A Comparative Study of AutoML Approaches for Short-Term Electric Load Forecasting

Zhaorui Meng*, Xiaozhu Xie, Yanqi Xie, Jinhua Sun

School of computer and information engineering, Xiamen University of Technology, Xiamen, Fujian, 361024, P.R. China

Abstract. Deep learning is increasingly used in short-term load forecasting. However, deep learning models are difficult to train, and adjusting training hyper-parameters takes time and effort. Automated machine learning (AutoML) can reduce human participation in machine learning process and improve the efficiency of modelling while ensuring the accuracy of prediction. In this paper, we compare the usage of three AutoML approaches in short-term load forecasting. The experiments on a real-world dataset show that the predictive performance of AutoGluon outperforms that of AutoPytorch and Auto-Keras, according to three performance metrics: MAE, RMSE and MAPE. AutoPytorch and Auto-Keras have similar performance and are not easy to compare.

Keywords: Automated machine learning, load forecasting, deep learning.

1. Introduction

Accurate load forecasting is of great significance to power network planning and management decision of economic development department. Power consumption prediction based on the study of different users' power consumption characteristics can help power enterprises better understand users' personalized service demand, and provide data support for future power grid development [1].

However, due to the characteristics of intelligent power distribution big data, such as multiple types, large volume, high dimension and fast generation speed, the traditional load forecasting method has certain limitations in mining massive data information, and it is difficult to accurately grasp the relevant factors and change rules of users' electricity consumption. How to study users' electricity consumption characteristics and related factors of electricity consumption in the big data environment and predict their electricity consumption is a challenge for researchers [2].

At present, machine learning approaches have been widely applied to load forecasting, including: XGBoost [3], recurrent neural network (RNN) [4], and long short-term memory (LSTM) [5] etc. To implement the best prediction model in each data set, there are several procedures required in traditional machine learning methods, for instance: data pre-processing and cleaning, selecting and constructing appropriate features, selecting appropriate models, optimizing model super parameters, post process processing of machine learning models, etc.

The processing of these tasks is usually very complex, which cannot be handled by non-machine learning experts. With more and more models being developed, how to choose an appropriate model becomes more and more difficult, and parameter tuning needs to traverse all possible values, which requires a lot of manual operations, resulting in low process efficiency and difficult management.

Auto Machine Learning (AutoML) technology is emerging in the past two years. Although it is still in its infancy, it has already achieved good results. AutoML technology is an algorithm that enables machine learning to learn how to learn. In traditional machine learning, it's mainly achieved by automatic parameter tuning, while in deep learning, it's mainly achieved by Neural Architecture Search (NAS) so far. Because the most important parameter in deep learning is the number of layers of network structure and the number of neurons in each layer.

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*Corresponding author: mengzhaorui@xmut.edu.cn

In recent years, the application of AutoML in various industries has been extensively studied. Tsiakmaki et al. [6] proposed an approach using autoML to predict student academic performance. Johnson et al. [7] explored the AutoML usage in digital forensic of crime analysis and prediction. Gerassis et al. [8] introduced an AutoML-based approach for the construction of environmental impact assessment. In general, AutoML has lowered the threshold for artificial intelligence applications. With its low threshold and automated nature, AutoML is expected to revolutionize traditional machine learning methods in the coming years and make artificial intelligence truly universal.

In this paper, three AutoML methods are used for short-term load forecasting, including AutoGluon, Auto-Keras and AutoPytorch. For load forecasting data of different regions, the network structure suitable for the data set are designed automatically, without the need to manually select the network structure and parameters. On the premise of ensuring accuracy, manpower is saved. A real-world load forecasting data set is used to compare the performance of the three AutoML methods.

2. Automatic machine learning methods

2.1 Auto-Keras

AutoKeras uses a repetitious trained RNN controller to sample candidate sub-models and then train them to measure their performance in the desired task [9]. Then, the controller uses performance as internal metrics to find a more promising architecture. However, neural architecture search is computationally expensive and time-consuming. To solve this problem, AutoKeras uses efficient neural architecture search (NAS). NAS adopts a concept similar to transfer learning. The parameters learned for a specific model on a specific task can be used for models on other tasks. Therefore, NAS forces all generated sub-models to share weights, to deliberately prevent training each sub-model from scratch. ENAS can not only share parameters among sub-models, but also obtain outstanding performance.

2.2 Auto-Pytorch Tabular

Early AutoML methods are implemented by optimizing machine learning pipelines and hyperparameters. More recent autoML models use neural architecture search. To better utilize positive interaction effects between the best learning hyperparameter and the best network architecture, Zimmer et. al. proposed Auto-Pytorch Tabular framework [10], which combines meta-learning, ensemble learning and multi-fidelity optimization. In addition, Auto-Pytorch Tabular combines traditional machine learning baselines with tuned deep neural networks to achieve state-of-the-art performance on tabular data.

2.1 AutoGluon-Tabular

Unlike other frameworks that focus on hyperparametric search optimization, AutoGluon-Tabular [11] tends to use multi-model ensemble, multi-layer stacking and K-fold bagging to achieve better and more stable model results. Furthermore, in the selection of the basic model, AutoGluon-Tabular includes the gradient ascending tree model with excellent performance in various tabular data competitions to achieve better performance for tabular data, instead of blindly pursuing the lofty deep learning model. Finally, AutoGluon-Tabular optimized the neural network model particularly for tabular data. For example, per-variable embedding for class variables is added, and skip-connection is used to further improve model training.

3. Experiment

3.1 Dataset description

To evaluate the performance of AutoML in short-term load forecasting, a real-world dataset from GETCom2012 [12] was used in this paper. Originally GETCom2012 dataset was used for load forecast competition 2012. The dataset includes hourly load from 20 geographical zones and hourly temperature from 11 weather stations in the United States. As the purpose of this paper is short-term load forecasting, instead of using full GETCom2012 dataset, data from 5 of the 20 zones are selected as experimental data. And the training dataset is from January 1, 2007 to June 30,2007, and the testing dataset is from July 1, 2007 to July 7, 2007.

3.2 Performance metrics

To evaluate the performance of short-term load forecasting models, three performance metrics were used in this paper, including mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE). The definitions of these three metrics are shown as below:

$$MAE = \frac{\sum_{i=1}^{n}|\widehat{y_i}-y_i|}{n} \qquad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\widehat{y_i}-y_i)^2}{n}} \qquad (2)$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\widehat{y_i}-y_i}{y_i}\right| \qquad (3)$$

where n is the total number of testing data, y_i is the actual value and $\hat{y}_i$ is the predicted value.

Above all three metrics are widely used metrics. Each metric has its own advantages and disadvantages. In a general way, MAE is less sensitive to outliers. RMSE has greater penalties for large error samples. MAPE is the average error percentage. If the actual value at one point is very low and the error is large, it can have a big impact on the value of MAPE. The selection of metrics should be based on data distribution and experimental results. Generally speaking, the lower value of the above metrics, the closer are the predicted values to the actual values.

3.3 Experimental results

In this section, we present the experiment results for comparing three proposed AutoML short-term load forecasting approaches. Table 1 summarizes the prediction results of each model compared with MAE, RMSE and MAPE. In Table 1, the minimum values of the evaluation metrics for each zone are identified in bold. From Table 1, we observe that AutoGluon model has the lowest value for all three metrics in all five zones. As for AutoKeras and AutoPytorch, it is not easy to distinguish between the performance of the two models. In some zones, models generate by AutoKeras have lowest MAPE value, while models generate By AutoPytorch have lowest RMSE value in some zones.

Table 1. Comparison of MAE, RMSE and MAPE for three AutoML approaches.

	AutoGluon			Auto-Keras			AutoPytorch		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE
Zone 1	**1127.61**	**1434.87**	**6.53**	2314.07	2843.26	24.32	1668.86	2243.59	22.36
Zone 11	**6872.97**	**8583.76**	**7.01**	10098.78	12205.02	20.21	7640.68	9295.38	22.25
Zone 12	**7383.35**	**9366.14**	**6.08**	15808.85	19269.01	19.34	10819.81	13340.86	21.78
Zone 15	**5057.28**	**6148.74**	**10.53**	6818.92	8863.6	16.39	5168.67	6087.19	19.01
Zone 20	**5116.38**	**6152.78**	**6.41**	7263.26	9661.15	16.4	5127.29	6186.55	17.14

4. Conclusion

In this paper, three AutoML methods are applied to short-term load forecasting, which solves the current problem of retraining and network selection for different data sets. Through the analysis of the experimental results, it can be seen that the method based on AutoML can automatically construct the network structure, and at the same time ensure the same accuracy as the manual selection of the classical network. In addition, different AutoML methods show different forecasting performance. The experiment on a real-world data set shows that the forecasting accuracy of AutoGluon method is significantly better than the other two methods: Auto-Keras and AutoPytorch. The AutoML approaches will be tested in more load forecasting data sets for further comparison.

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