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Forecasting Call Center Arrivals Using Multilayer Perceptron Combined with Time Lags

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Abstract

A call center is an office equipped to handle a large volume of telephone calls for an organization, for which the ability to forecast calls is a key factor. By forecasting the number of calls accurately, a company can plan staffing needs, meet service level requirements, improve customer satisfaction and benefit from many other optimizations. In this paper, we develop Multilayer Perceptron (MLP) based models combined with time lags to forecast the number of call arrivals in a call center. We forecast 12, 24, 36 and 48 values ahead and the performance of the forecasting models has been evaluated using the Mean Absolute Error (MAE). The results show that the MAE values change between 1.50 and 13.58.

Keywords: Machine learning, Call center, Forecasting, Time lags

1. INTRODUCTION

One of the most important concepts that directly affects the growth, success and prestige of companies in today's business world is customer satisfaction. Call centers that have become prominent in the service sector have become the primary communication tool for the majority of companies and companies aim to increase customer satisfaction through call centers.

60-80% of a call center budget is allocated on labor costs [1]. Therefore, capacity planning is one of the most important areas for call center performance. Determining the minimum number of agents to achieve the set targets directly affects the profitability and customer satisfaction of the company. Capacity planning is done according to the workload. One of the most significant inputs to the workload is the number of call arrivals. Therefore, forecasts of the number of call arrivals are needed. It is very important for companies to make an accurate forecast of the number of call arrivals.

In the last few years, numerous methods have been used to forecast call arrivals in a call center. [2] forecasted the number of call arrivals by developing a normal copula model for the arrival process in a call center. [3] forecasted peak call arrivals of rural electric cooperatives call center. They used Gaussian copula for capturing the dependence between non-normal distributions. [4] tried to forecast the number of call arrivals by using artificial neural network. [5] offered a strategy for selecting a model in call centers. The strategy was based on flexible loss function, statistical test and economic measure of performance. [6] forecasted the number of call arrivals by using a prediction model based on the Elman and Nonlinear

Autoregressive Network with Exogenous Inputs (NARX) Neural Network and a back-propagation algorithm. [7] proposed an agent personalized call prediction method that encodes agent skill information as the prior knowledge for call prediction and distribution. [8] used a data-driven approach to predict an individual customer's call arrival in multichannel customer support centers. [9] used a simulation-based machine learning framework to evaluate the performance of call centers having heterogeneous sets of servers and multiple types of demand. [10] used artificial neural networks to forecast the number of call arrivals.

This paper is structured as follows: Section 2 provides description of the dataset. Section 3 presents the results and discussion. Section 4 concludes the paper.

2. DATASET GENERATION

In this study, we used a data set that has been collected in 15-minute time intervals and obtained from Comdata in Turkey. The data set includes number of call arrivals from 1/1/2018 12:00:00 AM to 11/23/2019 11:45:00 PM. Figure 1 shows the number of calls on a daily basis.

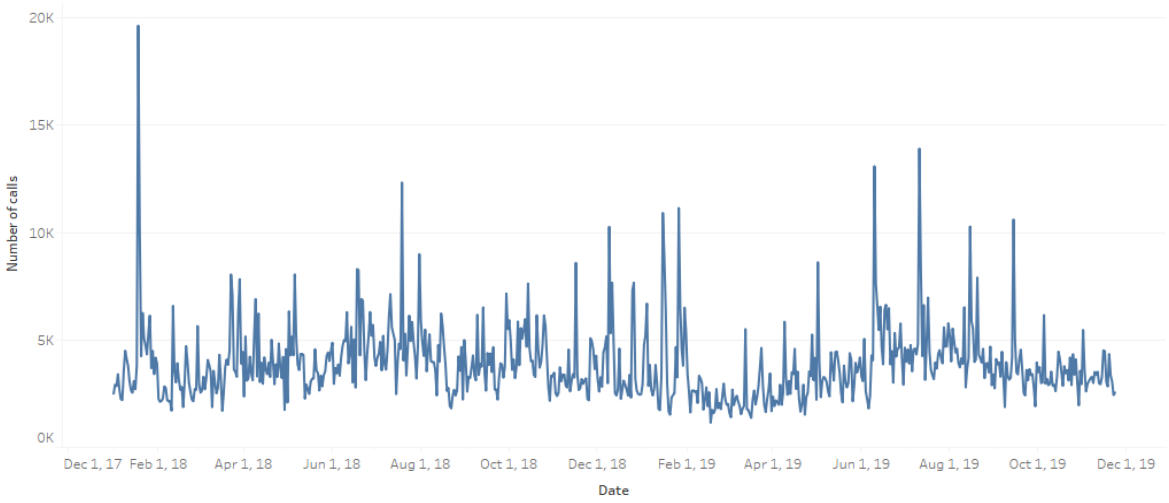


Figure 1: Number of calls on a daily basis

3. RESULTS & DISCUSSION

In this study, 24 forecast models have been built in order to forecast the number of call arrivals. The models have been developed by using different MLP hyperparameter values and time lag options.

The forecast strategy that has been used for all models is a recursive strategy, which consists of using a one-step model multiple times where the prediction for the prior time step is used as an input for making a prediction on the following time step.
For example:

Prediction(t+1) = model(obs(t-1), obs(t-2), ..., obs(t-n))
Prediction(t+2) = model(prediction(t+1), obs(t-1), ..., obs(t-n))

Feature selection is a vital problem to model time series. That is, finding the best sliding time window for a time specific time series is a very important issue. A sliding time window means a group of time lags

which employ to utilize a forecast. The length of the sliding windows is important issue in the forecasting performance. A small window gives limited information to the model. In this study, three rules have been utilized to build forecasting models. The rules of the sliding windows are given below;

- 1 to N: use all lags starting from 1 till a given value.
- Autocorrelation (AC) > Threshold: use all lags for which the autocorrelation values are above a given threshold.
- Best N AC: use lags which have the highest N autocorrelation values.

Table 1 shows forecasting models and results.

Table 1 Forecasting Models and MAE Results

Models	**Number of Forecasts**	**Time Lag Option**	**Hidden Layer Neuron Number**	**Selected Time Lags**	**MAE**
Model 1	12	Best 10 AC	13	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	4.95
Model 2	12	Best 20 AC	5	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 95, 96, 97, 98, 99, 100, 193, 194	1.37
Model 3	12	AC > 0.7	15	1, 2, 3,10	4.72
Model 4	12	AC > 0.8	13	1, 2	5.05
Model 5	12	1 to n	6	1 to 8	2.29
Model 6	12	1 to n	6	1 to 16	5.67
Model 7	24	Best 10 AC	9	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	3.77
Model 8	24	Best 20 AC	9	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 95, 96, 97, 98, 99, 100, 193, 194	3.07
Model 9	24	AC > 0.7	6	1, 2, 3,10	10.90
Model 10	24	AC > 0.8	6	1, 2	8.43
Model 11	24	1 to n	13	1 to 8	8.71
Model 12	24	1 to n	13	1 to 16	3.55
Model 13	25	Best 10 AC	35	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	4.32
Model 14	36	Best 20 AC	35	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 95, 96, 97, 98, 99, 100, 193, 194	3.18
Model 15	36	AC > 0.7	17	1, 2, 3,10	5.52
Model 16	36	AC > 0.8	17	1, 2	3.73
Model 17	36	1 to n	20	1 to 8	3.87
Model 18	36	1 to n	20	1 to 16	4.22
Model 19	48	Best 10 AC	30	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	10.96
Model 20	48	Best 20 AC	30	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 95, 96, 97, 98, 99, 100, 193, 194	5.12
Model 21	48	AC > 0.7	5	1, 2, 3,10	9.83
Model 22	48	AC > 0.8	10	1, 2	13.59
Model 23	48	1 to n	5	1 to 8	12.99
Model 24	48	1 to n	11	1 to 16	12.53

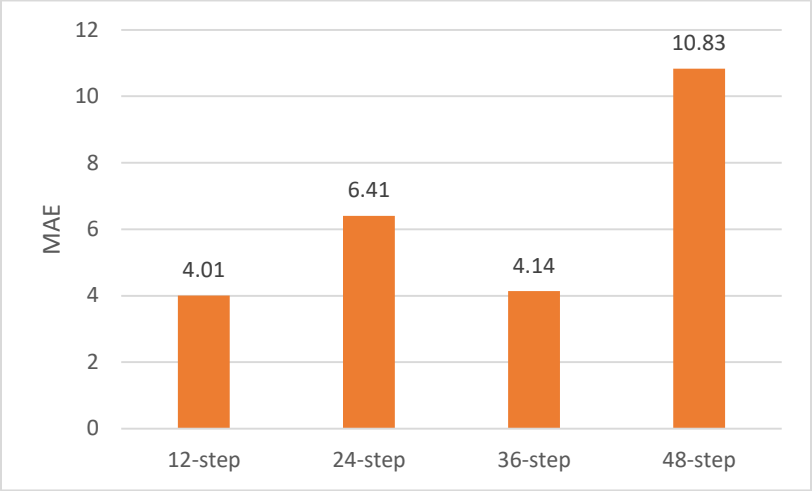


Figure 2: Comparison of the number of forecasts.

It can be clearly seen from Figure 2 that forecasting the next 12 values yields lower error rates as opposed to the other values (24, 36 and 48). The arithmetical mean of the MAE values for the 12-step is 4.01 while the mean value is 6.41 for 24-step, 4.14 for 36-step and 10.83 for 48-step.

According to the MAE's given in Figure 3, between the three options of selecting time lags, the arithmetical mean MAE for the first option (i.e. Best N AC) has been calculated as 4.59, for the second option (i.e. AC > Threshold) the mean value is 7.72 and finally the mean value for the third option (i.e. 1 to N) is 6.73. By comparing these options of time lags, one can say that Best N AC option gives more accurate results than other options.

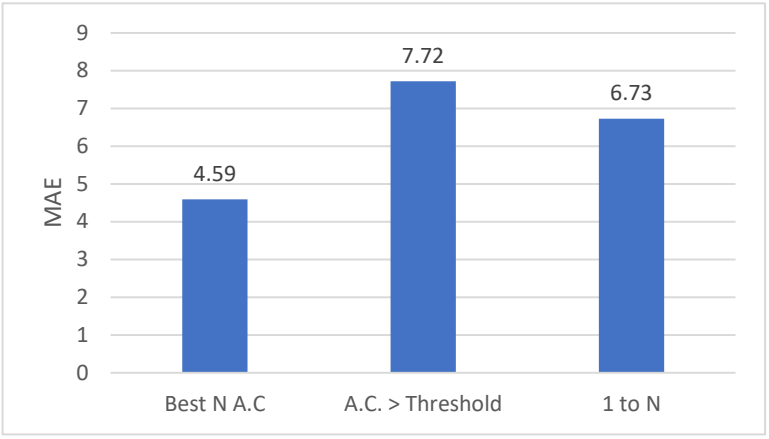


Figure 3: Comparison of time lag options

4. CONCLUSION

The main purpose of this study is to develop MLP based models combined with time lags, which can forecast the number of call arrivals. Among all the models that were developed in this study, a total number of three options have been used for determining the time lags. According to the results, it has been observed that the changes of the time lags options used in the forecasting models does change the forecasting MAE significantly. The most favorable option appears as “Best N AC”, and the least favorable option is “AC > Threshold". According to those observations, we concluded that the usage of data set autocorrelations plays important role in finding the optimal time lags values.

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