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A novel passenger flow prediction model using deep learning methods

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ABSTRACT

Currently, deep learning has been successfully applied in many fields and achieved amazing results. Meanwhile, big data has revolutionized the transportation industry over the past several years. These two hot topics have inspired us to reconsider the traditional issue of passenger flow prediction. As a special structure of deep neural network (DNN), an autoencoder can deeply and abstractly extract the nonlinear features embedded in the input without any labels. By exploiting its remarkable capabilities, a novel hourly passenger flow prediction model using deep learning methods is proposed in this paper. Temporal features including the day of a week, the hour of a day, and holidays, the scenario features including inbound and outbound, and tickets and cards, and the passenger flow features including the previous average passenger flow and real-time passenger flow, are defined as the input features. These features are combined and trained as different stacked autoencoders (SAE) in the first stage. Then, the pre-trained SAE are further used to initialize the supervised DNN with the real-time passenger flow as the label data in the second stage. The hybrid model (SAE-DNN) is applied and evaluated with a case study of passenger flow prediction for four bus rapid transit (BRT) stations of Xiamen in the third stage. The experimental results show that the proposed method has the capability to provide a more accurate and universal passenger flow prediction model for different BRT stations with different passenger flow profiles.

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1. Introduction

Bus rapid transit (BRT) is a high-quality bus-based transportation system that delivers fast, comfortable, and cost-effective services at metro-level capacities. As of May 2017, a total of 205 cities in six continents have implemented BRT systems, accounting for 5568 km of BRT lanes (EMBARQ, 2017). Taking the Xiamen BRT as an example, the average daily passenger flow is nearly 400,000 (Xiamen Daily, 2016). As the most popular public transportation system, BRT is an effective mode for relieving the pressure of passenger congestion, especially during rush hours. The passenger flow prediction is the basis for the design, construction, operation, and adjustment of a BRT network. It is beneficial for improving the transport service, giving early-warning for sporadic urban traffic events, and making the cities smarter and safer.

Big data has revolutionized the public transportation. The rapid development of big data applied in the real world is providing us with better theoretical methodologies for addressing the issue of passenger flow prediction. Real-time data

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of passenger flow collected by traffic management departments contains rich information, which creates opportunities to broaden the real-world applications of intelligent transportation systems (ITS) with big data.

Deep learning is a rapidly growing area at the intersection of research into neural networks, artificial intelligence, graphical modeling, optimization, pattern recognition, and signal processing (Sun et al., 2012; Deng and Yu, 2013; LeCun et al., 2015; Silver et al., 2016). Some scholars offer a variety of high-level descriptions of deep learning (Arel et al., 2010; Anthes, 2013; Schmidhuber, 2015), generally from the two key perspectives: (1) models consisting of multiple layers or stages of nonlinear information processing; and (2) methods for supervised or unsupervised learning of feature representations at successively higher, more abstract layers. Recently, general-purpose graphical processing units (GPU) are widely used in big data processing, which drastically increases chip processing abilities and reduces hardware costs. These advances have enabled deep learning methods to effectively exploit complex, compositional, and nonlinear functions, to learn distributed and hierarchical feature representations, and to make the effective use of labeled and unlabeled data. Since passenger flow prediction is a complicated and nonlinear problem influenced by many fixed and stochastic factors (Zhou and Zhang, 2014), this method inspires us to reconsider the issue of passenger flow prediction with deep learning architecture. This may yield better performance than other benchmark methods.

In this paper, we propose a novel passenger flow prediction model using deep learning methods and apply it to predict the hourly passenger flow for Xiamen BRT stations. We make three major contributions:

(1) An unsupervised training model based on a stacked autoencoder (SAE) combined with a supervised training model based on deep neural network (DNN) is presented for passenger flow prediction. We directly visualize the high-level features learned in different hidden layers, and explain why the hidden nodes can robustly extract and represent the valuable features embedded in these inputs. Previous researchers rarely make such powerful explanations in the field of passenger flow prediction models using deep learning methods.
(2) The selections and combinations of the input features have a great impact on the accuracy of the prediction results. We found that even using the same fitting model, different input features combined as training data yield different performances. Moreover, in addition to the temporal features and real-time passenger flow, the previous average passenger flow, public holidays, the inbound and outbound, and the tickets and cards are key features in passenger flow prediction.
(3) The experimental results show that a universal and robust hourly passenger flow prediction model can be realized using our proposed method (SAE-DNN) for different BRT stations with different passenger flow profiles.

The remainder of the paper is organized as follows. Section 2 provides a review of passenger flow prediction. Section 3 presents the training and prediction procedures of SAE-DNN. In Section 4, a case study of passenger flow prediction of the four selected BRT stations in Xiamen is presented. A comparative analyses of the prediction performances are provided. Section 5 directly visualizes the high-level features learned from different hidden nodes. Finally, conclusions are drawn and future research directions are indicated in Section 6.

2. Literature review

Many successful models of passenger flow prediction have been developed. These can be generally divided into four categories: models based on traditional classical algorithms, regressive models, machine learning-based models, and the hybrid models. Comparisons of these models are listed in Table 1 in detail.

Table 1
Comparisons of the selected passenger flow prediction studies.

Studies	Modes	Methodologies	Time periods	Data	
				Temporal data	Spatial data
Chen et al. (2016)	Urban Rail Transit	ARIMA	Short-term	2 Months	1 Station
Jia et al. (2016)	Urban Rail Transit	GM + ARMA	Short-term	4 Weeks	1 Station
Jiao et al. (2016)	Urban Rail Transit	Kalman filter	Short-term	1 Month	15 Stations
Milenković et al. (2016)	Railway	SARIMA	Long-term	136 Months	Unknown
Z. Lv et al. (2015)	Coach	Regression	Short-term	1 Month	1 Station
Sun et al. (2015)	Urban Rail Transit	Wavelet + SVM	Short-term	40 Days	1 Station
Cai et al. (2014)	Urban Rail Transit	Multiply ARIMA	Long-term	29 Months	12 Stations
Jiang et al. (2014)	High-speed Rail	EEMD + GSVM	Short-term	22 Months	13 Stations
Ma et al. (2014)	Bus	IMMPH	Short-term	1 Year	1 Line
Xie et al. (2014)	Air	Seasonal LSSVR	Short-term	107 Months	HKIA
Zhou and Zhang (2014)	Urban Rail Transit	SW + LS + SVM	Long-term	1 Year	30 Stations
Moreira-Matias et al.(2013)	Taxi	Time-series	Short-term	Online	Unknown
Wei and Chen (2012)	Urban Rail Transit	EMD + BPN	Short-term	1 Month	1 Line
Hou and Ma (2011)	Railway	Grey linear regression	Long-term	9 Years	1 Line
Zhang et al. (2011)	Bus	Kalman filter	Short-term	1 Month	4 Stations
Tsai et al. (2009)	Railway	NN	Short-term	4 Years	1 Line
Li and Yang (2007)	Railway	NN	Long-term	18 Years	1 Station

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