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A Unified Approach for Detecting Traffic accident's severity using Neural Network

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Abstract- Obtaining the accurate information about future traffic severity of al links in traffic network has a wide range of applications, including traffic forecasting, vehicle navigation devices, vehicle navigation routing and congestion management. A major problem in getting traffic accident severity information in real time is that the vast majority of links is not equipped with traffic sensors. Another problem is that factors affecting traffic accident severity. In this paper, we first use a dynamic traffic simulator to generate flows in all links using available traffic information, estimated demand, and historical traffic data. The prediction of the traffic state can give the people the important traveling information. In this paper, the traffic state prediction problem is studied. A Random Forest approach is proposed for the traffic state prediction, which consider the prediction process as a classification problem instead of predicting the traffic accident severity parameters. The traffic state is defined as six classes according to the level of service. The Random Forest approach is introduced to model this prediction process. In the ME framework, more different features can be used regardless of the features' dependence. The temporal and spatial features can be used together, which is hard to be accomplished in the previous methods.

Keywords— Traffic network, Traffic accident severity, Random Forest approach

1.0 Introduction

Motorcycles and bikes form an integral part of personalized transportation in India. However, unfortunately, it also involves innumerable accidents and subsequent loss of lives. Every year, about 300,000 teenagers go to the emergency department because of bike injuries, and at least 10,000 teenagers have injuries that require a few days in the hospital. Statistics say, motorcycle deaths accounted for 15 % of all motor vehicle crash deaths in 2015 and were more than double the number of motorcyclist deaths in 1997. Through an ONEISS survey conducted by the Department of Health, it was found that 90% of the motorcycles rider killed in accidents were not wearing a helmet at the time of impact. This, along with drunken driving are a major reason of accidents. We aim to mitigate these problems and hence the associated casualties by ensuring that the rider will wear the helmet all the time during his/her ride, thus ensuring safety. The helmet can understand if the person is wearing the helmet, using the pressure sensors, fitted inside the padding foam. The helmet can detect a possible accident, using the onboard accelerometer and pressure sensor. If the values detected exceed a threshold, it is reported as an accident. Emergency contacts, specified by the rider during app setup, are informed about the possible accident, via a system generated email and text message, containing the address and GPS coordinates where the accident had been detected. The values of the accelerometer are also constantly sent to a remote server using an online application interface (API), and the server trains a support vector machine (SVM).

2.0 Existing system

The existing system present a new analytical tool that predicts highway congestion in real time by utilizing a macroscopic traffic accident severity model, and to investigate a data collection strategy that is adaptable to the quality of traffic information. A stochastic Lagrangian traffic accident severity model is proposed to capture the transition into traffic jam and randomness in the traffic accident severity. To calibrate the model, vehicles in a traffic accident severity are divided into cells, and only the first and last vehicles in each cell are probed.

Model parameters and traffic information are updated in real time by the unscented Kalman filter, and an advance warning is provided for stop-and-go traffic jam. Adaptive data collection is done by adjusting the probing cell size based on the variance of the prediction from the stochastic model. While collecting data from every vehicle in the traffic is expensive and may not be possible in reality, data probing should be tailored to the usage of the traffic accident severity model. Because of the nature of the Lagrangian LWR model, it is convenient to track a platoon of vehicles instead of a single vehicle to calibrate. The Kalman filter technique is commonly used to provide the optimal estimation for linear space models, the stochastic traffic accident severity model such as the one proposed here would require nonlinear Kalman filter.

3.0 Proposed system

The features in spatial and temporal are more useful for the description of the traffic state. In the ME framework, all these features can be used together, regardless of the features' dependence. An autoregressive model of the link flows is introduced that takes into account the uncertain nature of traffic and historical traffic data including the most recent ones as well as historical time traffic accident severity in its coefficients. From the original data using the bootstrap method to select the k different sample set of data, each bootstrap extracted by the sample set is the decision tree of all the training data, and the number of samples per sample set is equal to the original data set. The k sample sets selected by the bootstrap method are used to construct k unrouted decision trees. In the process of generating each decision tree, in order to generate the nodes of the decision tree, we need to select m attribute attributes (m < M) from the M attribute of the original data set as the candidate feature attribute. The decision tree is constructed by using the m candidate attribute attributes randomly selected, and the complete growth of the pruning trees is not carried out. Each tree of decision tree is classified as a complete decision tree, finally get k classification results.

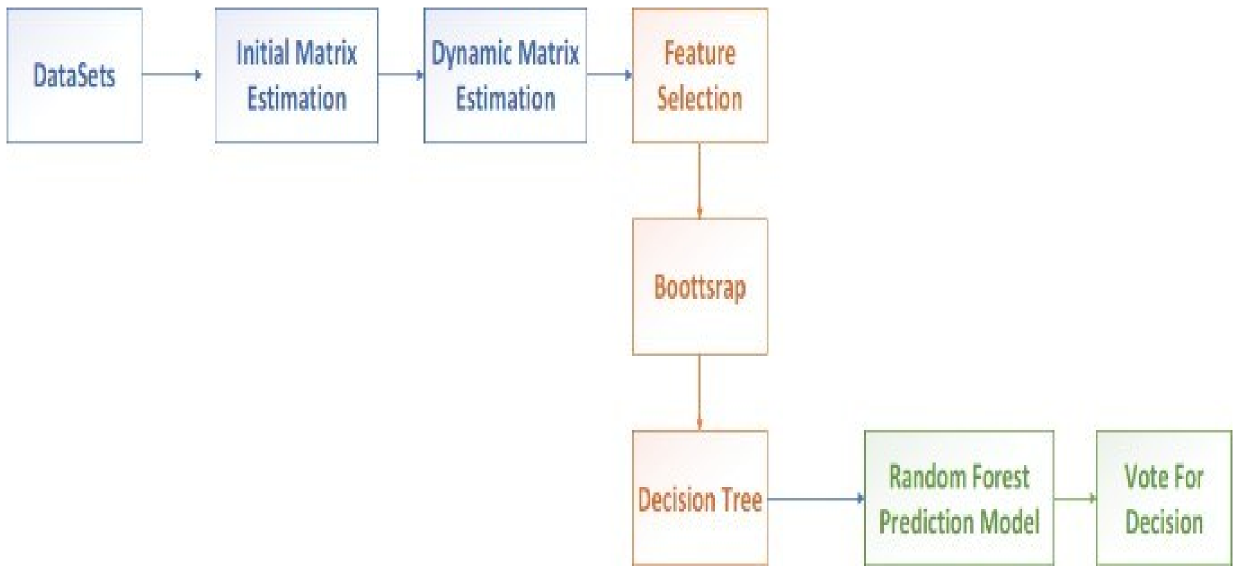
4.0 Drawbacks of Existing system

- Future prediction is not available
- Difficult for highly complex non linear system.
- Low sampling frequency
- Incur high initial implementation cost
- Pose privacy issues
- Highly varying speeds and travelling time
- No GIS implementation

5.0 Advantages of proposed system

- Low computational cost
- Prediction can be done with low computational burden and high accuracy
- Higher prediction accuracy
- It can be very responsive
- High reliability

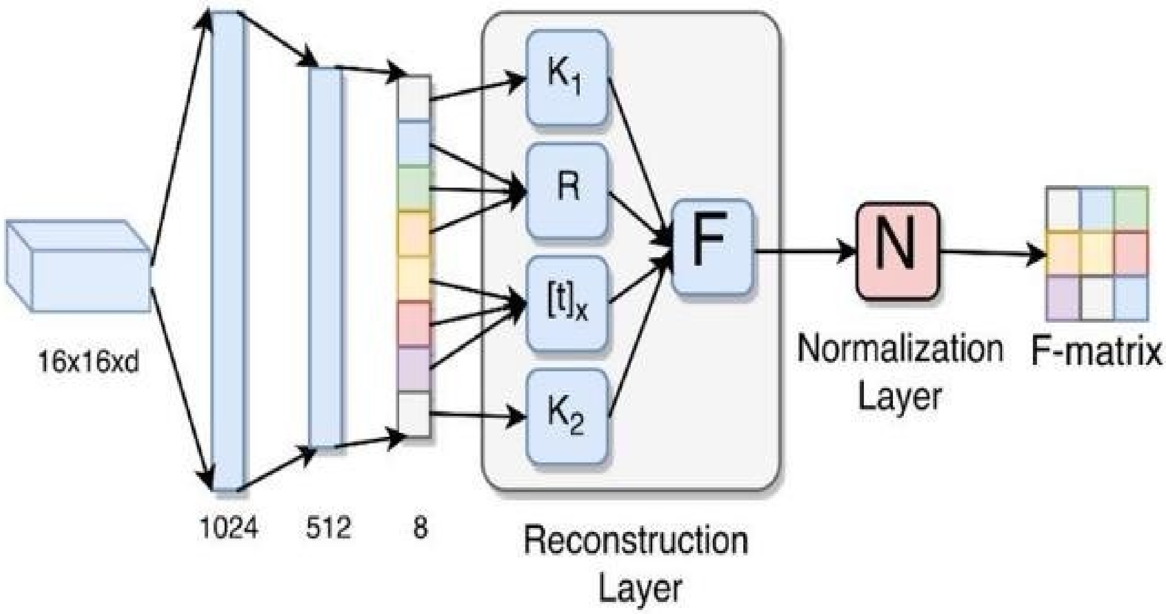
6.0 Architecture



7.0 Modules Description

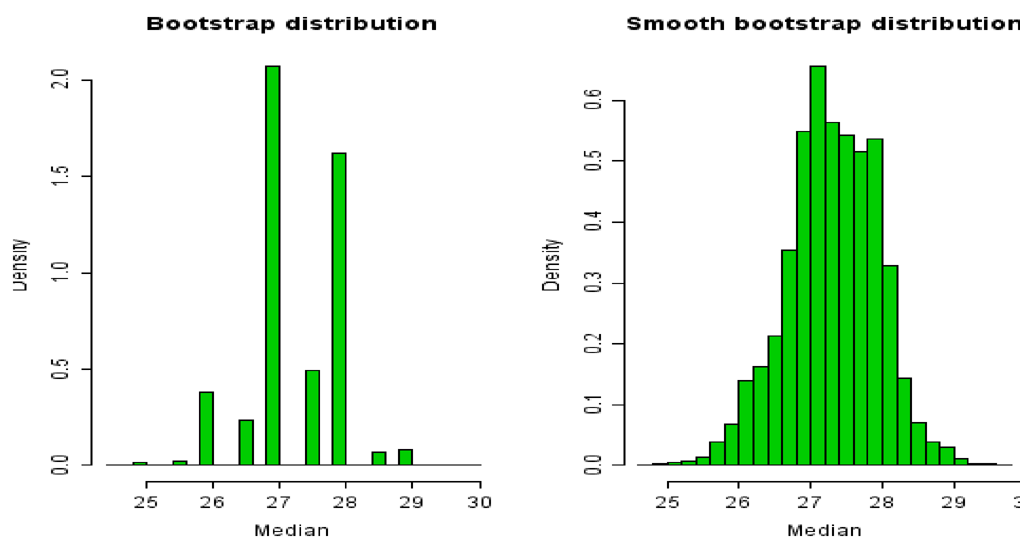
i. Matrix estimation

It is an approach to robust estimation of fundamental matrices from noisy data contaminated by outliers. The problem is cast as a series of weighted homogeneous least-squares problems, where robust weights are estimated using deep networks. The approach can be trained end to-end and yields computationally efficient robust estimators. It will enable to train robust estimators that outperform classic approaches on real data by a significant margin.



ii. Bootstrapping (statistics)

In statistics, bootstrapping is any test or metric that relies on random sampling with replacement. Bootstrapping allows assigning measures of accuracy (defined in terms of bias, variance, confidence intervals, prediction error or some other such measure) to sample estimates.



iii. Random forest

The RF is the ensemble of decision trees. Each decision tree, in the ensemble, process the sample and predicts the output label (in case of classification). Decision trees in the ensemble are independent. Each can predict the final response. The Neural Network is a network of connected neurons. The neurons cannot operate without other neurons - they are connected. Usually, they are grouped in layers and process data in each layer and pass forward to next layers. The last layer of neurons is making decisions.

id	name	rows	cols
3	kr-vs-kp	3196	36
24	mushroom	8124	22
31	credit-g	1000	20
38	sick	3772	29
44	spambase	4601	57
179	adult	48842	14
715	fri_c3_1000_25	1000	25
718	fri_c4_1000_100	1000	100

8.0 Backend technologies

Python
Numpy
Sci-learn
Eclipse IDE

id	name	rows	cols
id	name	rows	cols
3	kr-vs-kp	3196	36

9.0 Frontend technologies

Web Technologies
Bootstrap

10.0 EXISTING ALGORITHM

i. Lagrangian Algorthim

Lagrangian methods have become widely accepted as the preferred approach for RDO in recent standards, primarily due to their effectiveness and simplicity. Initially we will consider the case where each coding unit, i (the basic optimization building block), can be optimized independently of all others and where the only optimization parameter is a quantization index, j While this assumption clearly breaks down in cases where context dependence or prediction are invoked, it can provide a useful and tractable solution.

11.0 PROPOSED ALGORITHM

i. Random Forest Algorithm

The Random Forests can only work with tabular data. (What is tabular data? It is data in a table format). On the other hand, Neural Network can work with many different data types: Tabular data Images (the NN become very popular after beating image classification benchmarks, for more details please read more about Convolutional Neural Networks (CNN)) Audio data (also handled with CNN) Text data - can be handled by NN after preprocessing, for example with bag-of-words. In theory, RF can work with such data as well, but in real-life applications, after such preprocessing, data will become sparse and RF will be stuck.

ii. Advantages of Proposed Algorithm

- The predictive performance can compete with the best supervised learning algorithms
- They provide a reliable feature importance estimate
- They offer efficient estimates of the test error without incurring the cost of repeated model training associated with cross-validation

12.0 Conclusion

Scientific correct prediction of traffic congestion can ensure a safe traffic environment, and can be very good to prevent traffic congestion, to avoid traffic accidents. The random forest model does not need to set the weight of the property first, how to classify it, the calculation process is simple and the calculation quantity is small. The model needs to be set with fewer parameters, suitable for wide range of platforms, simple and easy to implement, and is a fast and effective data mining model. The final test results show that the prediction model established by RF algorithm can effectively predict the traffic congestion and can also find the relative important environmental factors that affect the traffic congestion. This paper presents an effective method for traffic congestion forecasting and provides effective scientific basis for traffic management to prevent traffic congestion.

13.0 Future Enhancement

In the future we will advance this concept to identify both the cause of an accident and also prediction of an accident.

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