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Automobiles Presence Recognition using RNN

Venkata Sai Sriharsha Sammeta[1], Avinash Tammineni[2], Jairam Naik[3]

Computer Science, Vasavi College of Engineering, Osmania University & Intern@Oracle India [1]

Computer Science, Vasavi College of Engineering, Osmania University, India [2]

Professor, Ph.D from JNTUH, Vasavi College of Engineering, Osmania University, India[3]

ABSTRACT: Recurrent Neural Networks are widely used for time-series modeling and prediction. We propose a path for automatic construction of a binary categorize based on Long Short-Term Memory RNNs (LSTM-RNNs) for disclosure of a vehicle passage through a checkpoint. As an input to the categorize we use multidimensional signals of different sensors that are installed on the checkpoint. Acquired results demonstrate that the previous path to handcrafting a classifier, containing of a set of deterministic rules, can be successfully recovered by an automatic RNN training on nearly labeled data.

KEYWORDS: Hidden Markov Models; Complex Neural networks; Machine Learning; Deep Learning; Data Clustering; Neural Networks; Natural language Processing, Classification; Auto-encoder; De-convolutional; Un-pooling; AVC;Recurrent Neural Networks; Classification; Time-Series.

I. INTRODUCTION

This paper defines an Automatic Vehicle Classifier (AVC) for toll roads, based on video categorized and installed on best of Russian toll roads. Vehicle Passage Detector is one of the most valuable parts of the AVC system. VPD utilizes as input several binary signals from other AVC subsystems (binary detectors), and generates decisions about a vehicle passage. VPD is based on aa vehicle passage is identified if most of the binary detectors support a positive answer. This logic is improved by a set of empirical rules, supported by a human expert to quantify and take into account time delays among switches of the binary signals, properties of a series of these switches and other information. These rules were continued and modified during AVC test deployment based on an analysis of encountered errors.

The former paper devoted to VPD in AVC [3], cases that the VPD accuracy is 99:58%. Since then the test dataset has been continued by new detection and classification error cases. It should be noted that in the present paper we use tests which run with an incapacitated trailer coupler detector. AVC version, characterized in the previous paper, supports 83.47 % accuracy on the new dataset if the coupler detector is inactivated. At the same time the current category version supports 88.90% accuracy without the coupler detector and 91:10% with it. Comparing to the former version the new classifier has optimized algorithms for a shield and trailer couplers detection, a correlation detector and an amended fusion method for binary detectors aggregation.

Creating rules of this type is a painstaking job needing creative approach. It would be interesting to develop computerized method where a machine learning algorithm could change a human expert. This path potentially could also produce a higher classification feature. Therefore, in this paper we solve the problem of creating a method for computerizing an AVC synthesis and minimizing a human involvement.

II. RELATED WORK

The input information consists of AVC log records. Each file includes one or various vehicles passages. All the numerical experiments are carried on a dataset existing of 4761 log files. The system log is suffused with three-dimensional signal samples Xt, each component of which is binarized and created by one of the following sensors: a correlation detector, an induction loop, a shield detector. Also the records consist of a frame series number, manually conceived reference signal and indications of a basic classifier, which is depend on human tweaked rules [1]. A file record is conceived and rescued in a database if and only if at least one of the input signals has changed.

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stand No.	Shield	Loop	Cor	Basic clf	Ref. pass
196	1	0	0	0	0
201	1	1	0	0	0
202	0	1	1	1	0
208	1	1	1	1	1
246	0	1	1	1	1
266	1	1	1	1	0
268	1	1	0	1	0
269	1	0	0	0	0
270	0	0	0	0	0

Table 1: A log and a labeledmodel

The problem details dictates that a special quality passage assessment metric should be used, which is equal to the regular pointwise two-class classification metric Accuracy only in intense cases. The reason is that the standard metrics using pointwise difference among a reference signal and a predicted signal are not able to approximate a passage allotted condition from a physically sensible viewpoint.

The metric utilized in this paper is a Pass Quality (PQ):PQ= R/R+Err where R is a number of correctly disclosed passages, while åErr is a sum of allotted error costs on a whole test dataset. Calculation of åErr for various error types is a complicated action, see also table 2. Here L denotes the true number of passages in the reasoned test signal; K denotes the number of disclosed passages.

Ref. pass.	Detected pass.	Err. Desc.	Err. Weight
1	1	no error	0
1	0	missed passage	1
0	1	false passage	1
L	1	combined passages	L
1	K	divide passage	K
L	K	multiple issue	max(L, K)

Table 2: Classification issue cost

This quality metric does not exercise into account how far the identified passage is shifted from the ideal one. However they conducted experiments show that this is not necessary for applications, since the series of correct passages and their crossings with real passages at least in one moment are important, not the delays themselves.

III. PROPOSED ALGORITHM

In this section we analyse results obtained with various machine learning methods: gradient tree boosting XGB, logistic regression LR from the scikit-learn package, fully related neural network NN with a one hidden layer existing of 12 neurons, simple recurrent neural network SimpleRNN from the Keras package [6].

Due to an a typical task partitioning of the information into the training and the control sets were arranged as follows: logs for a respective set are anyhow selected in a order, but the order of frames under every log remaining part unchanged.

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Classifier	R	åErr	PQ
XGB_1	3090.2	2802.3	0.532
LR_1	3090.2	2802.3	0.532
NN_1	3090.2	2802.3	0.532
XGB_2	1806.0	453.0	0.799
LR_2	1794.1	302.6	0.856
NN_2	1758.0	276.6	0.864
Simple RNN	1784.8	214.3	0.892
Basic Classifier	1684.3	158.7	0.914

Table 3: Comparison of classifier models

The Basic Classifier uses an additional appearance from the trailer coupler detector. This appearance allows distinguishing among vehicles moving at a close distance and vehicles with trailers thus grows the basic method accuracy PQ from 0:889 to 0:914. In our experiments we do not utilize this appearance, although this additional data could potentially grows classification quality.
The primary logic for a low prediction accuracy is that all algorithms optimize not the target supports metric but a distant value — the mean squared prediction error MSE, which is not in a good agreement with the destination metric PQ. Hereinafter by an error we mean PQE = 1 PQ.
From the effects of section 4 we can notice that only the RNN model supports results with the accuracy analyse to that of the baseline classifier, constructed manually by accumulating and resembling rules, d in time delivered. Thus, RNNs is a promising path to automate construction of classifiers and further advance the accuracy of VPD.

A.*RNN ARCHITECTURE*

The original recurrent neural network system Simple RNN comprises only one hidden layer; the output signal of each neuron is utilized as an input to the same neuron at the next bit of time. In case an input signal has a period, the collapsing and the vanishing gradient problem displays when training the sample and calculating gradients of a neural network performance function. This effect stems from the fact that the gradients of the RNN's accomplishment function rely upon on the product of the grades of neurons in the hidden layer, calculated for all following values of the training signal, see Fig. 1; as a result, this product can take big exact values as well as tends to zero.
One path to avoid this effect is to use the Long Short-Term Memory Neural Network architecture (LSTM), which allows productive modelling of long range dependences in signals.

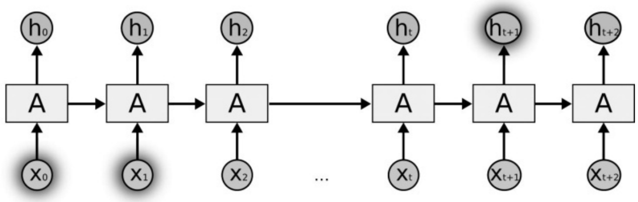

Figure 1: Long Range Dependence in RNN

In [17] (2014) the authors projected the neural network architecture called Gated Recurrent Unit, based on the same principles as the LSTM, but it utilizes a more economical parameterization and fewer operations to compute an output signal. More broad overviews of RNN architectures can be found in [14, 15].

B.*SELECTION OF RNN ARCHITECTURE*

To use RNN in practice, it is required to search for its optimal architecture. This section explains results on this matter. In experiments we utilize the following types of RNN: LSTM, GRU and Simple RNN. All experiments are accomplished utilizing the Keras framework [6], which is a wrapper of the Python-libraries Theano [18] and TensorFlow [19].

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For each of the RNN types we perform a sequence of experiments: we play with network hyper-boundaries, activation function types and a window length w. Since the couching time of an RNN with several layers is rather big, we fix the number of secrete layers to be equal to one, number of neurons in one layer is restricted from above by eight, the maximum number of learning epochs is restricted from above by 40. We support results of optimal architecture selection for each RNN type. One may see that choice of hyper-parameters, even in a limited space significantly increases the quality of Simple RNN model, cf. with the first experiments performing in table 3. According to these results we agree to continue to use architecture containing LSTM layers, since it supports the highest accomplishment.

Model	R	åErr	PQ
SimpleRNN	1723.0	161.1	0.915
LSTM	1751.8	145.3	0.923
GRU	1699.0	175.0	0.907
initial Classifier	1684.3	158.7	0.914

Table 4: Comparison of different RNN models

C.FURTHER IMPROVEMENTS

Since when training a neural network we amend a mean square point-wise error, which is not related for the considered problem, in this section we consider different additional approaches to improve further the detection accuracy, judged by the PQ value. In particular, we contemplate the following tweaks: weighting of the mean square error, used as a accomplishes capacity when training a neural network; smoothing the input signal by a morphological filter [20]; adding a penalty on a result of the neural network output, used when calculating the accomplishes function; optimization of a threshold value, utilized to binarize the output signal, according to the marked feature criterion PQ on the coaching set; containing the morphological filter to the neural network output signal.

It turned out that improvement of the identification accuracy can be obtained when expanding significantly the structure of the neural network. In fig. 2 we supports the modified architecture we use: one input LSTM-layer and two unseen dense layers. However, if we do not utilize Dropout transformation, despite the fact that the normal error MSE reduces on the validation sample up to 0:06 0:07, the target error PQE grows on the test set. In turn, if we utilize Dropout transformation before each Dense layer, then MSE grows up to 0:13, but at the same period the marked error PQE decreases for about 0:005 0:010.
Also we can achieve additional important improvement of the detection accuracy by selecting the threshold value of the output signal via the cross-validation path on the training set and the consecutive application of the morphological reign to the neural network output, binarized utilizing the selected threshold value.
Also we judge an importance of each input signal component by estimating its consequence on the accuracy of the final model. In table 5 we provide values of accomplishes criterion for models, constructed using all available combinations of input features. We can see the best set of characteristics is a pair (Shield; Cor).

IV. CONCLUSION AND FUTURE WORK

We can perform significantly better quality of classification according to 0:952 using only two input characters, whereas in order to achieve the detection accomplishes PQ equal to 0:914, the original classifier takes as input additional fourth point from the trailer coupler identifier, without which the accomplishes drops to 0:889. Thus, in this study we developed the computerized approach for constructing and training a classifier which is greater in terms of VPD accomplishes to the previously constructed classifiers. At this stage, further research is available in various ways.

First, we can increase the classification efficiency by a direct increase of the PQ criterion when training the neural network. The exercise of such learning algorithm is possible through the use of gradient-free optimization algorithms.

Second, we can create an accumulate mechanism for calculating a final decision from outputs of different detectors.And finally, we can exercises an integrated solution in order to eliminate the initial input data pre-processing, provided by classical image identification methods and other additional steps of data processing, which happen among the position “a automobile is shot using a camera” and the event “a binarized input signal X_t is produced”. In other

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words, we suggest using the following neural network structure, which appreciates all VPD subsystems by a single stack of convolution neural networks and RNNs:

- On the first level we use a set of convolution neural networks, converting images from all available cameras to derived features;
- On the next levels features, derived by the set of convolution neural networks, are connected through the RNN architecture with signals, collected from the induction loop and other devices of the AVC model;

Finally, the RNN type sample with the structure identical to the one, shown in Fig. 2, is used for passage identification.

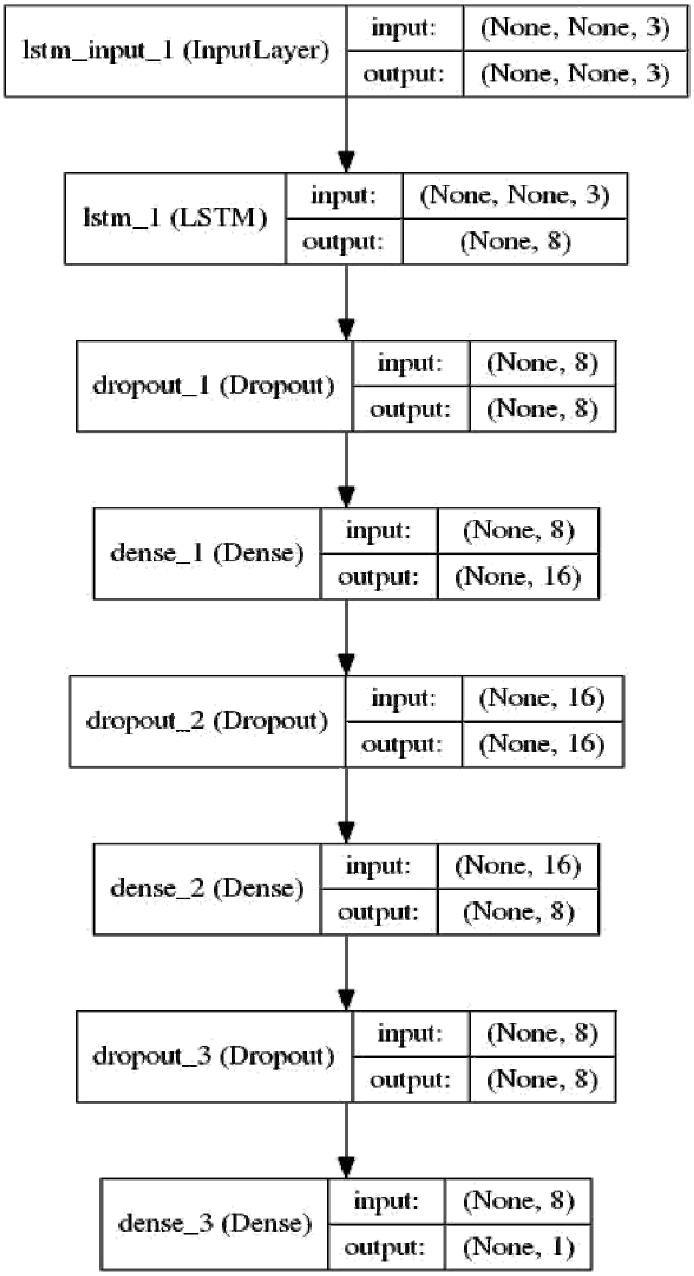

Figure 2: Final LSTM-RNN model

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Qualities	R	åErr	PQ
Cor	1714.1	153.9	0.918
Loop	1621.7	255.8	0.864
Shield	1679.5	200.8	0.894
(Loop; Cor)	1713.4	170.6	0.910
(Shield; Loop)	1738.6	130.7	0.930
(Shield; Cor)	1769.9	91.8	0.951
(Shield; Loop; Cor)	1767.6	93.2	0.950
Base Classifier	1684.4	158.8	0.914

Table 5: Accuracy of the total LSTM-RNN model for different subsets of input signal components.

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BIOGRAPHY

Venkata Sai Sriharsha Sammeta is an undergrad Machine Learning researcher in Computer Science department of Vasavi College of Engineering, Osmania University. Previously, he did internship in Oracle R&D India Private Limited, developing machine learning models for Ordering and Service Management (OSM) systems to predict future orders and improved the performance of Order Lifecycle Management (OLM) significantly. His current research sections are in the fields of Artificial Intelligence, Machine Learning, Deep Learning, Natural Language Processing and Recommender Systems.

Avinash Tammineni is a computer Science student at Vasavi College of Engineering, Osmania University. Previously, he did an internship in Eidiko Systems Inc, an IBM business partner that develops mobile and cloud solutions for enterprise. He worked in SR Deep Learning Lab, building Neural Networks for Image Captioning techniques. His research areas are in the fields of CNN, Machine Translation and Natural Language Processing.

K Jairam Naik received his Ph.D in Computer Science from JNTU University, Hyderabad. He is well known for his recent work in grid computing defining novel ways to improve the performance of grid by using Ant-colony optimization for balanced job scheduling algorithm. He is currently Professor in Vasavi College of Engineering, Osmania University, Hyderabad teaching Machine Learning and advanced Statistical Learning. His current research includes Machine Translation, Natural Language Processing and Convolutional Neural Networks. He has presented and published over 30 research papers in National and international Conferences and Journals. He is also an editor and part of the selection-committee for journals like IJSETI and IJIEECR.