KDD99Cup dataset summery

|  |  |  |  |
| --- | --- | --- | --- |
|  | 10% KDD | KDD | Stmp+http |
| Size | 73M | 725M | 101M |
| Training (normal) | 6.8M |  |  |
| Validation (normal) 1 & 2 | 2M & 2M |  |  |
| Validation (anomaly) | 14M |  |  |
| Test (normal) | 2M |  |  |
| Test (anomaly) | 42M |  |  |

Related works

* **LSTM-based Encoder-Decoder for Multi-sensor Anomaly Detection (Autoencoder, Anomaly detection,batch)[1]**

The EncDecAD (short for Encoder-Decoder scheme for Anomaly Detection) is Long Short Term Memory Networks(LSTMs) based anomaly detection architecture for time series. The utilization of LSTMs enabled the model to avoid missing the temporal information in the time series. The EncDecAD model consists of two parts, namely an encoder and a decoder, which have identical LSTMs based structure. The encoder takes a mini-batch of time series as input and outputs a hidden vector, and then follows the decoder, taking the hidden vector as input and trying to reconstruct the original input mini-batch as output. The reconstruction error is the main criterion of anomaly likelihood, while the model is only trained with normal instances, so for unacquainted anomalous data, the reconstruction error is considered to be relative higher.

According to their experimental results, the EncDecAD model could separate normal and anomalous points with a large margin. It works on different kinds of datasets, even non-periodic unpredictable data. However, The model is designed only for batch data, and need to train on the whole dataset. Time series data always comes continuously along with time, and sometime also with concept drift. If we consider the velocity and volume feature of time series data, an online incremental model is then necessary. Also, in the online fashion, it is challenging to learn from a massive stream of data the optimal number of features.

* **Online Incremental Feature Learning with Denoising Autoencoders**

**(Autoencoders over streams)**

The authors introduced an incremental feature learning algorithm to determine the optimal model complexity for streaming data based on the denoising autoencoder. The main idea is feature adding and merging. Specifically, it adds new features to minimize the objective function’s residual, and if features are redundant, then merge them to prevent overfitting and obtain a more compact feature representation. The result shows that it’s a good way to learn features from a large dataset by starting with a small set of initial features and automatically adjusting the number of features. And this method leads comparable or lower reconstruction and classification error than the stationary fashion.

* **Threaded ensembles of autoencoders for stream learning**

**(outlier detection over streams, streaming autoencoders, concept drift)**

This paper proposes a multi-threaded neural network model to deal with streaming data. On each thread running a autoencoder model and two buffers connecting data stream and model, in order to avoid model being idle or data stream being delayed. The thread ensemble enables the model with continuous learning capacity. They use a reconstruction error based criterion for anomaly detection, and maintain a buffer containing only normal data for decision of anomaly threshold. In order to distinguish between anomaly and concept drift, they check the points before and after a specific data point, while continuous founded anomalies indicate the possibility to be concept drift.

However, they didn’t talk about how the arrival rate of data stream and the fluctuations in the volume of data would impact the detection of anomalies. In addition, how emergent of the concept drift happens could also be a influence factor.

**(new/emergent class detection over streams)**

Structure

Abstract

1. Introduction
   1. Background, use case examples, importants
   2. Existing anomaly detection methods
   3. Challenges of current data\Time dependency
   4. Lack of model for time series and streaming data anomaly detection
   5. Autoencoder based data streaming AD model
2. Related works
3. Outlier detection on static data
   1. Distance based
   2. Density based
   3. Neighborhood based
   4. Waveform based
   5. One-class SVM
   6. HMM based

But those models do not consider the temporal dependency

1. Outlier detection for streams
2. Deep Learning approaches: unsupervised Autoencoder based models

(solved the multi-dimensional time series anomaly detection problem)

1. EncDecAD
2. TimeNet

But those model always needs have all data in advance, could not deal with data changes (they work with stationary data).

1. Neural network based online learning architecture
   1. Add & merge
   2. Threaded ensembles of autoencoders for streaming learning

But not exactly take time series as input (didn't apply any window, namely temporal combination)

1. From the super-/unsuper-/semisupervised learning perspective
2. Basic concepts
   1. Definition of a stream
   2. Method of processing the stream
   3. Definition of an outlier (point & window)
   4. Autoencoders | LSTMs
3. An autoencoder-based framework for unsupervised anomaly detection
   1. Overview / architecture of the framework
   2. Autoencoder component initialization
      1. EncdecAD based architecture (input, output, hidden layer)
      2. LSTM Input format
      3. Reconstruction error, anomaly score, parameters

Autoencoder might get outdated--> how to update the autoencoder

* 1. Online learning for batch-based outliers
     1. Updating stratergy

* + - Model
      1. Start from scratch -- if reconstruction error continuously being high
      2. Continue training with last-seen data -- if reconstruction error shortly high
    - Parameters(mu, sigma, threshold)
      1. Update, if prediction performance bad (e.g. F-beta low, miss alarm etc.)
      2. To avoid overfitting, previous parameter still as a part of the new parameter
    1. Maintenance of dataset for retraining
* Keep storing N batches streaming data in the buffer
* Store summarization of all seen batches
* Label data that the model mistakenly predicted, to pay more attention on them by retraining

1. Experimental setup
2. Datasets description
   1. Amount of anomaly
   2. Normal, anomaly proportion
   3. Periodicity
   4. Dimensionality
3. Initialization with first n batches streaming data
   1. Wait until accumulated enough data for initializing the model
   2. Split into normal sets
4. Sn: Training normal set
5. Vn1: Validation normal set1 for early stopping
6. Vn2: Validation normal set2 for parameter learning
7. Tn: for testing of training

And anomaly sets

1. Va: Validation anomaly set for parameter learning
2. Ta: for testing of training
   1. Dropout rate of autoencoder
   2. Save to disk
3. Streaming data generation
   1. Apache Kafka
   2. Kafka setup and configuration
   3. Deal with latency problem
4. Evaluation metric
   1. #False alarm, # miss alarm
   2. F-beta for performance
   3. Reconstruction error of normal data for model fitness of data
   4. \*Area under the curve based on anomaly score

1. Experiment results
2. Hyperparameter grid search
3. Generally performance
4. When updating is triggered
5. Reaction of concept drift, non-significant anomalies
6. Comparasion of performance before/after updatng, with/without updating
7. Runtime comparasion
8. Conclusion
   1. How online learning helps the model to adjust the stream trend
   2. Is the general performance comparable to troditional batch approaches
   3. Possiable reasons of suboptimal performance during experiment
   4. Future works

Abstract

Data stream is a data format appears in plenty of big data research scenarios, for example, manufactural sensors, production line data etc. Here anomaly detection plays an important role for use cases like predictive maintenance, event detection, and could potentially avoid large amount of financial costs. However, different from traditional anomaly detection tasks, anomaly detection in streaming data is especially difficult while data comes along the time with latent changes, so the model doesn’t fit the data all the time.

In this paper, we introduce a novel autoencoder based anomaly detection methods specially designed for streaming data. The model takes mini-batches of data from the stream as input, and try to reconstruct it using autoencoder, and the anomaly likelihood is informed from the reconstruction error. Experimental results shows that our model can sufficiently detect anomaly from data stream and update model online to fit the latest data.

**Key words**

LSTMs, autoencoders, anomaly detection, online learning

Introduction­

(Problem introduction, problem importance)

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

(why problem hard, short coming of previous works)

There is no lack of approaches that perform really good for anomaly detection, however, most of them are focusing on batch data, 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 also been changed. Specifically, the IoT application. Assume that we collect data from sensors attached to IoT devices, the data comes continuously and everlasting. During data analysis, we should always consider the volume and velocity of data, which means, on one hand, with traditional batch-based classifier, the infinity data stream will lead to out of memory, on the other hand, streaming data usually comes with a high speed that leaving the system few processing time. 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 definition of normal and anomalous automatically. 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.

(short coming of approaches similar to this paper, problems need to be solved, lead to inspiration & good ideas)

Malhotra et al. introduced similar autoencoder based anomaly detection approaches in [1],[2], and achieved good performance in multiple different time series dataset. However, in this approach, they assume that the whole datasets are available beforehand, and didn’t considered the aforementioned online learning difficulties. Hence, we enhanced this kind of autoencoder based anomaly detection approaches with the online learning ability by using incremental knowledge learning and model updating strategies based on the streaming data.

(high level ideas and concepts of approach in this paper)

In this paper, we introduce a novel and robust incremental autoencoder-based anomaly detection model, which designed specifically for time series data in a streaming fashion using Long Short-Term memory (LSTM) units as neurons, with also online learning ability for model updating. The model need only one pass of the streaming data. For each accumulated mini-batch of streaming data, the autoencoder try to reconstruct 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 update itself online according to criterions based on performance.

(summary of tested examples, summary of results)

(Todo: about label: semi-supervised, label for scoring, one-class for training)(Todo: we experimented with datasets: \_, \_ , \_. The model shows robustness )

Related works

There is already pretty much research based on anomaly detection, some of them referred to deal with streaming data.

**Classical machine learning based approaches**

As an important component of data mining and machine learning, anomaly detection has been investigated using plenty efficient models.

**LOF**

In anomaly detection, the Local Outlier Factor(LOF) is a common distance-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 use get a numerical factor from LOF model, it is actually hard to define a threshold automatically for the judgement of anomaly.

**OCSVM**

Another widely used model is the domain based One-class Support Vector Machine. As an unsupervised 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.

Although classical machine learning approaches can handle most of the normal anomaly detection, only few of those approaches could be directly or after some modification used for time series or streaming data, while they ignore the temporal dependency between samples.

**Autoencoder-based anomaly detection approaches**

LSTMs-Autoencoders are originally widely used for text generation. 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. As text data are relevant between sentences or in the sense of words within a sentence, it is similar to the streaming data temporal dependency problem.

Sutskever et al. \cite{seq2seq} 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. did similar research on long paragraph text or even entire document generation using LSTMs-autoencoders. Their main contribute is the hierarchical sentences representation. They learn words level, sentence level, paragraph level and document level each with respectively a LSTMs layer, so that the model captures very long-term temporal information. Moreover, they introduced a 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 shows 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 \cite{eps} 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. Sakurada et al. \cite{ dimensionalityreduction} 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. \cite{lstmad}\cite{encdecad} 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. The 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 \cite{timenet} has been shown that achieves better performance in the anomaly detection tasks. The author tells that, using a constant as input of decoder instead of read time series value improves the performance of model.

**Online incremental learning with autoencoders**

Zhou et al. 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, merging hidden layer neurons if there are information redundancy, and adding hidden layer neurons to capture new knowledge. 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 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.

Preliminaries

1. **Definition of a stream(time series, dimensionality, volume, velocity, label)**

Assuming that there are some devices or data warehouse that generate data continuously with a velocity **V** (here we only taking about numerical data). The data stream from 1st timestamp until ith timestamp is descripted as:

i=1,2,3….

Where represent the instance at timestamp t in the data stream. And we assume the volume of data stream is infinity, which means, there are always available data instances generated by the data source.

To be more generally, we consider as either univariate or multivariate, is defined as

N = 1,2….

Where is the feature space of the data stream with size N. For each instance , the label = {0,1} tells either the instance is normal or abnormal.

1. **Method of processing the stream(sliding window)**

For further online processing and detection, we generate mini-batches upon the data stream. The streaming data is accumulated as window **W,** and a mini-batch consist of one or more windows.

t=1,2,3…. , **WN**= 1,2,...

t=1,2,3…. , **WN**= 1,2,... **BN**=1,2,…

Where is a window with length **WN** start from instance at timestamp **t**, is a mini-batch consists of **BN** windows starting from window .

1. **Definition of an outlier (point & window)**

**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 calculate the anomaly score of a given window, it’s hard and sometimes not necessary to find out which data points of this window are anomalous.

The target is to achieve higher true positive rate (predict normal data correctly) and while remain lower false positive rate (miss classify anomalies as normal).

1. **LSTMs and autoencoder**

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 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.

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 single LSTM unit can be unfolded over time. The LSTM unit take a data window as input, one data point at a specific time point for each step. Therefore, the LSTM unit extracts useful and drop useless temporal information for the window of data.

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. ( TrainingandAnalyzingDeepRecurrentNeural Networks)

An autoencoder 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 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 () of the autoencoder, and the symmetrical component between hidden layer and output layer is called decoder (). For input X, the objective function is to find weight vectors for encoder and decoder to minimize the reconstruction error.



LSTMs-autoencoder has the same encoder-decoder architecture, while the neurons are LSTM units and connected in the way described in section \ref{LSTMs}. \Fref{fig:encdecad} 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 structure. 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 \Fref{fig:encdecad2}, 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 \ref{LSTMs}, 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. \cite{phraserepresentation} feeds the input sequence to the decoder for a learning phrase representation task, Malhotra et al. \cite{encdecad} feed to decoder LSTM unit at each time step the prediction of last time step as input, and in a extended work \cite{timenet} 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.

**Proposed model**

**Overview / architecture of the framework**

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 \Fref{fig:kafka}. 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 in section \ref{sec:apachekafka}, 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 Consumer2 in** \Fref{fig:kafka} 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 \ref{alg:pipeline}, 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.

**Kafka structured data stream generation**

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. In the experimental setting, our data source is static databases, Kafka generate real-time data stream pipeline as data source publish records to the specific topic (the data category mechanisms used in Kafka), 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.

**Autoencoder component initialization**

* + 1. EncdecAD based architecture (input, output, hidden layer)

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 <Batch\_num, Step\_num, Elem\_num>, where Batch\_num is the number of data windows contained in a mini-batch, Step\_num is the numbers of data points within each data window, and Elem\_num represents the number of data dimensionality. Here, Batch\_num and Step\_num are learned as hyperparameter in the process beginning. And on the decoder side, it will output exactly the same format data vector for each mini-batch. As introduced in last section, 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[sutskever et al 2014], 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, N1 for hyperparameters tuning, N2 for model training, N3 for early stopping, and scoring parameters learning, N4 for testing. And abnormal data are split into two subsets, A1 for decision of anomaly score threshold, A2 for testing.

* + 1. Reconstruction error, anomaly score, parameters

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.

**Online learning for batch-based outliers**

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. The main contribution of this paper is the incremental learning setting of the autoencoder model.

**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 \ref{eq:score}. The system maintains two data buffers for retraining, 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 $\mu$ 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.

**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.

**Retraining**

**Once retraining process is triggered, the model will be retrained using data from retrain buffers. Windows of normal buffer are divided into retraining set and retraining validation set. The retraining is a continuation of the initialization or previous retraining with identical data format. Parameters mu, sigma as well as threshold are learned from the retraining validation set and anomaly buffer data. The parameters are learned in the same way as in initialization phase.**

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 $\mu$ and $\sigma$ 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.

* + 1. Updating strategy

* + - Model
      1. Start from scratch -- if reconstruction error continuously being high
      2. Continue training with last-seen data -- if reconstruction error shortly high
    - Parameters(mu, sigma, threshold)
      1. Update, if prediction performance bad (e.g. F-beta low, miss alarm etc.)
      2. To avoid overfitting, previous parameter still as a part of the new parameter
    1. Maintenance of dataset for retraining
* Keep storing N batches streaming data in the buffer
* Store summarization of all seen batches
* Label data that the model mistakenly predicted, to pay more attention on them by retraining

1. Experimental setup

**Datasets description**

We use 5 datasets in our experiments, Power demand, SMTP, HTTP, SMTP+HTTP and ForestCover, those are widely used streaming datasets in the streaming data mining area \cite{encdecad}\cite{threaded}\cite{tan}. Statistical features are listed in Table. Power demand 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. \cite{tan}, 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. \cite{threaded}, we defined the smallest class Cottonwood/Willow with 2747 instances as anomaly, and the rest 5 classes as normal class with distribution changes.

**Datasets separation**

We separate each dataset into initialization set and streaming set, both contain normal and abnormal data. Further, the initialization set is divided into

G(n&a): for grid search

Tr(n): for model initial training

P(n&a): for model parameter learning

Te(n&a): for initial testing

Where “n” represents normal data and “a” represents abnormal data.

And the streaming set is published to Kafka to generate data stream.

**Parameter tuning for each dataset** (window length, number of hidden neurons, epochs, batch size)

For each dataset, we carry out a grid search step to tuning the model hyperparameters that fit the data best. Here we try multiple combinations of window length and hidden size for each data set.

For each dataset, the grid search set G contains 5% -15% anomalies, and same amount of normal data together with the anomalies make up the testing set in grid search. The rest normal data is used for training. Because of the uncertainty of the random neural network weight initialization, we do each experiment 10 times and take the average result to reduce the impact. To be noted that during every divisions, the consistency of streaming data is persisted, or in other words, no random sampling took place. The aim function is \Fref{eq:target}. A good model should make the reconstruction error as large as possible in order to make the classification easier.

Where N and A are the number of normal and anomalous examples in the testing set.

Transform the observations to have a specific scale. Specifically, to rescale the data to values between -1 and 1 to meet the default hyperbolic tangent activation function of the LSTM model. (from internet)

Each experiment 10 times, in order to reduce the impact of the random initial weights of LSTMs

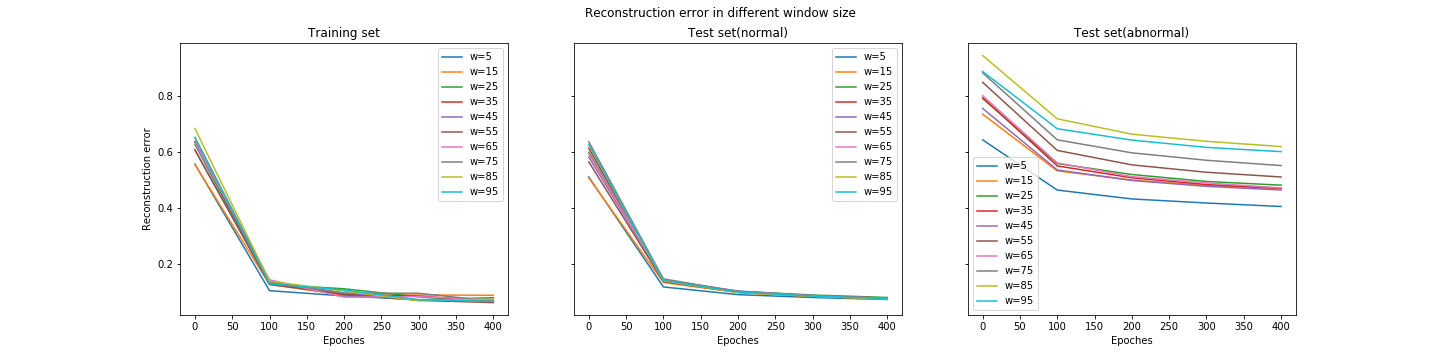
Epochs: 100 -1000, 100

Hidden neurons: 1 – 100, 5

Window length: 5 – 100, 10

Batch size: 1 – 10, 1

**Reconstruction error & window size**



Firstly, we experiment with different window size with 30 hidden units. As shown in FIGURE, with training epochs raising, the reconstruction error of all data deceases. The reconstruction error of normal testing data doesn’t change a lot with different window size, however, larger window size generally makes the anomalous data reconstruction error larger, so that could be easier to be separated from normal data. With experiment on other hidden layer size setting, the results show similar character.

In order to figure out how many hidden neurons are necessary to capture the information of input data, we experiment with different hidden layer size and window length. The target is maximum difference between normal and anomalous reconstruction error. If we fix epochs to 400, FIGURE shows that more hidden layer will make the difference larger. For the smtp dataset, there is a knee point around 15-20 neurons, the increase over 20 neurons show no more remarkable performance improvement. And in this experiment, larger window size also goes towards out target.

1. Initialization with first n batches streaming data
   1. Wait until accumulated enough data for initializing the model
   2. Split into normal sets
2. Sn: Training normal set
3. Vn1: Validation normal set1 for early stopping
4. Vn2: Validation normal set2 for parameter learning
5. Tn: for testing of training

And anomaly sets

1. Va: Validation anomaly set for parameter learning
2. Ta: for testing of training
   1. Dropout rate of autoencoder
   2. Save to disk
3. Streaming data generation
   1. Apache Kafka
   2. Kafka setup and configuration
   3. Deal with latency problem
4. Evaluation metric
   1. #False alarm, # miss alarm
   2. F-beta for performance
   3. Reconstruction error of normal data for model fitness of data
   4. \*Area under the curve based on anomaly score
   5. Retrain efficiency (time & effect)

To test the performance of the online anomaly detection system, less false alarm and more correct alarm are two basic criteria.

1. Experiment results

With parameters learned from \Fref{sec:parametertuning}, autoencoders are learned for each dataset with the beginning of streaming data. The anomaly detection performance is described by AUC. For each dataset, we compare the AUC of online phase that without and with continuously model and parameter retraining.

In order to show the benefit of model retraining along the stream, we demonstrate the online learning process of the small set Power demand in this section. The power demand dataset does not contain clear incremental or sudden concept drift, but the normal pattern still different slightly to each other. Lack of overall impression during the model initialization phase can lead to failures in the online phase. \Fref{fig:power\_retraining} shows 3 continual days power demand in normal state. Due to the lack knowledge of current pattern, the autoencoder reconstructs the input time series high than desired. A model retraining process is triggered after the second day with last seen data, and the model performs well again on the third day.

After each retraining process, the parameters mu, sigma and threshold of anomaly scores are also updated. \Fref{fig:parachanges} shows the parameter changes over the stream.

During the online phase, each normal window that is not given with a low enough anomaly score is appended to the retaining buffer to accumulate the retaining set. In order to find out what kind of data is used for retaining and how much retraining data is enough for model updating, we experiment with different retraining buffer size on the power demand stream.

1. Reaction of concept drift, non-significant anomalies

The main advantage of online model is its ability to take reaction against sudden data distributional changes in time. The SMTP+HTTP data set is composed by directly connect HTTP set after SMTP, so there is a sudden concept drift in between. The model is initialized with only SMTP data, so HTTP is completely unknown knowledge for the model. \Fref{fig:smtp+http} is a box plot of anomaly scores of normal instances from different part of the stream. The block B1 is statistic of normal instances’ anomaly scores between the last model updating on the SMTP side and the concept drift happening, which is relative lower due to the good grasp of SMTP data. Once the concept drift takes place, namely, HTTP data arrives with the stream, more normal instances with higher anomaly score appears in B2. Although a retraining process is triggered soon after the concept drift, the normal instances’ anomaly scores still increase due to lack of HTTP instance. Gradually, with the increasing amount seen HTTP data, the model gives normal data lower anomaly score again during B4 to B6. As a result, we can observe that, when a sudden concept drift happened in the stream, our model needs only 3 to 4 times retraining with totally 3500 instances for retraining to master the new data distribution again.

Sometimes concept drift over the stream are slight, periodically, and potentially repeated. A single slight concept drift may not be able to trigger the retraining, but new knowledge should be save to retraining buffer, so that once the model retrained with the fresh knowledge, the model should perform well when the same concept drift happens. We experiment with the FOREST dataset. There are 7 kinds of forest cover types as labels. We take the least type No.4 as anomaly while the rest 6 kinds as normal. Cover types appears alternately over the stream, so that it could be treated as slight concept drift.

The FOREST model is trained with hidden size 45 and window length 20. In the beginning, 3000 windows are used for initialization, and 26050 windows comes as stream. Every normal window contains more than 10 scores over threshold is treated as hard window and appended to retraining buffer. Also, every abnormal window is saved for threshold updating. When retrain buffer size reaches 750, a retraining process will be triggered. The is triggered 3 times over stream.

As shown in \Fref{fig:init}, normal instances from class 1 and 2 are the majority of initialization set, and all kinds of cover types appears.

1. Comparison of performance before/after updatng, with/without updating
2. Runtime comparasion
3. Conclusion
   1. How online learning helps the model to adjust the stream trend
   2. Is the general performance comparable to troditional batch approaches
   3. Possiable reasons of suboptimal performance during experiment
   4. Future works

Edit

There is no lack of anomaly detection approaches that perform good with respect to different kinds of data. Supervised approaches take anomaly detection as a binary classification problem of “normal” instances and “abnormal” instances, and all instance labels should be available in advance. The key difference to other classification problem is the amount of class label is extremely biased to the normal class. In order to avoid doing data augmentation or down sampling, unsupervised approaches are more direct solutions to this problem, which find out the instances that fit least to the majority as the anomalies. Furthermore, in most situations, partial labels are available, and semi-supervised and one-class models are more efficient. They learn the pattern from labeled normal data, test data that not fit the learned pattern perfectly is likely to be the anomalies. Different kinds of anomaly detection approaches fit different use cases and data character. 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 in the traditional way. 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. Data distribution changes should not be classified as anomaly, and anomaly show up rarely in over the stream, they should also not be oversighted. 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. 4) model should be able to deal with the biased class problem.\\

LSTMs are a kind of recurrent neural network and proposed for temporal dependently data. In the last decade, LSTM are used widely in time series prediction, text prediction. And LSTMs-based autoencoder is a good choice for sequence to sequence problem, e.g. language translation, time series data embedding.

Neural networks, including autoencoders, are normally used in batch fashion, namely the whole training set is available, and trained by backpropagation. When come to online setting, only small subset accumulated data from stream are available for model initial training, which may be suboptimal. Assume that the initialization set is enough to train a convergent model, the further streaming data are used for further model updating to adjust latest streaming data changes and the patterns never seen ever. Unlike batch models, instead of aiming at best overall performance, online neural networks are learned to achieve best sequential performance for current streaming data. The difficulty is to detect when model should be updated according to latest data and updating with which part of data. The short-term changes of data distribution should not cause model variation, while permanent concept drifts should trigger model updating as soon as possible.

Ghazikhani et al. introduced an online neural network model for streaming data towards to the two major problems of online learning, concept drift and imbalanced classes. In term of concept drift, they applied a forgetting function that weights recent instances to navigate the model to the drifted model, so that the model always learns pattern from latest data. Besides, for class imbalance, they proposed a error function for two-class imbalance problem with the basic idea that the error function generating higher error signals for instances in the minority class.

Kochurov el at. \cite{bayesian} designed incremental learning framework for deep neural networks based on Bayesian inference. They argued that, naïve deep learning approaches for incremental learning applies Stochastic Gradient Descent (SGD), which intent to keep previous learned model remembered, and enhanced with current batch of new data. However, by SGD, the neural network model is likely to converge to the local optimal of the latest batch of data with of preserve the previous knowledge. Their Bayesian framework estimate the posterior distribution over the weights of the model in the condition of previous knowledge and use the Bayesian rule to sequentially update the posterior distribution in the incremental learning.

LSTMs-autoencoder training

The model training refers to two phases, initialization and online retraining. The loss function of LSTMs-autoencoder is intuitively the average reconstruction error of a window, and the model optimizer we used is Adam Optimizer \cite{adam}, same as in \cite{timenet}. Although Stochastic Gradient Descent (SGD) is a common approach to training neural network

\section{Synthetic example}

\label{sec:synthetic}

In order to show the benefit of model retraining along the stream, we demonstrate the online learning process of the small set Power demand in this section. The power demand dataset does not contain clear incremental or sudden concept drift, but the normal pattern still different slightly to each other. Lack of overall impression during the model initialization phase can lead to failures in the online phase.

\subsection{Reaction of concept drift}

\label{sec:reaction}

\Fref{fig:power\_retraining} shows 3 continual days power demand in normal state. Here, the trigger strategy is performance based. Due to the lack knowledge of current pattern, the autoencoder reconstructs the input time series high than desired on day 1(left diagram). This could be caused by seasonal changes on the power demand, which is slightly, gradually, and not able to cause misclassify directly. However, the increase of normal data reconstruction error makes the margin between two classification classes smaller, and harder to make decision. As a consequence, the model retraining process is triggered after the second day with last seen data in the retrain buffer, and the model performs well again on the third day.

\begin{figure}[h]

\centering

\includegraphics[width=15cm, height=4cm]{power\_retraining}

\caption[Retraining effect on Power Demand dataset]{Retraining effect on Power Demand dataset}

\label{fig:power\_retraining}

\end{figure}

\subsection{Retaining}

\label{sec:retrainig}

During the online phase, the model is retrained two times, before batch No.10 and No. 27. After retraining, the normal data reconstruction error becomes lower while for abnormal data becomes higher, so that the classification becomes easier.

\begin{figure}[h]

\centering

\includegraphics[width=10cm, height=4cm]{power\_online\_score}

\caption[Power Demand dataset online learning scores]{Power Demand dataset online learning scores}

\label{fig:power\_online}

\end{figure}

In addition, it is also meaningful to figure out how effective the retraining. Another experiment based on the power demand dataset is the normal reconstruction error comparation without any retraining, with performance-based retraining and retraining after every batch. As shown in \Fref{fig:power\_retrain},

\begin{figure}[h]

\centering

\includegraphics[width=10cm, height=4cm]{power\_retrain\_compare}

\caption[Power Demand dataset retrain effectiveness]{ Power Demand dataset retrain effectiveness}

\label{fig:power\_retrain}

\end{figure}

After each retraining process, the parameters mu, sigma and threshold of anomaly scores are also updated. \Fref{fig:parachanges} shows the parameter changes over the stream. As there is no clear concept drift during the power demand stream, the parameters changes just slightly, and learn latest knowledge from the retrain buffer.

\begin{figure}[h]

\centering

\includegraphics[width=6cm, height=4cm]{para\_update}

\caption[Online parameter updating]{Online parameter updating}

\label{fig:parachanges}

\end{figure}

During the online phase, each normal window that is not given with a low enough anomaly score is appended to the retaining buffer to accumulate the retaining set. In order to find out what kind of data is used for retaining and how much retraining data is enough for model updating, we experiment with different retraining buffer size on the power demand stream.

Once 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 stream, 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 \Fref{eq:score}. The system maintains two data buffers for retraining (\Fref{fig:buffer}), 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. After each batch, the label for each data window is determined by either expert or the model itself. We predefine a performance threshold for normal data. Normal data windows that containing more that performance threshold over-anomaly-score-threshold instances 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 score threshold determination during retraining.

Because the out-of-date buffer not might be collect from previous concept drift time period, and not benefits to current retraining, we maintain the retain buffers with a queue structure, so that only a specific amount of most fresh data can stay in the buffer. To this end, when a retraining process is triggered, only not well mastered fresh normal data are used for retraining.

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 trigger the retraining so long as the anomaly buffer is not empty. If the anomaly data are not enough to make up a single batch, then we duplicate the anomaly buffer until the batch size.

The first retraining trigger strategy depends on the buffer size. In case of the normal buffer reaches a predefined size and anomaly buffer is not empty, the model is retrained in a sub thread while the main thread keeps processing the stream. The approach is suitable for larger, relative stationary data, while even concept drift happens, large amount of data arrives quickly to enrich the retrain buffers, and trigger retraining in time. And this approach highly depends on the performance threshold that decides when a data window from stream should be appended to the buffers, namely, retraining is not directly depends on the real-time prediction performance.

Another retraining trigger strategy is designed for smaller data set, where the waiting time of retrain buffer full might be long after concept drift happening. During the waiting time, there can be other concept drifts, and the prediction performance is suboptimal during this time period. So, for smaller data sets, the retraining trigger should directly relate to real-time performance. A simple way is, compare the batch performance with the first batch after last retraining or streaming beginning. The reason is, the model is only retrained with normal data, therefore every retraining brings new knowledge to the model, and improve the performance, so the batch performance should at least same as or better that the first batch performance, otherwise it indicates concept drift.

Once retraining process is triggered, the model will be retrained using data from retrain buffers. Windows of normal buffer are divided into retraining set and retraining validation set. Once the online phase starts, the LSTMs-Autoencoder is loaded into memory, and further model retraining are all done in memory. The retraining is a continuation of the initialization or previous retraining with identical data format. Parameters mu, sigma as well as threshold are learned from the retraining validation set and anomaly buffer data. The parameters mu and sigma are the mean and variance (or covariance for multivariate data) of reconstruction error estimated by normal validation set during training. So we learn new parameters in the retraining using normal validation set as well.

For each dataset, we use half data for initialization and the other half for online prediction. The experimental results reported are averaged over 10 runs. For each run, the model is given with random initial weights. Each subset used for training and prediction are preprocessed with locally, in order to scale them into [0,1] to fit the LSTM activation function.

With parameters learned from \Fref{sec:parametertuning}, autoencoders are trained for each dataset with the beginning of streaming data. The anomaly detection performance is described by AUC. For each dataset, we compare the AUC of online phase that without and with continuously model and parameter updating (\Fref{tab:performance}). The Power demand set retrain trigger depends on the batch performance, and for the rest datasets, retraining only triggered when retrain buffers are full. The retraining brings overall performance improvement on all datasets comparing to stationary models. Especially in the SMTP+HTTP dataset, the stationary without learning concept drifted knowledge performs clearly worth than the model with updating.

In order to compare the performance with and without retraining, and after each retraining, another example is to calculate the AUC value for each specified time period. As Shown in \Fref{fig:compare}, the x-axis is the periods before first retraining(shown as P1 in each subplot), between first and second retraining, and so on. For each dataset, we compare the AUC value of stationary model (trained with only initialization set) and adaptive model (online updated). For most cases, the adaptive models outperform stationary models, which shows the models profits from the knowledge updating over streaming data. To be notice that the SMTP+HTTP set contains sudden concept drift around P3, which leads to a sharp decline of the stationary model. In the meantime, the adaptive model is slightly influenced by the mixed knowledge at P3 but keeps outstanding performance when the stream turned to HTTP side.

Anomaly detection attract more and more attention in the data mining field and have been applied to plenty of industrial use cases, which achieved perfect effectiveness and avoids large amount of financial spending. At the same time, the industrial applications need critically anomaly detection models under the big data background, specifically, ability to deal with high-volume, high-velocity data. In this paper, we proposed an adaptive LSTMs-autoencoder for streaming data anomaly detection. In the previous works, autoencoders are widely used in NLP tasks, e.g. language translation, sentence understanding. Vanilla autoencoders and deep autoencoders are also have been used to anomaly detection based on reconstruction error. \cite{encdecad} is the first work that use LSTMs-autoencoder for anomaly detection, with concentration to protection of temporal dependency between time series data. Our work uses similar LSTMs-autoencoder architecture, and enable the model to work with streaming data, and update model according to criterions. Our model shows good performance in detecting anomalies and outperforms the stationary model with the online updating setting.

In terms of streaming data anomaly detection, we mainly focus on the concept drift over steam and model reinforcement by the last seen data. In the experiment with SMTP+HTTP dataset, our model shows robustness against sudden concept drift and adjusted the new data distribution very quickly. In the experiment with FOREST dataset, the model masters serried and slight concept drifts also well. We also demonstrated an intuitive model online learning process with the small Power Demand dataset. The run time of adaptive models are significantly higher than stationary models due to the long model retraining time and the retraining data collection process.

Our model is designed under the assumption that there are expert labeling available during the online phase, which make the hard window collection become possible, and they are used for model updating. In the future work, a further research direction is to scale the model into fully automated without expert labeling online. Similar verification step as in \cite{threaded} could be added after online prediction to make the model prediction more reliable, so that the data labeling can be directly according to the model prediction.

Sehr geehrte Frau Freyt,

Ich bedanke mich herzlich für die Einstellung und freue mich auf die Arbeit am Fraunhofer ISST. Ich würde gerne die genanten Unterlagen schnell wie möglich abzugeben. Darüber habe Ich jedoch noch folgenden Fragen,

1. Ich habe noch keinen Führerschein, so geht es?

2. Muss die 4.0 Bescheinigung bis 20.07. abgegeben werden?

3. Frage über ‘02\_Li\_Personalbogen‘: Ist Ja/Nein oder Abschlussnoten an der Spalte „Abschluss“ von „schul- und Berufsausbildung, besondere Kenntnisse“ auszufüllen?

Ansonten würde ich auch gerne mal fragen, wie die Reisekosten vom Vorstellungsgespräch erstattet werden sollen? Brauche ich entsprechenden Formular ausfüllen? Vielen Dank

\subsection{Reaction of a series of concept drifts}

\label{sec:reaction}

Sometimes concept drift over the stream are slight, periodically, and potentially repeated. A single slight concept drift may not be able to trigger the retraining, but new knowledge should be saved into retraining buffer, so that once the model retrained with the fresh knowledge, the model should perform well when the same concept drift happens. We experiment with the ForestCover dataset. There are 7 kinds of forest cover types as labels. We take the least TYPE4 as anomaly while the rest 6 kinds as normal. The ForestCover stream is generated type by type, as shown in the bottom chart of \Fref{fig:fcd}. During the beginning phase, TYPE1 data appears in the stream, part of which is used for model initialization. Afterwards follows instances from TYPE2, TYPE3, TYPE5, TYPE6, TYPE7 and finally TYPE2 appears again during the ending phase. Anomaly data (TYPE4) is randomly distributed in the stream. Because the model is only initialized with TYPE1 data, every appearance of a new cover type will potentially cause a performance decrease. The concept drift under this setting is then the type changes over stream.

The points on the time axis in \Fref{fig:fcd} indicates the model updating. In the anomaly score chart, the scores for anomaly data are generally larger than normal data except when concept drifts take place. Once data stream from a new cover type appears in the stream, there are always peaks in the normal data score plot, and the difference to anomaly data scores decreases. After performance being impacted, the normal buffer is filled with hard windows shortly, that triggers the model updating quickly after the concept drift.

During the experiment, there are two cases delay the updating. Firstly, because of the fixed size of buffer, if a model updating is just triggered shortly before a concept drift, then the hard windows from new cover type need more time to fill the buffer and trigger updating. In \Fref{fig:fcd}, before TYPE3 arrive, there was a updating at the end of TYPE2, and buffered was emptied, so that the model didn’t take any action against the concept drift. Secondly, if a concept drift only appears in a short period, e.g. the TYPE7, which is also not enough to fill the buffer and trigger updating. However, under both aforementioned cases, the new information of concept drift, namely the new cover types, are stored in the buffer, and will be used for next model updating. If the concept drift missed model updating due to too short appearance period, we suppose that this would also not cause catastrophic effect over the stream prediction.

\begin{figure}[h]

\centering

\includegraphics[width=15cm, height=10cm]{ forest\_conceptdrift}

\caption[ForestCover stream concept drift]{ ForestCover stream concept drift. The chart on the bottom shows the cover type over the stream. The top chart shows average anomaly scores for every 100 windows}

\label{fig:fcd}

\end{figure}

|  |
| --- |
|  |

The main advantage of online model is its ability to take reaction against sudden data distributional changes over time. The SMTP+HTTP data set is composed by directly connecting HTTP set after SMTP, so there is a sudden concept drift in between. The model is initialized with only SMTP data, so HTTP is completely unknown knowledge for the model. \Fref{fig:smtp+http} shows the scores for both normal and abnormal data over the SMTP+HTTP stream. In the beginning, only SMTP data in the stream, and partially used for model initialization. In the online prediction phase, once the HTTP data arrives, the first peak of normal data scores’ curve appears, and then the model updating is triggered, with buffer data being few hard SMTP data and most HTTP data. After the first model updating, the performance of model is still suboptimal due to the lack of enough HTTP data, therefore there are two further model updating process triggered during the following stream. As a result, the overall anomaly detection for SMTP+HTTP stream is good only except the short period after concept drift. The model updating are triggered in time after concept drift, and afterwards no redundant updating are triggered.

In this section, the streaming data and the model basic will be introduced. At first, we formally define a data stream used in the experiments. Furthermore, we figure out the definition of anomalies in streaming data, and metrics to evaluate anomaly detection. And finally we refer the main concept of autoencoders and LSTMs, which are the basic architecting and component of our model. \Fref{tab:noration} is a summarization of notations used in this section.

\begin{table}[h]

\begin{center}

\begin{tabular}{ll}

\hline

Notation & Description \\ \hline

DS & Data stream

x\_T & Instance arrived at time T

$t\_T$ & Timestamp of time T

MB & Batch size

$c \in R^hs$ & LSTM unit cell state with hs dimensions.

a & Cell output

$\chi$ = R^d & Feature space with d dimensions

X & A random variable take values from $\chi$

$\Phi$ & Shaping function of autoencoders

$\Psi$ & Activation function of autoencoders

H & Hidden layer representation of autoencoders

$d\_T$ & Decoder input at time T

\end{tabular}

\end{center}

\label{tab:notation}

\caption{Table of notations }

\end{table}

Generally, the autoencoder reconstructs normal data with relative lower reconstruction error while anomaly data with significant larger reconstruction error. \Fref{fig:power\_re} demonstrates two typical data windows (weeks) in PowerDemand, one normal and one anomaly. The Monday of anomaly week (right) is a special data, which has an abnormally low power demand. Even so, the autoencoder still reconstructs the Monday as usual with a higher score, therefore the reconstruction error is obviously larger on Monday, and the model labels this week as anomaly.

Even there will be concept drift over the stream, which will lead to an entirely increase or decrease in the input side, and the decoder output side remaining, our model can still deal with this problem with its online parameter updating ability. While the anomaly scores are calculated by the **mahalanobis distance** to the estimated normal distribution of normal data reconstruction errors in the validation set, by every model updating, the model estimates new normal distribution and relevant parameters with the latest collected validation set, so that the reconstruction error based anomaly detection is robust against concept drift.

In this section, we experimented out online LSTMs-Autoencoder model with five different streaming data. With the PowerDemand dataset, we demonstrated a synthetic example of our model, which shows the reconstruction error based anomaly detection mechanism and how the reconstruction adapt to new coming streaming data through model updating. Furthermore, we use the two dataset that contains obvious concept drift, SMTP+HTTP and ForestCover. The model reacts quickly to sudden and drastic concept drift, and potentially more updating will be triggered after concept drift to catch enough valuable information from the drifted stream. And when multiple concept drifts happen temporally and shortly, the model misses some of them, but the fresh information of those concept drifts are still accumulated to the buffer and used by next updating.

The updating trigger strategy depends on the buffer size. If concept drift happens, large amount of data arrives quickly to enrich the updating buffers, and trigger updating in time. And the trigger highly depends on the hard window criterion that decides when a data window from stream should be appended to the buffers. In case it is necessary to react very quickly after the concept drift, then the criterion of ‘hard’ should be lower, so that more windows during concept drift will be added to the buffer.\\