Eastern Anatolian Journal of Science
Volume VIII, Issue I, 2022, 20-25

Eastern Anatolian Journal of Science

Forecasting Call Center Arrivals Using XGBoost Combined with Consecutive and Periodic Lookback

Mesut TARTUK[1], F. Taha NURDAĞ[2], Vedat ACAR[3], Sevtap ERDEM[4], M. Fatih AKAY[5] and Fatih ABUT[6]*

[1]*Comdata Teknoloji ve Müşteri Hizmetleri A.Ş., Turkey,* mesut.tartuk@comdatagroup.com
[2]*Comdata Teknoloji ve Müşteri Hizmetleri A.Ş., Turkey,* furkan.nurdag@comdatagroup.com
[3]*Comdata Teknoloji ve Müşteri Hizmetleri A.Ş., Turkey,* vedat.acar@comdatagroup.com
[4]*Çukurova University, Engineering Faculty, Department of Computer Engineering, Turkey,* sevtaperdem10@gmail.com
[5]*Çukurova University, Engineering Faculty, Department of Computer Engineering, Turkey,* mfakay@cu.edu.tr
[6]*Çukurova University, Engineering Faculty, Department of Computer Engineering, Turkey,* fabut@cu.edu.tr

Abstract

For companies operating in the call center service sector, it is essential to plan and manage call center employees regularly and optimize the costs. Therefore, agent planning needs to be performed in an optimum way in the call center sector. To make customer representative planning, information on the number of incoming calls is needed to forecast call counts. This study aims to forecast the number of calls using the Extreme Gradian Boosting (XGBoost) combined with consecutive and periodic lookback to be able to plan the number of representatives at specified intervals per operation in the call center sector. Models based on Moving Average (MA) have also been developed for comparison purposes. Mean Absolute Error (MAE) has been used to evaluate the performance of forecast models whereas the generalization errors of the models were evaluated using 80/20 split for training and testing. Forecasts were generated in daily format for four different weeks. The results show that XGBoost performs better than MA for all four different weeks and produces predictions within limits of acceptable accuracy.

Keywords: Machine learning, Regression, Forecasting, Call center.

Received:09.05.2022
Accepted:08.06.2022
Published:30.06.2022
**Corresponding author:* Fatih Abut, *PhD*
Çukurova University, Engineering Faculty, Department of Computer Science, Adana, Turkey
E-mail: fabut@cu.edu.tr
Cite this article as: M. Tartuk, F. T. Nurdağ, V. Acar, S. Erdem, M. F. Akay and F. Abut, Forecasting Call Center Arrivals Using XGBoost Combined with Consecutive and Periodic Lookback, *Eastern Anatolian Journal of Science, Vol. 8, Issue 1, 20-25, 2022.*

1. Introduction

Call Centers are interaction centers consisting of software, hardware, human resources, and workflows, where institutions communicate with the people or institutions they are in contact with. It is an inclusive name generally given to structures such as reservation centers, help desks, information lines, and customer relations. The main purpose of a call center for a company is to meet product or information requests from customers. The biggest advantage of call centers is that they increase the efficiency of the transaction depending on the business processes and add a plus to the customer transactions.

Call center managers are faced with multiple operational decision-making tasks. One of the most common tasks is to determine the weekly workforce limit to meet the customers' needs and ensure their satisfaction while keeping the service costs at a minimum level. The first step in producing a weekly schedule is to determine the number of agents that will work at intervals determined by the operation.

Representatives working in call centers are usually paid for the hours they work. However, an insufficient number of representatives to provide service in a busy working day planned in advance causes the call traffic to not be kept up and the waiting times to increase. This directly leads to customer dissatisfaction and complaints. On the other hand, hiring too many representatives for a day with low call traffic causes unnecessary travel, food, and wage expenses for the call center. Therefore, determining the number of customer representatives for the operation is crucial. Information on the number of incoming calls is needed in advance to plan the number of representatives to work at intervals determined based on the operation.

Numerous methods have been used to forecast call arrivals in call centers in the last few years. (Albrecht et al., 2021) introduced the capabilities of Machine Learning (ML) models for forecasting call center log calls regarding forecast accuracy and applicability. Relevant ML approaches and the most commonly used time series models were compared via cross-validation. Historical call center data was examined in (Kanthanathan et al., 2020). The study intended to learn the data trends and then estimate the number of incoming calls for the contact center. Traditional Recurrent Neural Networks (RNN) and their variants Long-Short-Term Memory (LSTM), Gated Repetitive Unit (GRU), and Bidirectional Long-Short-Term Memory-Bi-LSTM methods have been found to be successful in estimation. (Zhang et al., 2021) developed an Autoregressive Integrated Moving Average (ARIMA) model and a Long Short-Term Memory (LSTM) neural network model based on time series used to predict call traffic. (Ballouch et al., 2021) proposed MLP-based and LSTM-based models combined with time lags to forecast the number of call arrivals in a call center. (Leszko, 2020) estimated the expected number of calls from any company in the next 40 days. According to the study results, it was seen that the Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model, which is one of the evaluated ML models, achieved the best result. (Cao et al., 2020) predicted forward call traffic using a holistic method which analyzes and categorizes call traffic data for temporal features. After data preprocessing, an Erlang formula-supported method was developed for extracting time-dependent features to train the prediction model. In (Cao et al. 2019), an effective method was proposed to predict search traffic with multiple forecast results for future periods. In the method, seasonal dependencies are summarized by data analysis, and then different features based on these dependencies are extracted to train the forecast model. (Barrow and Kourentzes 2018) evaluated various univariate Time Series forecasting methods to predict intraday outlier call arrivals. In addition to statistical methods, ANNs were also evaluated. The results show that ANNs accurately predict call center data and can model complex outliers using simple modeling approaches. (Jalal et al., 2016) proposed a model consisting of a combination of Elman and NARX Neural Networks for call duration estimation. The data was divided into training and test sets for model performance review. 80% and 20% of the data were used for training and testing, respectively. As a result, it has been seen that E-NARXNN, which incorporates the advantages of Elman and NARX networks, is more successful than other evaluated models. (Li, 2018) aimed to predict the next peak season call volume using the time series approach. ARIMA and Holt-Winters Exponential Smoothing (HWES) methods were used to estimate call volume's baseline and peak season. The results show that the HWES model outperforms the ARIMA model. In (Motta et al. 2013), a hybrid system using ARIMA and Erlang model for call prediction was introduced. While training the model, day and time parameters were considered. (Kim et al., 2012) forecasted peak call arrivals of rural electric cooperatives call center. They used Gaussian copula to capture the dependence between non-normal distributions. (Rafiq 2017) proposed an agent personalized call prediction method that encodes agent skill information as the prior knowledge for call prediction and distribution. (Moazeni and Andrade 2018) used a data-driven approach to predict an individual customer's call arrival in multichannel customer support centers.

This study aims to forecast the number of calls using the XGBoost method combined with a consecutive and periodic lookback. Models based on MA were also developed for comparison purposes. The MAE has been used for evaluating the performance of the forecast models, whereas the generalization errors of the models were evaluated using 80/20 split for training and testing. Forecasts were generated in daily format for four different weeks. The results show that XGBoost performs better than MA for all four different weeks and produces predictions within limits of acceptable accuracy.

This paper is structured as follows. Section 2 provides information on dataset and methodology. Section 3 presents the results and discussion. Section 4 concludes the paper along with possible future research direction.

2. Dataset Generation and Methodology

This study utilized a data set collected in hourly time intervals obtained from Comdata in Turkey. The dataset includes call counts that arrived at the call center from January 1st, 2018, to October 31st, 2021,

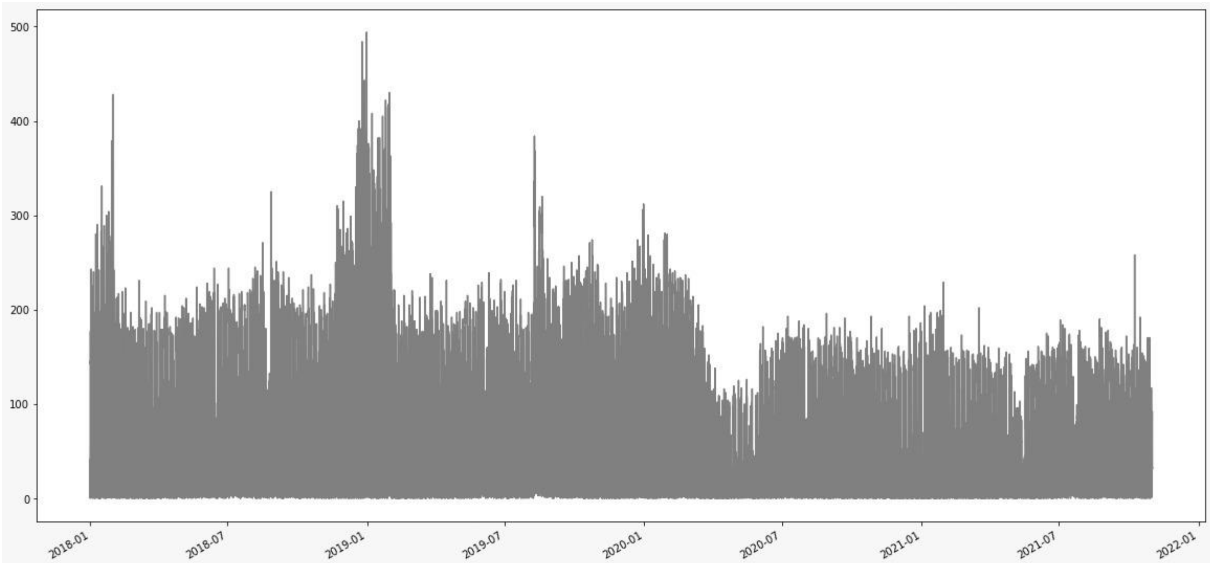

Figure 1: Number of calls on an hourly basis

on an hourly basis. Figure 1 illustrates the number of calls on an hourly basis. The predictor variables are year, month, hour, and weekday and the target variable is the number of call arrivals.

The boosting algorithm creates new weak learners and sequentially combines their predictions to improve the model's overall performance. For any incorrect prediction, larger weights are assigned to misclassified samples and lower ones to correctly classified samples. Weak learner models that perform better have higher weights in the final ensemble model.

Another variation of the boosting algorithms is XGBoost. The most important features of the algorithm are that it can achieve high predictive power, prevent over-learning, manage empty data and perform quickly. Software and hardware optimization techniques have been applied to obtain superior results using fewer resources. XGBoost is considered as one of the best decision tree-based algorithms.

One of the important factors that make the XGBoost algorithm powerful is that the tree structure created tends to minimize the error of the next tree from the previous tree. The important parameters that will affect the successful performance of the XGBoost model are the booster value, the learning rate, the gamma (i.e., minimum split loss), the maximum depth, the minimum number of leaves, lambda (i.e., the parameter that prevents over-learning), and alpha (i.e., the parameter that controls the regulation of the weights).

Consecutive and Periodic Lookback Integration is an algorithmic improvement developed to use the historical data of the target variable to be predicted on the side of supervised learning in the training dataset. Sequential lookback is how much data of the target variable will be taken as a basis for predicting, e.g., how much past sales will be used to estimate future sales. There are two values in periodic lookback. The first value is the number of periods which indicates how many times the operation to be entered into the second value will be performed, e.g., if a daily forecast is to be made, how many Fridays will go back to predict the next day. The second value is calculated according to the period of the series (i.e., weekly: 4, daily: 7, hourly: 7x24, etc.). To summarize, if the values of 2-7 are selected in a dataset in the periodic lookback daily format, this means that one goes back 7 days from the day the training data ended and adds that value to the training set, and repeats this process 2 times. In future forecasting problems, the size of the sequential and periodic historical data to create forecasting models plays an important role.

The performance of the models has been evaluated by calculating the MAE metric, shown in Eq. (1). n is the number of forecasts, A is the actual value, and F is the forecasted value. The generalization errors of the models were evaluated using 80/20 split for training and testing.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|A - F|, \tag{1}$$

3. Results and Discussion

The hourly call counts in the fourth week of June, the second week of July, the third week of August, and the second week of September were forecasted, and the rest of the data was used to train the models. According to weekly forecasts, the consecutive and periodic lookback values are 7/8-7, 14/4-7, 7/4-7, and 21/8-7, respectively.

Figure 2 through Figure 5 show MAEs of XGBoost-based models combined with consecutive and periodic lookbacks and MA-based models.

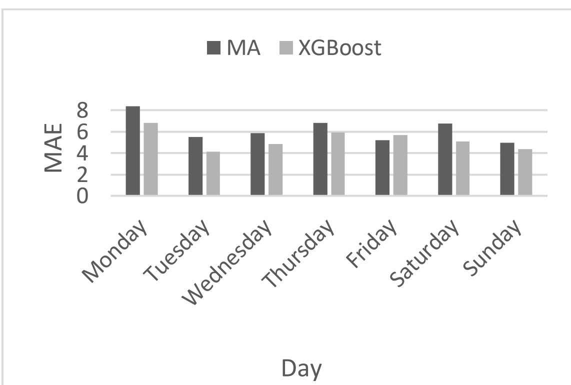

Figure 2. MAEs of forecast models for the fourth week of June using XGBoost and MA

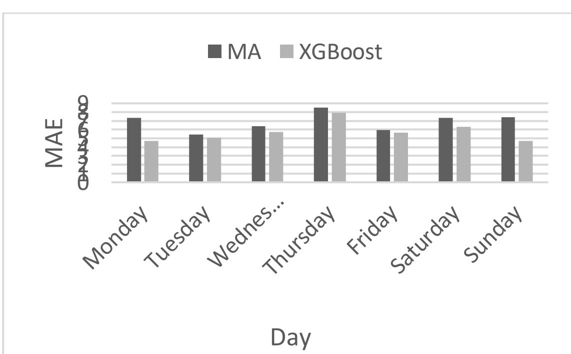

Figure 3. MAEs of forecast models for the second week of July using XGBoost and MA

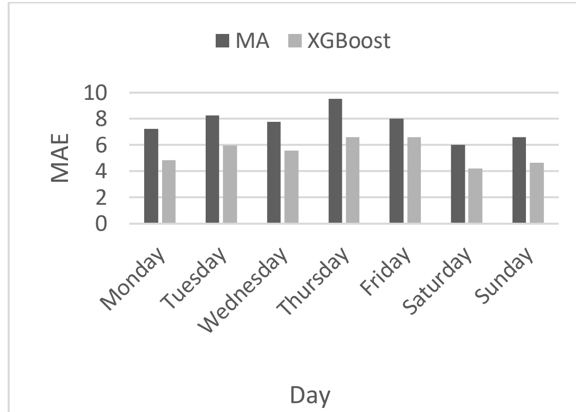

Figure 4. MAEs of forecast models for the third week of August using XGBoost and MA

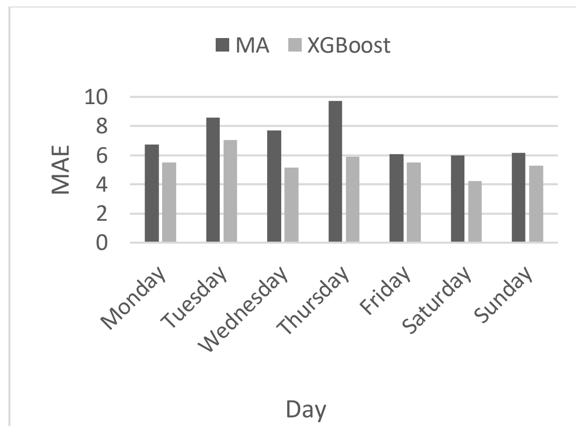

Figure 5. MAEs of forecast models for the second week of September using XGBoost and MA

The results show that

- the MAE values of XGBoost-based forecast models for the fourth week of June change between 4.11 and 8.39, whereas the MAE values of the MA-based models range from 4.95 to 8.39.
- the MAE values of XGBoost-based forecast models for the second week of July change between 4.70 and 7.94, whereas the MAE values of the MA-based models range from 5.55 to 8.50.
- the MAE values of XGBoost-based forecast models for the third week of August change between 4.23 and 6.61, whereas the MAE values of the MA-based models range from 6.00 to 9.54.
- the MAE values of XGBoost-based forecast models for the second week of September change between 4.23 and 7.04, whereas the

MAE values of the MA-based models range from 6.08 to 9.70.

It is clearly seen that the XGBoost-based models consistently outperform the MA-based models in forecasting the call center arrivals. It can be concluded that

- the average MAE value obtained with XGBoost in the fourth week of June is 15.59% lower than that obtained with MA.
- the average MAE value obtained with XGBoost in the second week of July is 16.78% lower than that obtained with MA.
- the average MAE value obtained with XGBoost in the third week of August is 28.01% lower than that obtained with MA.
- the average MAE value obtained with XGBoost in the second week of September is 24.41% lower than that obtained with MA.

4. Conclusion and Future Work

In this study, we proposed XGBoost-based models combined with consecutive and periodic lookback for forecasting the number of call arrivals in call centers. For comparison purposes, models based on MA were also developed. The dataset was created by including call counts that arrived at the call center of Comdata in Turkey from January 1st, 2018, to October 31st, 2021, on an hourly basis. Weekly forecasts have been produced on hourly periods. MAE has been utilized to assess the performance of the forecasting models. Models' generalization errors were evaluated using 80/20 split for training and testing. The results show that XGBoost models combined with consecutive and periodic lookbacks are superior to MA models. We can conclude that XGBoost-based forecasting models can be effectively used for predicting the call arrivals of a call center.

As future research direction, another interesting direction would be extending the existing forecasting models to simultaneously predict different call types, such as call counts related to receiving information about products, campaigns, and solutions to technical problems. Furthermore, quarterly and yearly call arrival forecasting models can be developed to enable long-term capacity planning in call centers.

References

ALBRECHT, T., RAUSCH, T. M., & DERRA, N. D. (2021). Call me maybe: Methods and practical implementation of artificial intelligence in call center arrivals' forecasting. Journal of Business Research, 123, 267-278.

BALLOUCH, M., AKAY, M.F., ERDEM, S., TARTUK, M., NURDAG T.F., YURDAGUL, H.H., "Forecasting Call Center Arrivals Using Machine Learning," Osmaniye Korkut Ata University Journal of Natural and Applied Sciences, vol. 4, no. 1, pp. 96-101, 2021.

BARROW, D., & KOURENTZE, N. (2018). The impact of special days in call arrivals forecasting: A neural network approach to modelling special days. European Journal of Operational Research, 264(3), 967-977.

CAO, B., WU, J., CAO, L., XU, Y., & FAN, J. (2020). Long-term and multi-step ahead call traffic forecasting with temporal features mining. Mobile Networks and Applications, 25(2), 701-712.

CAO, L., MA, K., CAO, B., & FAN, J. (2019). Forecasting long-term call traffic based on seasonal dependencies. In International Conference on Collaborative Computing: Networking, Applications and Worksharing (pp. 231-246). Springer, Cham.

JALAL, M. E., HOSSEINI, M., & KARLSSON, S. (2016). Forecasting incoming call volumes in call centers with recurrent neural networks. Journal of Business Research, 69(11), 4811-4814.

KANTHANATHAN, C., CARTY, G., RAJA, M. A., & RYAN, C. (2020). Recurrent Neural Network based Automated Workload Forecasting in a Contact Center. In 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS) (pp. 1423-1428). IEEE.

KIM, T., KENKEL, P., & BRORSEN, B. W., Forecasting hourly peak call volume for a rural electric cooperative call center. Journal of Forecasting 2012; 31(4), 314-329.

LESZKO, D. (2020). Time series forecasting for a call center in a Warsaw holding company (Doctoral dissertation).

LI, J. (2018). Forecasting and Improving the Call Center Operations-Time Series Approach and Queueing Theory Approach (Doctoral dissertation, UCLA).

MOAZENI, S., AND ANDRADE, R., "A Data-Driven Approach to Predict an Individual Customer's Call Arrival in Multichannel Customer Support Centers," 2018 IEEE

International Congress on Big Data (BigData Congress), San Francisco, CA, 2018, pp. 66-73.

MOTTA, G., BARROERO, T., SACCO, D., & YUO, L. (2013). Forecasting in multi-skill call centers: a multi-agent multi-service (MAMS) approach: research in progress. In 2013 Fifth International Conference on Service Science and Innovation (pp. 223-229). IEEE.

RAFIQ, M., (2017). Using Personalized Model to Predict Traffic Jam in Inbound Call Center. ICST Transactions on Scalable Information Systems. 4. 152101. 10.4108/eai.18-1-2017.152101.

ZHANG, M., SHENG, Y., TIAN, N., LIU, W., WANG, H., ZHU, L., & XU, Q. (2021, April). Research and Application of Traffic Forecasting in Customer Service Center Based on ARIMA Model and LSTM Neural Network Model. In Journal of Physics: Conference Series (Vol. 1881, No. 3, p. 032063). IOP Publishing.