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Adaptive Weights Based Ensemble Forecast for Bike Sharing Request Using XGBoost and Prophet

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Abstract. In intelligent urban transportation and enterprise market analysis, accurate lightweight bicycle demand forecasting is critical for frontline dispatchers. Complex real-world climatic conditions hinder workers from quick prediction and response. This significantly prolongs the time required for real-time bicycle dispatch. It leads to urban traffic congestion and revenue losses for enterprises. In this case, the research propose a Dynamic Weighted Stacked Ensemble (DWSE), which is composed of the XGBoost method and the Prophet algorithm. Study the use of sliding windows to record the most recent prediction error of each basic predictor. Automatically calculate their respective weights based on the size of the error. The smaller the error of the predictor, the higher the weight it receives. Experiments are conducted over the day-level trip data of Washington Bikeshare service. DWSE achieves better prediction accuracy than conventional methods such as LSTMs and random forests. The model is lightweight with substantially lower parameter complexity than most neural network ensemble schemes, offering an effective and reliable prediction tool for real-time bike-sharing dispatch tasks.

Keywords: ensemble forecast, xgboost, prophet, dynamic weight

1. Introduction

Nowadays, with the increase of urban population, the pressure of urban transportation is becoming greater and greater. Shared bicycles are a very convenient, green, and economical mode of transportation that citizens can use to facilitate their own travel. Bike sharing services contribute towards alleviating congestion, reducing greenhouse gas emissions and closing the modal gap of local trips within cities [1]. However, the distribution of bicycles has significant uncertainty and instability. The main challenges are the time-varying behavior and unexpected changes in weather. In order to tackle those challenges, the research propose a hybrid approach of XGBoost and Prophet models with the help of ensemble methods for building an adaptive model.

Traditional analysis approaches that are frequently used in the business industry such as ARIMA model (Autoregressive Integrated Moving Average) or exponential smoothing method. These models fail to capture complex non-linear relationships between inputs and outputs and various cyclic fluctuations observed in the data of bike sharing usage [2]. In the different study, researchers Kim analyzed "Tashu" bike-sharing system of Daegyong City (Korea). They used negative binomial regression model for modeling effects of weather variables like ambient temperature,humidity,

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precipitation, wind speed—on hourly bike share demand [3]. However, the limitations of traditional methods lead to poor prediction performance. They also show low usability in practical forecasting and operational management decisions [4]. Therefore, in analyzing complex patterns and a large number of predictive factors, integrating large models is the main research direction.

Currently, integrating large models has achieved remarkable results in various practical forecasting tasks. In terms of traffic volume prediction, integrating large models outperforms neural networks and traditional statistical methods in generalization ability and processing efficiency. It achieves higher prediction accuracy without affecting the clarity of interpretation [5].

Despite the great advances of prediction methods, the most current traffic demand prediction models are also based on staticweight ensembles [6]. In order to address this issue, the paper proposes an alternative approach for combining the predictions of XGBoost and Prophet dynamically. The function of XGBoost is to predict based on external information and the function of Prophet is to make predictions about weather seasons. The weight allocation of the two algorithms depends on their scores within the sliding time window to calculate dynamic weights [6]. This is different from the traditional static ensemble methods whose weights are fixed and cannot adapt well to temporal dynamics of time series data [7]. The paper's proposed dynamic weighted sliding-window ensemble(DWSE) approach can dynamically adjust the models' weights by using a sliding-window verification process. The model was validated on an actual shared bicycle dataset. The results illustrate that this method outperforms other methods in terms of prediction accuracy.

2. Method

2.1. Data source and description

This study uses the publicly available Capital Bikeshare data set that consists of trips taken on the Capital Bike share system in Washington from Jan. 2011 to Dec. 2012. This dataset contains 17,379 hours samples and 731 days samples of bike use records, weather conditions and time related information [8]. Following systematic processing on the raw data, this paper extracts following factors. Time consists of date, day-of-week, month, seasonality and holidays. Weather is divided into three main categories. The first category refers to clear sky and less than half of the clouds. The second one contains fog scenes with different levels of obscuration. The third one consists of light snow, rain with thunderstorms. Figure 1 shows the number of new users in each calendar month.

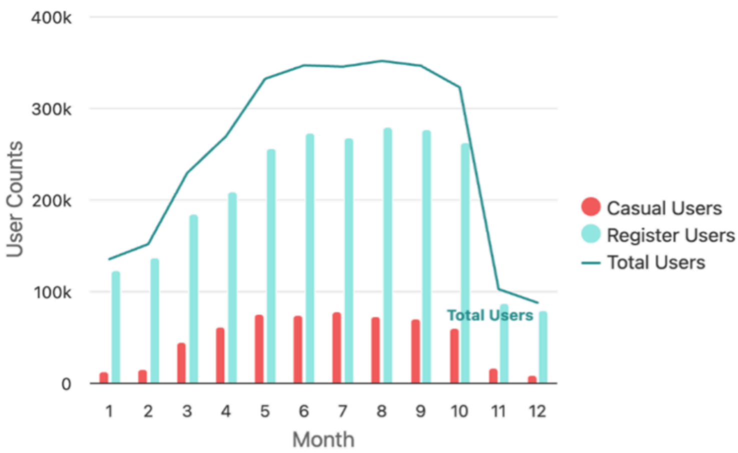

Figure 1. The monthly registration volume of users in the training set (picture credit: original)

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2.2. Variable selection and description

Based on experimental needs, the paper selected these 13 criteria from 16 candidate factors as important factors and divided them into four groups. The detailed information of the selected variables is shown in Table 1.

Table 1. Descriptions of variables used for training stacking models

Variable	Data type	Description
Time	Continuous	5 categories(working_day, day_of_week, month, season, holiday)
Weather	Categorical	3 categories(1=clear, 2=mist, 3=light rain/snow)
Cnt	Continuous	Hourly total bike rental count (casual + registered)
Interaction	Continuous	4 categories(temp, atemp, hum, windspeed)

2.3. Methodology

2.3.1. XGBoost base learner

XGBoost is employed to capture the intricate nonlinear relationships between exogenous variables and bicycle subscription demand.

$$\mathscr{D} = \{(x_i y_i)\}_{i=1}^{n} \tag{1}$$

Equation.1. is the demand prediction formula for the training set. It is necessary to input weather conditions including temperature, humidity, and date variables.

Based on a prediction model proposed by Pel´a ez-Rodrıguez [4]. It showed how GBM methods were able to predict the demand for bikes and cabins. For the present study uses the XGBoost algorithm, which constructs K decision trees used in regression, as shown in Equation.2.

$$\hat{y}_i = \phi(x_i) = \sum_{k=1}^{K} f_k(x_i), \quad f_k \in \mathscr{F} \tag{2}$$

The training of the proposed algorithm is performed by minimizing an objective function which consists on a regularized loss given by Equation.3:

$$\mathscr{L}(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{3}$$

The split rule defined by the second-order Taylor expansion is adopted to obtain the optimal tree structure, as shown in Equation.4.

$$Gain = \frac{1}{2}\left[\frac{G_L^2}{H_L+\lambda} + \frac{G_R^2}{H_R+\lambda} - \frac{(G_L G_R)^2}{H_L+H_R+\lambda}\right] - \gamma \tag{4}$$

Where G is a sum of first order gradients and H represents second order gradients on the left child node and right child node respectively. This model very suitable to study the relation between weather and demand. It handles sparsity in input very well and can also learn correlations between features automatically.

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2.3.2. Prophet base learner

The paper follows the multi-resolution temporal analysis approach of Wang et al. who proposed a separable blending method to find temporal patterns [9]. This study adopt Prophet's additive regression formulation, as shown in Equation.5.

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{5}$$

The above analysis is consistent with the results of the TimeMixer model [9]. Extracting different time patterns helps improve the accuracy of complex time series forecasting.

2.3.3. Dynamic weight stacking ensemble

In this paper, the propose an extension of the stacked ensemble method used for demand prediction in Zhou called Dynamic Weight Stacking Ensemble (DWSE) [6]. The research is focus on time series forecasting and introduce dynamic weighting schemes accordingly. Unlike traditional ensembles with static weights [6], the study proposed DWSE updates weights dynamically based on the latest performance. It achieves more accurate predictions for scenarios with variable demand [10]. The whole forecast takes the form of time-adjusted weighted average, as follows Equation.6:

$$\hat{y}_{ENS}(t) = w_{XGB}(t) \cdot \hat{y}_{XGB}(t) + w_{PRO}(t) \cdot \hat{y}_{PRO}(t) \tag{6}$$

The $w_{XGB}(t) + w_{PRO}(t) = 1$, $w_i(t) \geq 0$.

In the experiment, the allocation of weights is calculated based on the model's score within a sliding window. Given a length of the sliding window. For each component model, at each time instant t, the paper calculates the average absolute percent error (AAPE) on a sliding window of length T = 7 days, as follows Equation.7:

$$\mathrm{MAPE}_i(t) = \frac{1}{L} \sum_{j=t-L}^{t-1} \left| \frac{y_j - \hat{y}_i(j)}{y_j} \right| \times 100\%, i \in \{XGB, PRO\} \tag{7}$$

Numerical weights are calculated using the reciprocal error of softmax, as shown in Equation.8.

$$w_i(t) = \frac{\exp(-\beta \cdot \mathrm{MAPE}_i(t))}{\sum_{k \in \{XGB,PRO\}} \exp(-\beta \cdot \mathrm{MAPE}_k(t))} \tag{8}$$

Based on these core formulas, an accurate and convenient dynamic prediction model was experimentally designed. The workflow is shown in Figure 2.

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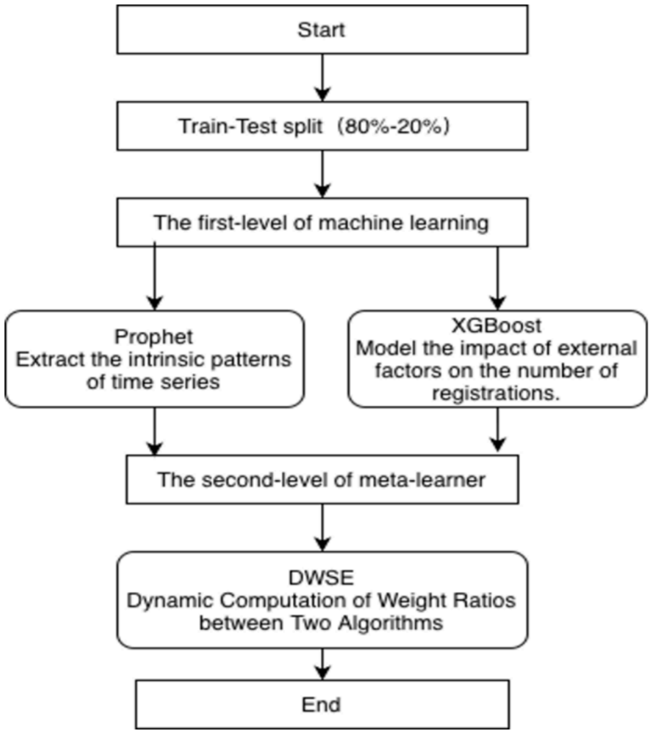

Figure 2. Architectural schema of the proposed stacking model (picture credit: original)

2.4. Evaluation metrics

In order to fully assess both the prediction performance and practicality of the developed model. The study defined three evaluation criteria in this paper. The first is the mean absolute error (MAE), which reflects the average error between predicted values and true values. It also serves as a measure of how accurately the model predicts each individual sample. The second is the coefficient of determination (R^2), which is a measure used to show the model and explain the variation in data. Its value ranges from zero to one and the closer R^2 is to one, the better the fit [2,6]. The third one is model size (Parameters). These indicators provide a standard parameter basis for evaluating the comprehensive performance of the DWSE model.

3. Result and discussion

3.1. Model training and error analysis

From the training loss graph in the left chart, the paper can see the average of training loss is 0.2479. The loss values are mainly concentrated between 0.1 and 0.3. The highest values is mainly concentrated around 0.1. As the loss value increases, the frequency gradually decreases. This illustrates that the loss of the training samples are relatively small. The model fits are good at the training set.

In the figure 3 on the right chart(Validation Loss), the average loss values set is 0.3267. Its loss values are mainly concentrated between 0.15 and 0.35. The highest frequency is mainly concentrated around 0.15 to 0.2. By contrast, the average of validation loss is higher than average of training loss(0.3267>0.2479). It illustrates a slight overfitting phenomenon. But different between the two is still relatively small. And it also illustrates that the overall fitting degree of the model is controllable.

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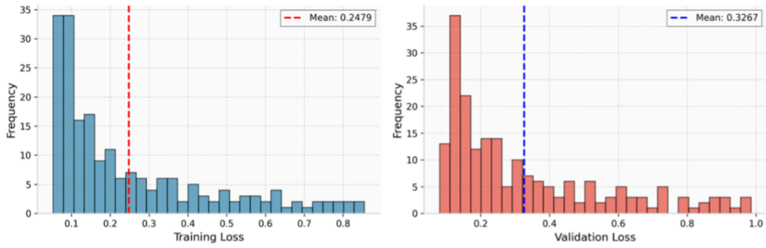

Figure 3. Training and validation loss curves (picture credit: original)

In the weight data of the influencing factors in Fig.4., the paper can find that the highest score is the temperature at 0.45. The sensible temperature ranks the second at 0.22. The humidity andsindspeed are 0.18 and 0.12 respectively. The weather and workingday are merely 0.02 and 0.01 respectively. These data illustrates that climate factories like temperature, sensible temperature and so on dominate in predicting bicycles separately.

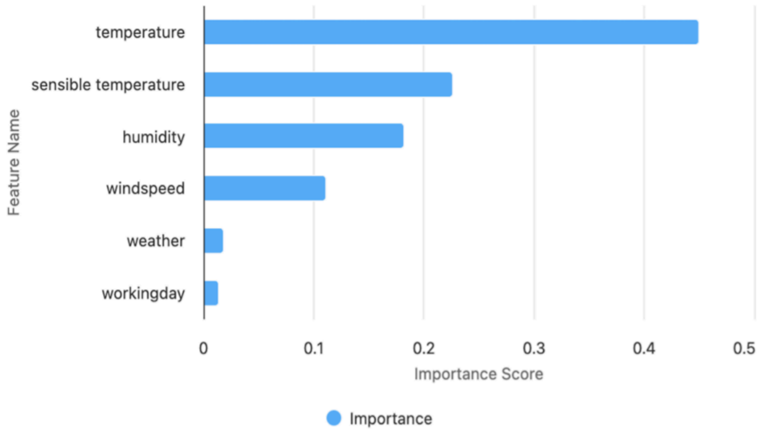

Figure 4. A comparative importance between features in the model given by percentages (picture credit: original)

3.2. Prediction results

Figure 5 shows the comparison between the predicted results of the model and the actual data. The paper can see that in most dates, the two curves basically overlap. This indicates that the model can effectively capture the periodic fluctuations in bicycle demand. However, during the period from November 21, 2012 to November 25, 2012, there was a significant deviation between the predicted values and the actual values. This indicates that it may not have captured the impact of abnormal events well. In real data, demand data fluctuates significantly(1.3k-5.5k). In predicting demand data, fluctuations are relatively flat. This illustrates that the model has smoothed out extreme fluctuations to a certain extent and has weak ability to capture sudden events. The overall prediction of the model is highly consistent with the actual demand, but there is still a need to strengthen the ability to handle and predict special events in the later stage.

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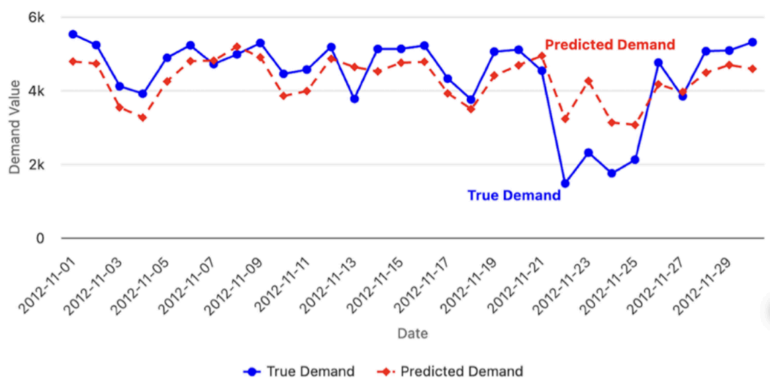

Figure 5. Temporal comparison of actual vs predicted demand (picture credit: original)

3.3. Comprehensive model performance comparison

The research conduct extensive comparisons with popular baselines including Context-Aware Ensemble [6], TimesNet + NHiTs + PatchTST and XGBoost. Here show their evaluation performance comparison with ours over the validation set in Table 2.

Table 2. Comprehensive model performance comparison

Rank	Model name	MAE	R^2	Parameters
1	DWSE	546.85	0.9234	45,200
2	Context-Aware Ensemble	2840.41	0.8807	294,974
3	XGBoost	899.81	0.8524	402,615
4	TimesNet+N-HiTs+PatchTST	3258.62	0.8524	402,615

The DWSE performs are good at every metric. It's MAD is 546.85 and r-square is 0.9234, this is much higher than other models. And its parameters just 45,200 less than all other models. In addition, it only has 45200 parameters, which means it has more than 84% fewer parameters than most deep learning requires. This research have shown that the resulting dynamic ensemble can be more accurate than its static counterpart. From a statistical perspective, it has significant significance and is easier to implement in practical operations.

4. Conclusion

The research proposed dynamic weighted ensemble model is able to integrate the advantage of XGBoost's consideration on exogenous variables and Prophet's ability of modeling trends. Its significantly improves the accuracy for estimating bike-sharing demands. A dynamic weighting mechanism has been introduced in the DWSE model. It can update the weights of the learning algorithm based on recent predictive performance. This makes it possible for the overall model to adjust weights of individual models as needed. The results show that the hybrid model achieved an improvement of 19.18% mean absolute percentage error on the validation. It also is reducing errors compared to individual reference models between 17 and 69% and showing that combining models can be beneficial in complex forecasting tasks such as load forecasting.

Furthermore, the method has a plug-and-play and easy-to-replicate process. It can be used for other time series prediction tasks.When it comes to transport and logistics, it can also use similar dynamic ensemble methods in other fields. For example, it can adjust the basic predictor based on

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the characteristics of the existing dataset. Used to predict the demand for carpooling services or the load of electric vehicle charging stations.

However, this stacked ensemble method has certain limitations. It relies on dynamic weights of historical performance within the sliding window. It cannot respond promptly to sudden and acute situations, such as extreme weather events and emergencies.

As edge computing and near-line processing are developing. Dynamic integration needs the ability of real-time reconfiguration. This ability allows iterative updates of weights. This ability also enables automatic adjustment to the optimal architecture.

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