Anomaly Detection Scheme for Intelligent Transportation System Using RNN-RBM Model

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Abstract— An intelligent transportation system (ITS) is an advanced application which aims to provide innovative services relating to different modes of transport and traffic management and enable users to be better informed and make safer, more coordinated, and smarter use of transport networks. Analysis of traffic data is an essential component of many intelligent transportation system applications where the quality of data plays an important role. Anomaly detection in intelligent transportation system is playing a key role in intelligent transportation systems. Anomalies can be caused by different factors, such as accidents, extreme weather conditions or, rush hours. In this paper, propose a deep learning method which can detect anomalies in intelligent transportation system by analyzing the dataset collected from traffic management centre .Here combine the Recurrent Neural Network and Restricted Boltzmann Machine to detect anomalies in intelligent Transportation System .The proposed model shows the accuracy of 99.82 percentage.

***Keywords*— ITS , anomaly, RBM, RNN, traffic data.**

1.INTRODUCTION

Intelligent Transport Systems[1],or ITS ,is a new transportation system which aims to resolve a variety of road traffic issues, such as traffic accidents and congestion, by linking people, roads, and vehicles in an information and communications network via cutting edge technologies. It includes, for example, a road traffic information provision system in which road traffic information is collected via roadside sensors and then provided to drivers. ITS provides people with a variety of convenient road traffic applications. In addition, the provision of new ITS applications through the use of a variety of information and communications technologies greatly contributes to the creation of new business opportunities and markets, as well as the vitalization of economic activities.

The benefits of intelligent transportation system includes creating an inter connected transport systems with open communication between devices and vehicles, actively managing traffic, helping public transport to keep on schedule and ensuring citizens have access to real-time information about traffic and public transportation conditions. The ability to detect anomalies in the data traffic can, among other things, help detect components that are close to breaking down, and help reduce downtime by making it possible to switch the component before it breaks down.

Anomalies are defined as observations that are inconsistent with the rest of the data. Generally, anomalies can be categorized in two main groups. First, outliers in the data that are due to malfunctioning sensors, and second, unexpected measurements that arise because of non recurrent traffic congestion on the road e.g. incidents or adverse weather. Here propose anomaly detection in intelligent transportation system using deep learning method. Deep learning is a machine learning technique. It teaches a computer to filter inputs through layers to learn how to predict and classify information. Observations can be in the form of images, text, or sound. The inspiration for deep learning is the way that the human brain filters information. Its purpose is to mimic how the human brain works to create some real magic.

The Recurrent Neural Network-Restricted Boltzmann Machine (RNN-RBM) model is different from many other models in that it use multivariate dependencies. The model is a combination of the RNN model and the RBM model and to better understand the combined RNN-RBM model, an explanation of each of these models is given below. A RNN makes use of the temporal dependence and use previous computations as input to each new computation.

RBM is a two-layered artificial neural network with generative capabilities. They have the ability to learn a probability distribution over its set of input[16]. RBM can be used for dimensionality reduction, classification, regression, collaborative filtering, feature learning ,and topic modelling. RBMs area special class of Boltzmann Machines and they are restricted in terms of the connections between the visible and the hidden units. This makes it easy to implement them when compared to Boltzmann Machines.

Here combined the RNN and RBM models into an RNN-RBM model. The purpose was to further utilize the forecasting capability of the two models and to create a model that allowed more freedom to describe the temporal dependencies involved. The model extends the RNN model by adding an RBM at each time step. The output layer of the RNN, is no longer a direct representation of the visible units intended to forecast, but instead lays ground to the parameters for the RBM model.

2. RELATED WORK

In recent years, Cyber security[2] researchers have designed many anomaly detection models to protect the network against attacks perpetrated by malicious users against different multimedia applications such as remote video-on-demand, video conferencing, real time content delivery, online gaming, etc. In this direction, deep learning architectures[3] such as Convolution Neural Network (CNN), Deep Belief Network (DBN), Restricted Boltzmann Machine (RBM), Stacked Auto Encoders, Recurrent Neural Networks (RNN), etc., are widely used.

For example, Chu et al. [4] devised an abnormal event detection scheme for videos where they used 3-dimensional CNN to extract the spatiotemporal information of the inputs. Xu et al. [5] proposed a method for detection of unusual events in videos via Stacked Sparse Coding and intra-frame classification strategies based on the probabilistic outputs of SVM. Sabokrou et al. [6] used a fully CNN to detect anomalies in crowded activities. Similarly, Ribeiro et al. [7] presented an anomaly detection approach using Convolution Auto encoder (CAE) where aggregation of high level features was done with the input frames to analyse their effect on the performance of CAE.

Similarly, Feng et al. [9] devised a deep learning based model for abnormal event detection where PCA Net was used for feature learning, and a deep Gaussian mixture model was proposed to explore the video event patterns. Sun et al. [10] propounded a hybrid neural network model for abnormal emotion detection on social media by integrating CNN and Long Short Term Memory scheme.

Since these methods are based on end-to-end training and representation learning, they are widely used in pattern recognition as compared to the traditional machine learning approaches. Although, training of deep learning methods is computationally expensive and requires a massive amount of data, the combination of these approaches with reinforcement learning could be potentially useful.

Similarly, Peng et al. [15] presented an SDN-based flow detection method using K-nearest neighbors algorithm where double P-value of transductive confidence machines was used for the classification of SDN flows. In [16], Ha et al. introduced a traffic sampling strategy for software-defined networking (SDN). Instead of analyzing all the packets, the sampling of suspicious traffic was performed which minimizes the capture-failure rate of the malicious flow. Carvalho et al. [17] presented an SDN-based ecosystem to detect unusual network traffic patterns where a multi-feature analysis was employed to profile the normal traffic usage.

3. METHODOLOGY

With the conception of smart city transmuting cities into digital societies, making the life of its citizens easy in every facet, Intelligent Transport System becomes the indispensable component among all[11]. In any city mobility is a key concern; be it going to school, college and office or for any other purpose citizens use transport system to travel within the city. Leveraging citizens with an Intelligent Transport System can save their time and make the city even smarter. Intelligent Transport System (ITS) aims to achieve traffic efficiency by minimizing traffic problems. It enrich users with prior information about traffic, local convenience real-time running information, seat availability etc. which reduces travel time of commuters as well as enhances their safety and comfort.

The application of ITS is widely accepted and used in many countries to- day[12]. The use is not just limited to traffic congestion control and information, but also for road safety and efficient infrastructure usage. Because of its endless possibilities, ITS has now become a multidisciplinary conjunctive field of work and thus many organizations around the world have developed solutions for providing ITS applications to meet the need.

Figure 1:Intelligent Transportation System

Traffic Management Centre (TMC) is the vital unit of ITS[13]. It is mainly a technical system administered by the transportation authority. Here all data is collected and analysed for further operations and control management of the traffic in real time or information about local transportation vehicle. Well organized and proficient operations of Traffic Management Centre depends on atomized data collection with precise location information than analysis of that data to generate accurate information and then transmitting it back to travelers.

4. ARCHITECTURE

Recurrent Neural Network and Restricted Boltzmann machine combined together form RNN-RBM model[14].The purpose was to further utilize the forecasting capability of the two models and to create a model that allowed more freedom to describe the temporal dependencies involved. The model extends the RNN model by adding an RBM at each time step. The purpose was to further utilize the forecasting capability of the two models and to create a model that allowed more freedom to describe the temporal dependencies involved. The model extends the RNN model by adding an RBM at each time step. The output layer of the RNN, is no longer a direct representation of the visible units intended to forecast, but instead lays ground to the parameters for the RBM model. This

can be seen graphically in Figure.

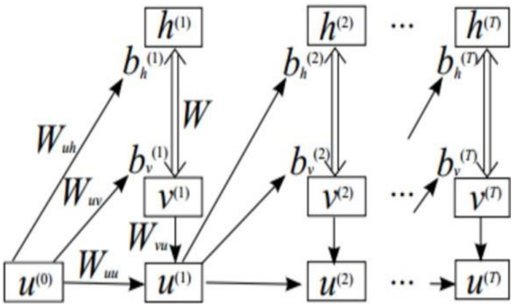

Figure2:RNN-RBM model.

The bottom layer constitutes the RNN model and the top two layers constitutes the RBM model. The model consists of nine parameters; W ,b_v and b_h as part of the RBM model, W_{uu}, W_{vu}, u(0) and b_u as part of the RNN model and W_{uh} and W_{uv} to connect them. The initial values for the matrices W , W_{uu} , W_{vu} , W_{uh} and W_{uv} can be set to small random normalized values and the initial values for the bias vectors b_v , b_h , b_u and u (0) can be set to zero. The dimensions of the parameters are given by the number of units in the visible layer, n_v , the number of hidden units in the RBM layer, n_h , and the number of hidden units in the RNN layer, n_{hr} .

The dimensions of the parameters are given by the number of units in the visible layer, n_v , the number of hidden units in the RBM layer, n_h , and the number of hidden units in the RNN layer, n_{hr} .The number of hidden units in the RBM layer and the RNN layer will be set by evaluating a number of combinations of parameters. The bias vectors for the RBM model b_v and b_h are updated through the hidden units for the RNN layer.

5.EXPERIMENT SETUP AND RESULT

A .SYSTEM SETUP

A.1 Data Collection and Data Preparation

Data collection is the process of gathering and measuring information from countless different sources. In order to use the data we collect to develop practical artificial intelligence (AI) and machine learning solutions, It must be collected and storedinawaythatmakessenseforthebusinessproblemathan d.Datapreparation is the process of transforming raw data so that data scientists and analysts can run it through machine learning algorithms to uncover insights or make predictions.

Here collected time series data of intelligence transportation system. A time series is a series of data points indexed (or listed or graphed) in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time. Thus it is a sequence of discrete-time data. Time series data have a natural temporal ordering.

A.2 Explore Dataset

Data exploration is an approach similar to initial data analysis, whereby a data analyst uses visual exploration to understand what is in a dataset and the characteristics of the data, rather than through traditional data management systems. The collected data is then explored using python libraries like seaborn, matplotlib,etc[18].Seaborn and Matplotlib are two of Python's most powerful visualization libraries. Seaborn uses less syntax and has stunning default themes and Matplotlib is more easily customizable through accessing the classes. And also specify the dataset into the train data and test data. In the dataset 80 percent- age of data is used for training and 20 percentage data is used for test data.

A.3 BuildRNN

After exploring the data ,build RNN model . Keras library in the python can be used to built the RNN model. Keras is an incredible library: it allows to build state-of-the-art models in a few lines of understandable Python code. Although other neural network libraries may be faster or allow more flexibility, nothing can beat Keras for development time and ease-of-use. Here specify number of nodes in input layer , hidden layers and number of nodes in the hidden layer in the RNN and RBM layers. And also needed to specify the weight for the method.

A.5 Train RBM

Steps for training a recurrent neural network is given below,

- In the input layers, the initial input is sent with all having the same weight and activation function.
- Using the current input and the previous state output, the current state is calculated.
- Now the current state ht will become ht − 1 for the second time step.
- This keeps on repeating for all the steps and to solve any particular problem, it can go on as many times to join the information from all the previous steps.
- The final step is then calculated by the current state of the final state and all other previous steps.
- Now an error is generated by calculating the difference between the actual output and the output generated by RNN models.

A.6 Apply RBM

The parameter initialized by the RNN model is given as input in the RBM model. RBM is applied for classifying the anomalies into different classes. The inputs are multiplied by the weights and then added to the bias. The result is then passed through a sigmoid activation function and the output determines if the hidden state gets activated or not. Weights will be a matrix with the number of input nodes as the number of rows and the number of hidden nodes as the number of columns. The first hidden node will receive the vector multiplication of the inputs multiplied by the first column of weights before the corresponding bias term is added to it.

After that the reconstruction process is carried out. It is similar to the first pass but in the opposite direction. Here the input will be the activation function and is multiplied with weight and sum up with bias value.

A.6 Detect Anomaly

After applying RBM on RNN ,Anomalies in intelligence traffic will be detected. In this Stage plot and visualize the anomalies and normal transmissions in intelligence traffic using TSNE.

B RESULT

After applying the RNN-RBM the anomalies in the intelligent transportation system is detected. It can be represented by using the t-SNE[19]. t-Distributed Stochastic Neighbor Embedding is a non-linear dimensionality reduction algorithm used for exploring high-dimensional data. It maps multi-dimensional data to two or more dimensions suitable for human observation.

The result is shown below.

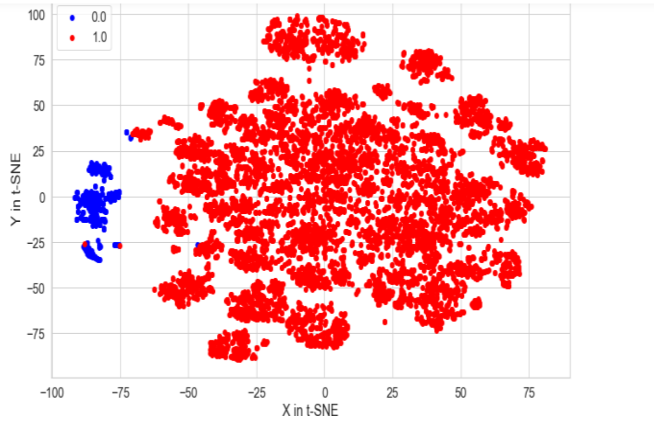

Figure 3:Before RNN-RBM

Here blue color denote the anomalies present in the intelligent transportation system, which is scattered.Red color denote the normal data present in the intelligent transportation system.

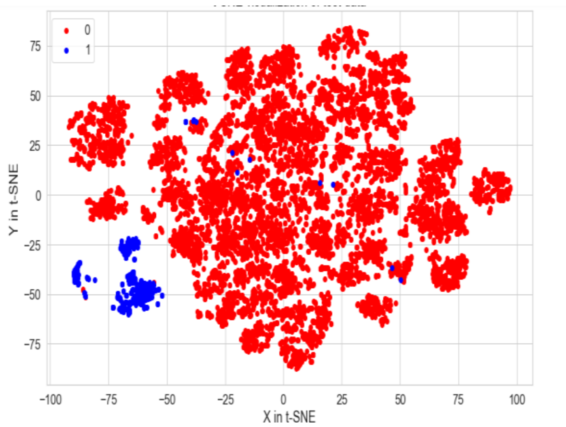

Figure 5:After RNN-RBM

6.CONCLUSION

An intelligent transportation system is an advanced application which aims to provide innovative services relating to different modes of transport and traffic management and enable users to be better informed and make safer, more coordinated, and ’smarter’ use of transport networks. The anomalies in the intelligent transportation system is detected using the RBM-RNN model. Training model is created using recurrent neural network and anomaly is detected using Restricted Boltzmann machine. The proposed model shows 99.82 percentage accuracy. Here the proposed scheme uses kaggler dataset for building the model.

7. FUTURE WORK

The proposed framework can be extended to different application domains such as smart home, smart grid, unmmaned aerial vehicle.

Smart grid is an electricity network based on digital technology that is used to supply electricity to consumers via two-way digital communication. This system allows for monitoring, analysis, control and communication within the supply chain to help improve efficiency, reduce energy consumption and cost, and maximize the transparency and reliability of the energy supply chain.

Unmanned aerial vehicle (adrone) is an aircraft without a human pilot on board and a type of unmanned vehicle. UAVs are a component of an unmanned aircraft system (UAS); which include a UAV, a ground-based controller, and a system of communications between the two.

Smart home technolog, also often referred to ashome automation provides homeowners security, comfort, convenience and energy efficiency by allowing them to control smart devices, often by a smart home app on their smart phone or other networked device. A part of thein-ternet of things (IoT), smart home systems and devices often operate to- gether, sharing consumer usage data among themselves and automating ac- tions based on the homeowners' preferences.

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