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Forecasting daily call arrivals within an inbound call center

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1 Introduction

When it comes to managing inbound call centers throughout the days of the week, we are met with a challenge concerning the incertitude revolved around the volume of incoming calls. By training either statistical or neural network forecasting models, we are able to anticipate the number of incoming calls within a certain degree of error. Of crucial importance is determining what type of model to train and how to configure this model's hyperparameters in an optimized manner. By benchmarking different optimized forecasting models, we were able to generate daily call volume forecasts for an inbound call center. This summary is presented as follows. Section 2 discusses hyperparameter optimization. Section 3 presents us with the forecasting model benchmarking. Section 4 previews our prediction results. Finally, section 5 wraps up the discussion with some concluding remarks.

2 Hyperparameter optimization

Depending on what prediction model we decide to use, there are certain tuning parameters to be chosen in order to train our models. For choosing our models' hyperparameters, we resorted to a python library named "HyperOpt" which utilizes a Bayesian-like optimization approach developed in [2].

In order to quantify the effectiveness of certain models over others, the Root Mean Squared Error (RMSE) was used for the model optimization phase and the Mean Absolute Percentage Error (MAPE) was used for the comparison of different model results. RMSE penalizes relatively large errors so that we would obtain an overall low-error prediction over the entire prediction horizon and not certain days in which we have perfect predictions and others where we have large errors. Not only does the MAPE provide a more intuitive insight into the results of our predictions, but it also allows us to compare the results of different month predictions with one another.

3 Forecasting model benchmarking

For the purpose of adopting the most effective forecasting technique which would result in the least possible errors, Table (1) represents a benchmarking of different statistical and machine learning prediction models. The data used within this section includes approximately three years' worth of historical phone log information which was provided by an inbound call center. Prior to the benchmarking phase, a pre-processing phase was carried out in order to ensure the cleanliness of the data.

The benchmark-tested models are presented as follows. The naïve model serves as a starting point for our benchmarking process. This model assumes that what occurred in the previous period would simply repeat in the next. The Holt Winters model generates forecasts that are the weighted sum of past observations. The weighting of these observations is done in an exponentially decreasing manner, leading to more recent observations having higher associated weights. Another widely used statistical model is the Seasonal Auto-regressive Integrated Moving Average (SARIMA) model. This model makes use of the correlation of our data points with previous values of itself. The Light Gradient Boosting (LGB) model is based on decision tree algorithms. The Long-Short Term Memory (LSTM) model is a recurrent neural network capable of learning seasonal patterns within our time series data.

Looking back at the available literature, one of the first articles to deal with call center incoming call volume forecasting was that of [3], in which a statistical Auto-Regressive Integrated Moving Average (ARIMA) model was used. A comparison between the usage of 8 different machine learning models showing their effectiveness can be seen in [1]. A hybrid ARIMA-Neural Network model for time series forecasting is used in [4], which concludes the fact that hybrid models can have better results than their individual constituent models.

The most performant individual model found through our benchmarking was the LGB model followed by the SARIMAX model. In an effort to test the previously mentioned hybrid model proposition, a hybrid SARIMAX-LGB model based on the arithmetic average of the LGB and SARIMAX models was built. This hybrid model was found to acquire the best overall results.

| Model | MAPE | Ranking |
|----------------------|------|----------|
| Naive | 22% | Baseline |
| Holt Winters | 24% | 5 |
| Theta | 24% | 5 |
| SARIMA | 20% | 4 |
| SARIMAX | 15% | 3 |
| LGB | 14% | 2 |
| LSTM | 24% | 5 |
| Hybrid (SARIMAX-LGB) | 9% | 1 |

TAB. 1: Daily call arrival prediction model benchmark.

4 Results

To verify the effectiveness of our hybrid model, Figure (1) presents incoming call predictions on a daily basis for the month of July 2022 by the use of a hybrid SARIMAX-LGB model. As we can see, the predictions during certain days possess a relatively high degree of error with respect to other days. For instance, the 5th of July prediction scored a MAPE of 33% compared to the overall month's MAPE of 9%. This error could be traced back to the unpredictable variability of the used data. However, further inspection of possible exogenous variables might render us capable of anticipating such events and possibly improve our predictions.

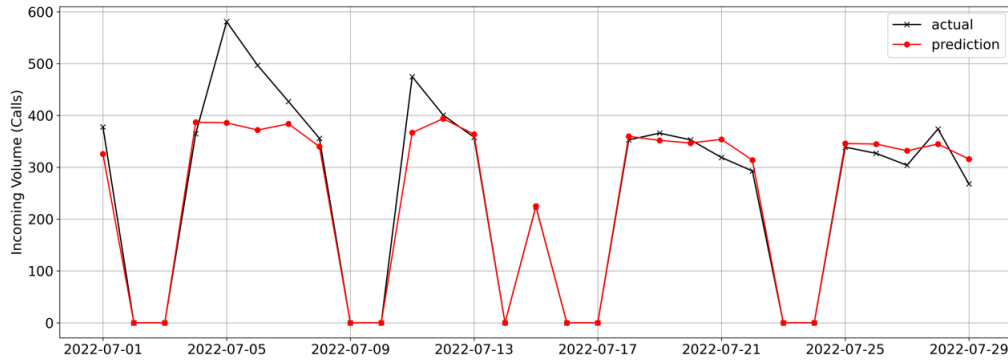


FIG. 1: Daily prediction results for July 2022.

5 Conclusions and perspectives

Within this summary, we constructed some statistical and neural network forecasting models in order to forecast a call center’s daily call arrival volume. An optimization procedure was implemented to optimize the tuning of the forecasting models’ hyperparameters. Our results indicated the out-performance of the SARIMAX-LGB hybrid model over other tested competing models. Further inspection of possible exogenous variables coupled with some feature engineering may yield even better results.

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