalies). A typical one-class model is the One-class Support Vector Machine (OCSVM).

As an semi-supervised one-class classifier, OCSVM takes only normal data as input, and generates a decision surface to separate them from the anomaly states. By analyzing anomalies, the datasets are always bias to the normal part, and anomaly appear only rarely. So, this kind of one-class classifiers avoid making balance between the two classes. Besides, they also take advantage of classical support vector machine, with the help of kernel method, they can also deal with linearly not separable data. However, in the meantime, the choosing a proper kernel becomes a hard point of OCSVM. A suboptimal kernel function can seriously impact the performance.

Although classical machine learning approaches can handle most of the normal anomaly detection, there a still a lack of pervasive models that fit different kinds of data characters. Moreover, only few of those approaches could be directly or after some modification used for time series and streaming data, while they ignore the temporal dependency between samples.

2.1.2 Autoencoder-based batch approaches

LSTMs-Autoencoders are originally widely used for text generation because that the LSTMs are able to capture the context dependency between words and sentences. Text data are usually embedded into vector as input of autoencoder. And the tasks are either generate temporal relevant text on the decoder side or learn text representation in the hidden layer [1]. Similar problem is faced in the time series data mining due to the temporal dependency of values at each timestamp. So, in later works, LSTMs-Autoencoder are also used for time series data.

Sutskever et al. [11] use a deep LSTMs-based sequence to sequence model for language translation. In their work, the deep LSTMs encoder take single sentence as input, and learn a hidden vector of a fixed dimensionality, and then a different LSTMs decoder decodes it to the target sentence. As a translation task, they found that this encoder-decoder architecture can capture long sentences and sensible phrases, especially they achieved better performance with deep LSTMs in compare with shallow LSTMs. In addition, a valuable found is, reversing the order of words in the input sentence makes the optimization problem much easier and achieved better performance. The LSTMs based model outperforms non-LSTMs model on the long input sentence cases (more than 35 words) since its long-term memory ability.

Li et al. [5] did similar research on long paragraph text and even entire document generation using LSTMs-autoencoders. Their main contribute is the hierarchical sentences representation. The model learns words level, sentence level and paragraph level information with each respectively a LSTMs layer, so that the model captures very long-term temporal information. Moreover, they introduced an attention based hierarchical sequence to sequence model that connect the most relative part between encoder and decoder like the works around a final punctuation. They experiment with documents over 100 words,

the results show that hierarchical and attention-based hierarchical LSTMs learns even better long-term temporal information than standard LSTMs-encoder-decoder models.

As autoencoders achieves great successes in text data and speech processing, they are also used on time series anomaly detection in terms of temporal dependently data. These models train autoencoders with only normal data, and anomaly data as unknown patterns. Then the autoencoder can only reconstruct normal patterns, large reconstruction error indicates anomaly. An early work [9] uses the vanilla autoencoder to detect abnormal status of the electric power system. In order to capture temporal information, they applied sliding window on the raw data as input. As anomaly scoring method, they evaluated each sliding window with respect to their reconstruction error. As some measures in the autoencoder output vectors are more sensible to anomalies than others, they use the average absolute deviation of reconstruction error as anomaly score. And the anomaly threshold is chosen by large amount of experiments over normal data.

An important reason of using autoencoder for anomaly detection is its ability of dealing with high-dimensional data. Sakurada et al. [10] experimented with time series data that consist of 10-100 variables with no linear correlation. Comparing with reconstruction using PCA or Kernel PCA techniques, using the autoencoder reconstruction error is more easily to recognize anomalies.

In further researches, Malhotra et al. [8][6] develop the application of LSTMs-autoencoder in sequence learning into anomaly detection problem. They proposed stacked LSTM networks model to learn high level temporal patterns. They show that LSTMs outperforms normal RNNs based anomaly detection model and avoid facing to the gradient vanishing problem. They also detect anomaly based on the reconstruction error. The scoring function is based on the parameters of a estimated normal distribution of a validation set. Their experiments show that the model performs good in variety kinds of datasets. A variation of this model [7] has been proved that achieves better performance in the anomaly detection tasks, while they tell that using a constant as input of decoder instead of read time series value improves the performance of model.

2.2 Online anomaly detection over data stream

2.2.1 classical online approaches

Recently, more and more attention is paid to streaming data mining, and many efficient classical models are modified to fit the online learning property. Cui et al. [2] proposed online anomaly detection approach with grid-based summarization and clustering algorithm. They show good performance in KDD dataset for network attack detection. However, they didn't take consider only isolated data point without any temporal information measuring. Another streaming data anomaly detection framework by Tang et al. [13] use sliding window to involve the contextual dependency and temporal changes in the

stream. The anomaly detection algorithm is a modified version of LOF while LOF's high time complexity can not be directly employed to streaming data. They use comentropy to filter out most normal windows, and feed the rest to LOF.

2.2.2 Autoencoder-based online approaches

Zhou et al. [14] proposed an online incremental updating method for denoising autoencoders by modifying the hidden layer neurons in order to deal with the non-stationary streaming data properties. The kern ideal are two steps, adding hidden layer neurons to capture new knowledge, and merging hidden layer neurons if information is redundant. Their experimental result shows comparable or better reconstruction result than non-incremental approaches with only few data used during initialization. And they show that their incremental feature learning methods performs more adaptively and robustly to highly non-stationary input distribution.

Dong et al. [3] proposed a 2-step anomaly detection mechanism with incremental autoencoders. The implemented the system with ensembled autoencoders in multithreads to leverage parallel computing when large volumes of data arrive. Besides their 2-step mechanism check anomaly in the first step and verify anomaly data with previous and subsequent data (to differ between anomalous state and concept drift) to reduce false-positive rate in anomaly detection. In the experimental results, they show that their model outperforms commonly used tree-based anomaly detection model especially when concept drift presents and speed up the online processing speed with mini-batch learning and online learning in multithreads.

In this work, we implement a LSTMs-autoencoder based incremental streaming data anomaly detection model. The LSTMs-autoencoder is close to the model by Malhotra et al. [6], and we design an online model updating strategy as well as the dataset used for model updating.

Chapter 3

Preliminaries

3.1 Definition of stream

Assume that a set of devices or data warehouses provide data continuously with a specific velocity V (here we only take about numerical data). A data stream DM is defined as

$$DS = \{(x_1, t_1), (x_2, t_2), ..., (x_T, t_T), ...\} \tag{3.1}$$

where x_T is the instance arrived at timestamp t_T represented by a multi-dimensional vector.

In order to feed the streaming data to LSTMs, the stream is accumulated to windows and batches as Figure 3.1. Every T instances are accumulated to a window as a single LSTM input. And MB is the predefine batch size, each batch contains MB windows.

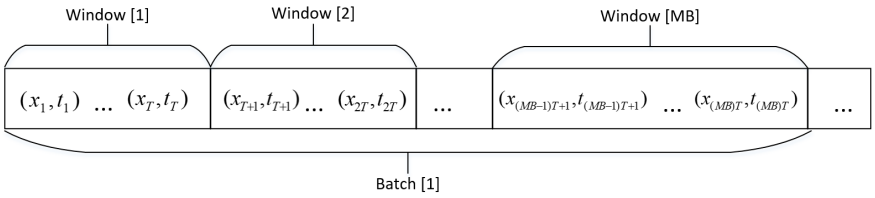


Figure 3.1: Data stream

3.2 Definition of anomlaies

Pointwise: A data point (instance) is anomalous if this point is distant from other observations according to some specific measurement metrics. This is used in fine-grained anomaly detection tasks, that need to find out every single anomalous instance, e.g. credit card fraud detection, spam email detection.

Window-based: A window is anomalous if the window contains one or more anomalous data points. For most of the window-based anomaly detection algorithm, they only calcu-

late the anomaly score of a given window, it's hard and sometimes not necessary to find out which data points in this window are those anomalies.

In the anomlay detection experiments, normal data is treated as positive class and anomalies as negative class. The confusion matrix is shown in Table **??**

		Actual value	
		Normal	Abnormal
Prediction	Normal	TP	FP
	Abnormal	FN	TN

Table 3.1: Confusion matrix

The target is to achieve higher true positive rate (equation 3.2, predict normal data correctly) and while remain lower false positive rate (equation 3.3, miss classify anomalies as normal). The evaluation metric is Area Under the Curve (AUC), where curve represents the receiver operating characteristic curve, and is created by plotting the true positive rate against the false positive rate at various threshold settings.

$$TPR = \frac{TP}{TP + FN} \tag{3.2}$$

$$FPR = \frac{FP}{FP + TN} \tag{3.3}$$

3.3 LSTMs

Recurrent neural networks(RNNs) are widely used for speech, video recognition and prediction due to its recurrent property that captures the temporal dependency between data in compare with other feed forward networks. However, the volume of RNN's memory is limited, and vanishing gradient is also a difficulty by training RNNs. Therefore, the long short-term memory networks (LSTMs) are a kind of reinforced RNN that is able to remember meaningful information in arbitrary time interval. A LSTM network is a recurrent neural network with neurons being LSTM units. Figure 3.2 on the next page shows a classical structure of a LSTM unit. LSTMs are able to capture long-term memory while there are a forget gate and a update gate in the LSTM unit, that select necessary previous information and new coming information according to the input data at each time step. The information is transferred to the next step within the cell state. Besides, each LSTM units also output its value by going through a softmax function.
A LSTM unit can be unfolded over time, as shown in Figure 3.3 on the facing page. The LSTM unit takes a data window as input, namyly takes one instance at a time. Therefore, the LSTM unit extracts useful and drop useless temporal information from the window of data.

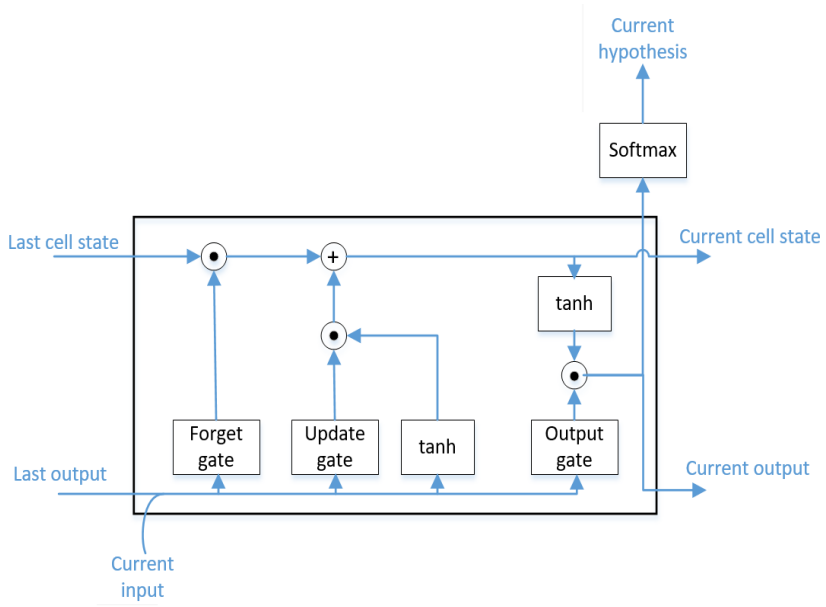


Figure 3.2: The LSTM unit

Deep LSTM RNNs are built by stacking multiple LSTM layers. Note that LSTM RNNs are already deep architectures in the sense that they can be considered as a feed-forward neural network unrolled in time where each layer shares the same model parameters. It has been argued that deep layers in RNNs allow the network to learn at different time scales over the input[4]. Figure 3.4 on the next page is a example of stacked deep LSTM neural network, there are 3 LSTM layers, each can be unfolded into 5 time steps, so the LSTMs take a window in length 5 as input and the output is in same size.

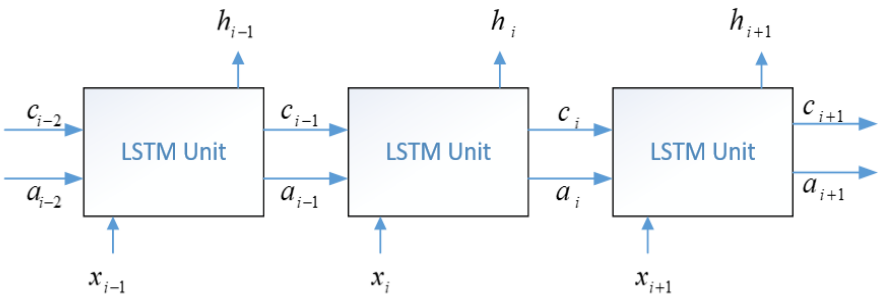
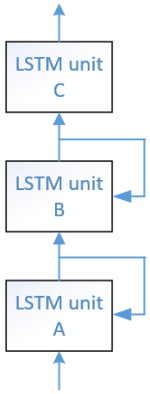


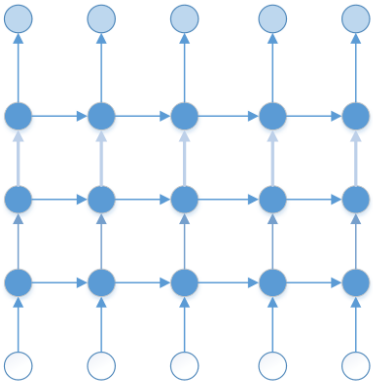
Figure 3.3: Unfolded LSTM unit

3.4 Autoencoders

An autoencoder (Figure 3.5 on the following page) is an artificial neural network with symmetrical structure. Normally an autoencoder has at least one hidden layer that consists of less neurons than input and output layers. And the basic aim of autoencoders is to reconstruct its own input and learn a lower dimensional representation (encoding) of



(a) Deep folded LSTMs



(b) Deep unfolded LSTMs. Each horizontal dark dot chain is an unfoldered LSTM unit over time, hollow dots and grey dots are windows of inputs and outputs.

Figure 3.4: Deep LSTMs

input data in the hidden layer. Moreover, the autoencoders are also used for anomaly detection by measuring the reconstruction error between inputs and predictions. Normally the component between input layer and hidden layer is called encoder, and the symmetrical component between hidden layer and output layer is called decoder. For input χ, the objective function is to find weight vectors for encoder and decoder to minimize the reconstruction error (3.4).

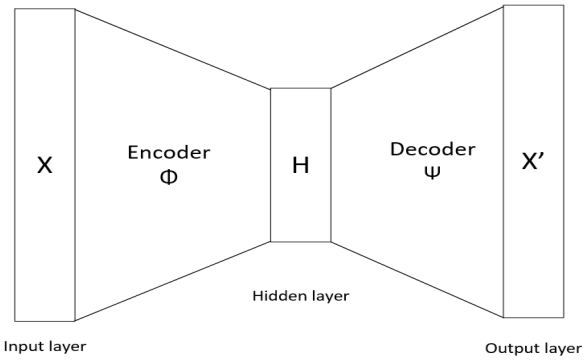
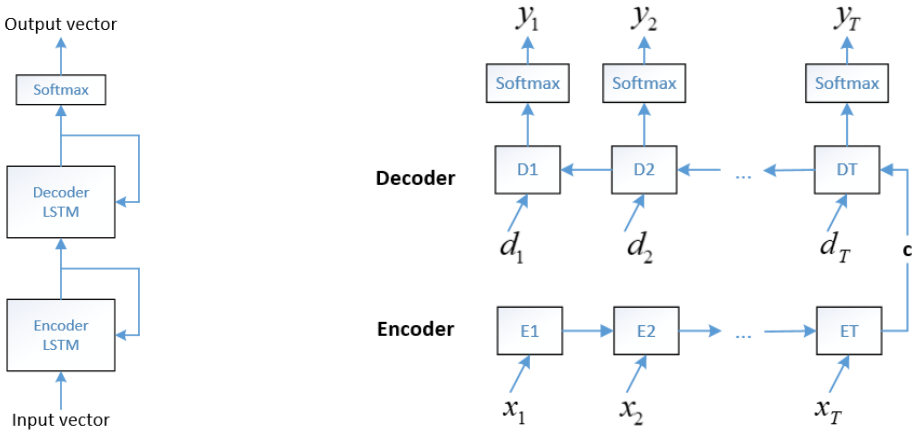


Figure 3.5: Autoencoder

$$\begin{aligned} \Phi &: \chi \rightarrow H \\ \Psi &: H \rightarrow \chi \\ \phi, \Psi &= argmin \, \| \chi - (\Psi \circ \Phi) \chi \| \end{aligned} \tag{3.4}$$

LSTMs-autoencoder has the same encoder-decoder architecture, while the neurons are LSTM units and connected in the way described in section 3.3. Figure 3.6 on the next page is a basic LSTMs-based autoencoder architecture with single LSTM layer on both encoder and decoder side. Our incremental LSTMs-autoencoder is based on this struc-

ture. The model takes window with length T as input (one instance in each step). The cell state carries sequence information and is passed through LSTM unit over time. When the encoder reaches the last encoder state, namely ET in Figure 3.6b, the cell state is actually the fix length embedding of the input window, and copied to the decoder as initial cell state of decoder, so that the input information is also transferred to the decoder. And the decoder predict the window in reversed order in order to make the optimization problem easier. To be notice is, different from aforementioned deep LSTMs in section 3.3, the encoder outputs at each time step are not directly used as inputs of decoder, while between the encoder and decoder is actually not the same logical connection as stacked LSTMs. Here, the outputs of encoder are ignored, and there are different works contributes to the research of decoder inputs. Cho et al. [1] feeds the input sequence to the decoder for a learning phrase representation task, Malhotra et al. [6] feed to decoder LSTM unit at each time step the prediction of last time step as input, and in a extended work [7] they feed the decoder always a constant vector for an anomaly detection task, because the finial cell state already carries all relevant information to represent the input window. In our model, we feed the decoder a constant vector.



(a) Folded LSTMs-Autoencoder (b) Unfolded LSTMs-Autoencoder

Figure 3.6: LSTMs-Autoencoder

3.5 Streaming data generator: Apache Kafka

We utilize Apache Kafka as the streaming platform. Kafka is a widely used Publish/Subscribe architecture streaming system. It different from classical message queue technique with its fault tolerant, durable and large capacity properties. Different application or database can publich data to a specific topic of Kafka (topic is the data category mechanisms used in Kafka), and other processors can consume data from this topic (Figure 4.1 on page 15). In our experimental setting, the data source is static databases, Kafka generate real-time data stream pipeline as data source publish records to the experiment topic, and furthermore the stream of records will be consumed by different consumers like our analysis model, visualization model etc. This configuration can be easily scaled up to

more complicated and demanding real world use cases. Each record in the Kafka stream pipeline is in the form of [Key, Value, Timestamp], where keys are used for positioning and values carry the data record.

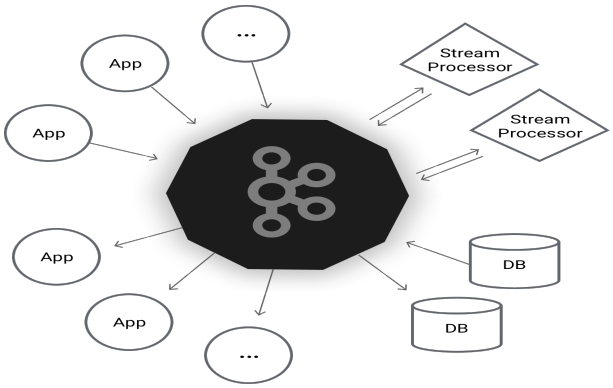


Figure 3.7: Kafka diagram

Chapter 4

Proposed model

4.1 Framework overview

The proposed model is a full flow from data stream generation, anomaly detection with autoencoder-based model and online model incremental updating. Apache Kafka is used as the stream generator as shown in Figure 4.1. The first received batches of streaming data are used for decision of model hyperparameters and the model initialization. Hyperparameters includes the hidden layer size, batch size, input window length as well as the number of epochs. Once the hyperparameters are learned, an autoencoder will be constructed and initialized with random weights. A subset of the streaming data is used for initial model training (only normal data used for training). Furthermore, the model is used for online anomaly detection, and will be retrained when the retraining condition is triggered. As aforementioned, topic is the data category mechanisms in Kafka. The streaming data are published to a topic, and the prediction results are send back to another Kafka topic for visualization.

The Consumer 2 in Figure 4.1 is actually the core component of the LSTMs-autoencoder model. Once the initialized model is available, the online phase is then start. As shown in Algorithm 1, if a batch of streaming data is available, the model will start do prediction, evaluation, and check whether current batch is useful to store for later retraining.

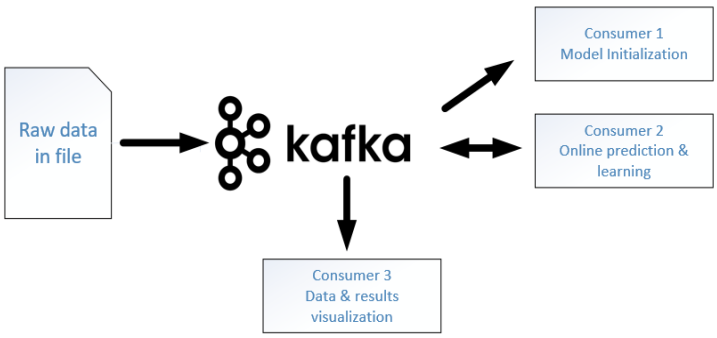


Figure 4.1: Data stream pipeline

Algorithm 1: Pipeline

```
input: performanceThreshold, retrainDataSize
needRetraining = False;
retrainBuffer = [ ];
while Batch data available do
    batch, label = getBatchData();
    if len(retrainBuffer) == retrainDataSize then
        retrain(retrainBuffer);
    else
        pred = predict(batch);
        result = evaluation(pred,label);
        if result >= performanceThreshold then
            continue;
        else
            if label == "normal" then
                retrainBuffer.append([B, label]);
            else
                continue;
            end
        end
    end
end
```

4.2 LSTMs-Autoencoder initialization

4.2.1 Encoder-decoder architecture

The LSTMs-Autoencoder is consist of two LSTM units, one as encoder and the other one as decoder. The encoder inputs are fix length vectors with shape <MB, T, D>, where MB is the number of data windows contained in a mini-batch, T is the numbers of data points within each data window, and D represents the number of data dimensionality. Here, MB and T are learned as hyperparameter in the initialization phase. And on the decoder side, it will output exactly the same format data vector for each mini-batch. The LSTM unit copies its cell state for itself as one of the cell input at next timestamp. At the last timestamp of encoder, the cell state of LSTM unit is the hidden representation of the input data vector and copied to the decoder unit as initial cell state, so the hidden information can be passed to the decoder. The size of hidden layer representation vector, namely the size of cell state is another hyperparameter need to be learn in the initialization phase. The larger the hidden vector, the more information can be captured during the process, so it is a feature highly depends on the data. Similar to previous study [11], we also train the encoder and decoder with time series in reverse order. For example, if the input data fragment are data points from timestamp t1 to t2, then the decoder will predict data point at t2 at first, and then back to t1 step by step, while this trick makes the gradient escarpment between last state of encoder and first state of decoder smaller and easier to learn.

In order to let the whole process happen online, the model initialization also utilizes streaming data. Once a small subset of streaming data is available, hyperparameters are learned, and then another dataset that consists only of normal data is collected from stream used for training. Assume that once an anomaly detection task is determined, the anomalous state is explicit defined and a subset of anomalous data is available for model initialization. We split the normal data into four subsets, N_1 for hyperparameters tuning, N_2 for model training, N_3 for early stopping, and scoring parameters learning, N_4 for testing. And abnormal data are split into two subsets, A_1 for decision of anomaly score threshold, A_2 for testing.

4.2.2 Anomaly detection mechanism

The autoencoder reconstructs the input with its knowledge of normal data, so if the input data contains anomalies, the reconstruction error will be obviously large due to the lack of anomalous knowledge. For input $X^{(i)}$, the reconstruction error is

$$e^{(i)} = \left| X^{(i)} - X'^{(i)} \right| \tag{4.1}$$

similar to [6], the reconstruction error of data points N_3 is used to estimate the parameters μ and $\Sigma$of a normal distribution $\mathcal{N}(\mu, \Sigma)$ using maximum likelihood estimation. The anomaly score for a point $x_t^{(i)}$ is defined as

$$a^{(i)} = (e^{(i)} - \mu)^T \Sigma^{-1} (e^{(i)} - \mu) \tag{4.2}$$

During the initialization phase, a anomaly score threshold τ is also learned using N_3 and A_1 as

$$\tau = argmaxAuc(a(N_3), a(A_1)) \tag{4.3}$$

The anomaly score of every instance in a window is compared with the threshold, and values over the threshold are predicted as anomalies. If a window contains more than τ_N anomalous values, this window is predicted as anomaly.

4.3 Online learning

However, if we consider using the model for streaming data, the autoencoder might get outdated because of the relative small and simple initialization dataset and concept drift happed along with time. So the update of model is necessary. In this section, we introduce the incremental learning function of the LSTMs-Autoencoder.

4.3.1 Retraining dataset

Normally when the LSTMs-Autoencoder is initialized, it is ready for online prediction. There is a multi-thread setting in the online learning architecture. A sub thread collects

data instances continuously from the Kafka publisher, and in the meantime, the main thread is working on real-time anomaly detection as long as mini-batches of data is provided by the sub thread. For each single window in the mini-batch, every instance is reconstructed and calculated the anomaly score using Equation (4.2) on the preceding page. The system maintains two data buffers for retraining (Figure 4.2), one for normal data, and the other one for anomalies.Considering the fact that a well mastered window leads to lower reconstruction error, and higher error indicates new features in the data, and we can measure this reconstruction error level by the predefined normal distribution on reconstruction error. Normal data windows with average mean error over μ are regarded as not good mastered and will be appended into the normal buffer for retraining. As anomalies appear rarely in the stream, we collect all anomalous windows in the abnormal buffer for threshold determination during retraining. To this end, when a retraining process is triggered, only wrong predicted normal data, those not well mastered, are used for retraining.

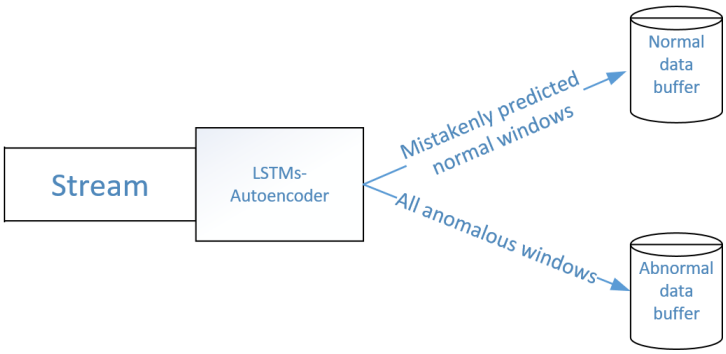


Figure 4.2: Retraining data buffer

4.3.2 Retraining trigger

During the online processing, if the system detected that the model doesn't fit the current data any more, then the retraining is triggered and done with the latest collected data in the two buffers. During experiments we found that, anomalies only appears rarely in the stream, so it often happens that the model need retraining to fit the latest data, but still lack of anomaly data in the buffer to update the threshold. To this end, we separate the updating of model and threshold, namely, when the retraining is triggered, update threshold only if there is enough abnormal data, otherwise only retrain model with the normal buffer. In case of the normal buffer reaches a predefined size, the model is retrained in a sub thread while the main thread keeps processing the stream.

4.3.3 Model retraining

There are two retraining strategies, continue training and start from scratch. Once the retraining is triggered, the system examines the normal buffer. The normal buffer is divided into two parts, hard examples and extreme hard examples with the boundary being

$\mu + 2\sigma$. When the number of extreme hard examples in the buffer exceeds a specific proportion, it means that a great change happened in the stream, and the model is retrained from scratch. Otherwise the model still contains valuable information, so it is continue trained with the buffer data.

Alternative: We use the hidden vector as the low-dimensional representation of input data. Hidden vector of all normal data is used to check, whether a new coming data is similar to the previous normal data.

Similar to the model initial training, parameters μ and σ are learned from a sub retraining set. They are combined with the previous parameters to generate the new one. If the anomaly buffer is large enough, a new threshold will also be learned, and combined with the previous value.

4.3.4 Optimizer

Adam, BPTT

Chapter 5

Experimental setup

5.1 Datasets

We use 5 datasets in our experiments, PowerDemand, SMTP, HTTP, SMTP+HTTP and ForestCover, those are widely used streaming datasets in the streaming data mining area [6][3][12]. Statistical features are listed in Table 5.1. PowerDemand is a small univariate time series that records the power demand over a period of one year. Weekdays' demand is higher than weekends' and daytime is higher than nights, demand of special days (e.g. festivals) are abnormal. We demonstrate a synthetic example with visualization using this dataset while the trends and anomalous states are relative obviously. SMTP, HTTP, SMTP+HTTP are streaming anomaly data extracted from KDD Cup 99 dataset. According to Tan et al. [12], HTTP contains sudden surges of anomalies and SMTP does not, but possibly exhibits some distribution changes within the stream. Because of the difficulty to point out where the distribution changes occur in the stream, the HTTP+SMPT dataset is derived by connecting SMTP and HTTP, so that a distribution change is occurred when the communication protocol is switched. The ForestCover dataset is from the UCI repository, which contains 6 kinds of forest cover types. Similar as Dong et al. [3], we defined the smallest class Cottonwood/Willow with 2747 instances as anomaly, and the rest 5 classes as normal class with distribution changes.

Table 5.1: Datasets information

Dataset	Size	Dimensionality	Anomaly proportion(‰)
PowerDemand	35 040	1	21.92
SMTP	96 554	41	12.25
HTTP	623 091	41	6.49
SMTP+HTTP	719 645	41	7.26
ForestCover	581 012	32	3.53

5.2 Parameter tuning

Grid search over:
batch size window length hidden layer size epoches

5.3 Baseline model

EncdecAD offline

Chapter 6

Experimental results

6.1 Grid search

best parameter for each dataset

Epoches
batch size
window length
hidden layer size

6.2 Anomaly detection performance

AUC for each dataset
False alarm count, miss alarm count

6.3 Retraining

6.3.1 Power demand example

6.3.2 Comparasion: with and without retraining

performance and reconstruction error
what data used for retraining

6.3.3 Reaction of concept drift and distribution changes

observation of model perfermance around positions of concept drift and distribution changes

6.3.4 Running time analysis

Chapter 7

Conclusion

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