Automated Demand Forecasting and Workforce Staffing Optimization System

Karthik Javvaji
MS Data Science
Regis University, Denver, CO, USA
kjavvaji@regis.edu

Abstract

Accuracy in demand forecasting is essential for operational planning in a service-based environment such as call centers, service systems like chat or email, and customer support teams. Forecasting errors in staffing may result in over or under staffing causing longer wait times and stress on employees. This automated demand forecasting and workforce staffing optimization system utilizes historical operational data to evaluate multiple forecasting models which produce future demand predictions that can suggest upcoming workforce needs. The system was developed in Python and deployed through an interactive Streamlit application. The analytical workflow begins with data ingestion and continues through preprocessing, exploratory data analysis, feature engineering, model benchmarking, demand forecasting and workforce staffing estimation. In our case forecasting pipeline used historical service request data from the New York City 311 dataset to demonstrate its capabilities. The system evaluates six forecasting models which include Seasonal Naïve, Moving Average, Exponential Smoothing, Linear Regression, XGBoost and Prophet. The evaluation process used three metrics to assess model performance which included weighted mean absolute percentage error and mean absolute error and root mean squared error. The best-performing model was automatically selected to generate a six-month forecast. The forecasting process used workforce management parameters which included average handle time, shrinkage and occupancy to translate demand predictions into staffing requirements. The final output is an automated forecasting system that helps workforce planning and operational decision-making.

I. Introduction

Organizations that provide services to customers must maintain capacity throughout their operations because the volume change throughout the day. Demand in contact centers and support operations show different patterns during the hour, day and week also even seasonal changes. Service quality decreases when staffing decisions do not match the existing demand patterns.

Workforce planning has traditionally depended on organizations that forecast needs through manual methods to analyze data using spreadsheets and use basic techniques to project future trends. The methods require cost to the organization and time to implement because they generate results for operational data patterns which show nonlinear or seasonal behavior. Machine learning and time-series analytics have made progress, which enables developers to create automated forecasting systems that provide better scalability and accuracy. The systems enables operational leadership to transition from basic performance reporting to developing future operational strategies. The system was created to handle all crucial stages of forecasting while enabling organizations to make effective workforce planning choices.

II. Problem Statement

The operational teams collect historical demand data in vast amounts yet lack technical expertise which could transform their data into forecasting and staffing predictions. Organizations use multiple spreadsheets and dashboards together with manual calculations to perform forecasting processes which create maintenance and scalability challenges for their forecasting operations. Organizations experience multiple difficulties when they lack an automated analytical workflow because they use different forecasting methods which create inconsistent results while their demand patterns remain hidden and they struggle to evaluate model performance and they experience delays when they need to translate demand forecasts into staffing requirements. The project investigates how operational leaders without technical expertise can use an automated forecasting system to create workforce staffing requirements which it generates from its future demand predictions. The project aims to create and execute a complete forecasting system which enables data processing together with exploratory research, model comparison, prediction creation and personnel planning activities.

III. Project Objectives

The main goals of the practicum project would be: Primarily the development of an automated forecasting system which will process operational demand data. The second requirement of the project requires the transformation of unprocessed timestamped data into a continuous time-series database. The third requirement of the project needs the creation of visualizations which will show how demand varies over different time periods while providing the top insights at a glance. The project needs to assess different forecasting methods through established assessment standards. The system will choose the most effective model which will produce predictions for upcoming events. The system needs to convert predicted demand into the necessary staffing levels which will be calculated through workforce management formulas.

IV. Dataset

Primarily we are using the New York City 311 Service Requests dataset which is a public dataset showing non-emergency service requests made by the city residents and also has time records of these complaints.

The most critical field for this project functions as the request creation timestamp, which helps scientists convert raw event-level records into hourly demand counts. The resulting hourly series provides a realistic representation of changing operational demand over time.

V. Methodology

The project follows a structured data science workflow consisting of data preparation, exploratory analysis, forecasting model development, evaluation, and workforce planning translation.

A. Data Inspection and Preparation

Project workflow starts off by inspecting the dataset to identify the datetime column, look at the structure of the data, to confirm whether the dataset can be transformed into a usable time series. Raw timestamps are converted into a consistent datetime format. Invalid or missing time stamps are removed. Then the entries are then grouped into hourly demand intervals to create a smoother time-series dataset suitable for forecasting analysis.

B. Data Cleaning

After time-series creation, the demand series is cleaned to improve forecasting stability. Which includes dealing with missing values, handling outliers, and smoothing by rolling average.

Outliers are delt with using the Interquartile Range (IQR) method so that extreme spikes do not throw off the forecasting models. A light smoothing step is then applied using rolling average method to reduce any noise while keeping the patterns intact.

C. Exploratory Data Analysis

The project employs a formal data science methodology which includes five stages starting with data preparation and followed by exploratory data analysis(EDA) and development of forecasting models which are then evaluated through workforce planning conversion.

D. Model Benchmarking

The research team developed and tested several forecasting models to compare their performance. The testing included both baseline statistical techniques and machine learning methods which allowed assessment of various modeling approaches.

E. Forecast Generation and Staffing Translation

The process of generating forecasts requires staff members to understand the translation requirements. The system selects the best performing model through automatic selection based forecast accuracy metrics. The model produces a demand forecast that extends for six months. The forecasted demand creates workforce needs which are determined through workforce management parameters that include average handle time and shrinkage and occupancy.

VI. Exploratory Data Analysis

A. Monthly Demand Trend

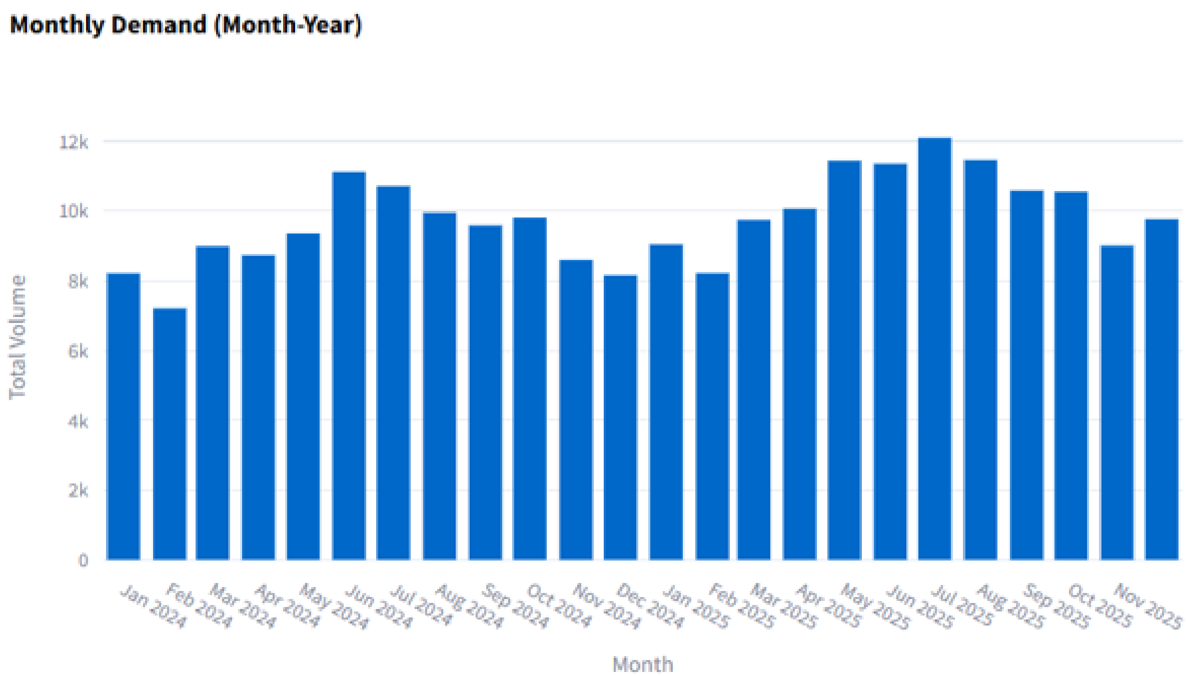

Fig. 1. Monthly demand trend derived from NYC 311 service requests

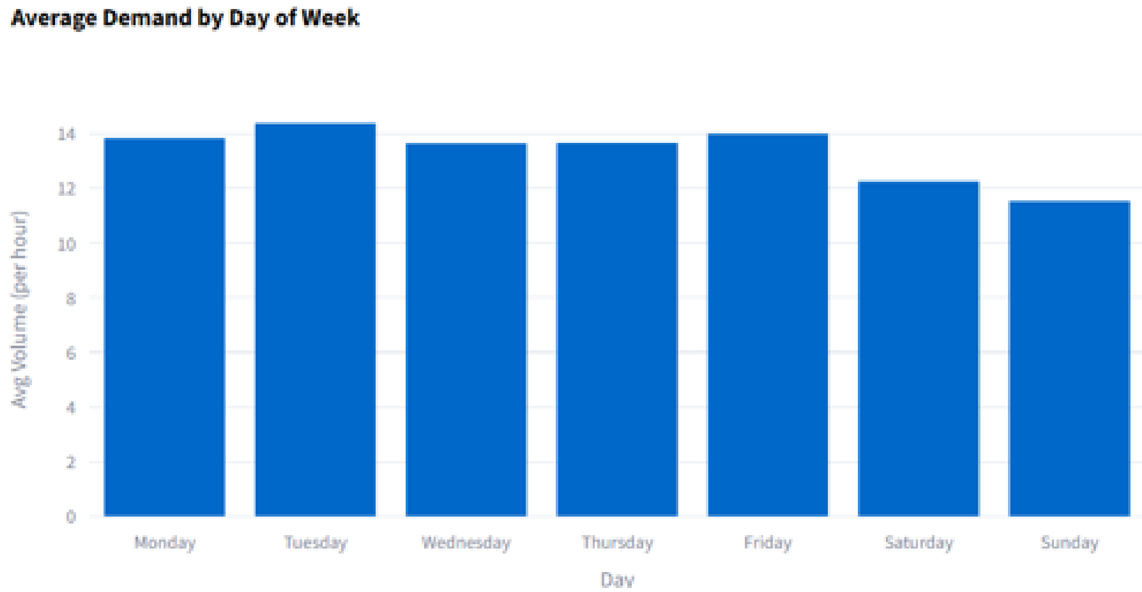

Fig. 2. Average demand by day of week

VII. Forecast Evaluation Metrics

$$wMAPE = \frac{\sum |y_t - \hat{y}_t|}{\sum y_t} \tag{1}$$

Run Model Comparison

Model Leaderboard

	Model	wMAPE	MAPE	RMSE	MAE
4	XGBoost	18.4908	29.0941	3.0735	2.2205
3	LinearRegression	19.2461	30.6466	3.12	2.3112
5	Prophet	51.0096	93.1678	7.4314	6.1257
1	ETS	53.831	102.6519	7.7665	6.4645
0	SeasonalNaive	57.0756	72.8779	9.8771	6.8542
2	MovingAverage	64.8628	180.5764	9.2789	7.7893

Best model selected: XGBoost

Fig. 3. Forecast model comparison results

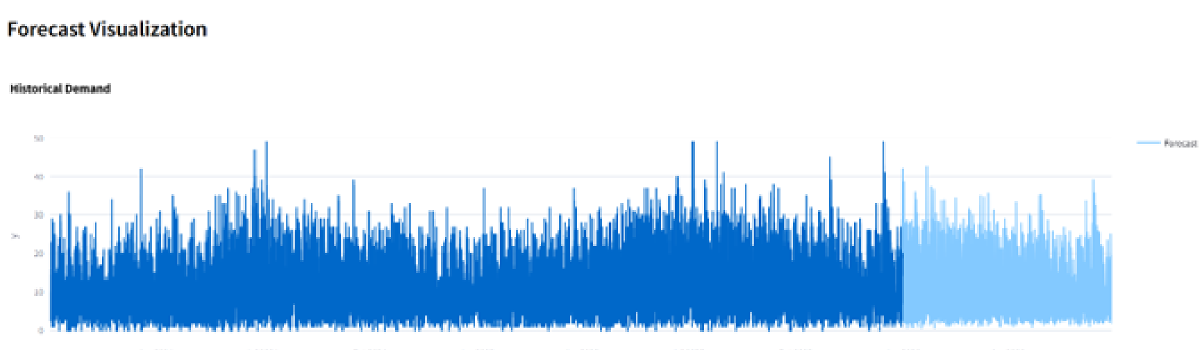

Fig. 4. Six month demand forecast visualization

$$Agents = \frac{Forecasted\ Demand \times AHT}{3600 \times Occupancy \times (1 - Shrinkage)} \quad (2)$$

	ds	yhat	required_agents
0	2025-12-31 13:00:00	18.9277	4
1	2025-12-31 14:00:00	19.9104	4
2	2025-12-31 15:00:00	20.4723	4
3	2025-12-31 16:00:00	28.9652	5
4	2025-12-31 17:00:00	24.5065	5
5	2025-12-31 18:00:00	20.4349	4
6	2025-12-31 19:00:00	20.1772	4
7	2025-12-31 20:00:00	35.8663	7
8	2025-12-31 21:00:00	42.1594	8
9	2025-12-31 22:00:00	38.7574	7

Fig. 5. Staffing levels calculated from forecasted demand

VIII. System Validation

Model Leaderboard

	Model	wMAPE	MAPE	RMSE	MAE
4	XGBoost	12.6082	14.9315	2.3276	1.6935
3	LinearRegression	12.9206	15.6952	2.3426	1.7354
0	SeasonalNaive	29.0051	30.9674	5.7183	3.8958
2	MovingAverage	40.0355	66.2175	6.4024	5.3774
5	Prophet	43.9718	52.6491	7.1497	5.9061
1	ETS	78.5357	107.2481	11.0731	10.5486

Best model selected: XGBoost

Fig. 6. Model comparison results using validation dataset

IX. System Implementation

The development team created the forecasting system using Python which they published through a Streamlit-based interface. The application enables users to upload operational datasets which they can use to examine data structure, conduct exploratory analysis while testing different models to create forecasts and examining staffing results through interactive features.

The project developed a modular system through which separate components handle data ingestion, preprocessing, feature engineering, model fitting, evaluation, exploratory analysis and staffing logic. The modular design system maintains operational efficiency while enabling work on future pipeline upgrades.

The interactive interface allows non-technical users to access forecasting and staffing analysis functions which they can use without needing to rewrite code directly.

X. Conclusion

The practicum project created an automatic system which forecasts demand and calculates workforce needs to assist operational planning through data analysis. The system combines data preparation with exploratory analysis, forecasting model evaluation, demand prediction and workforce staffing estimation into one unified process. The system offers an operational decision support tool which uses multiple forecasting methods to determine the most effective model through automatic selection. The project shows how organizations can use time-series analytics and machine learning to enhance their operational data forecasting capabilities and their workforce planning processes. The validation results demonstrate that the pipeline can handle various service-oriented datasets.

REFERENCES

[1] NYC Open Data. 311 Service Requests Dataset. https://opendata.cityofnewyork.us
[2] Montgomery County Open Data. 911 Emergency Call Dataset. https://data.montgomerycountymd.gov
[3] Vasudev, P., & Thomas, I. (2024). Important call center KPI benchmarks by industry.
[4] Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System.
[5] Taylor, S. J., & Letham, B. (2017). Forecasting at Scale.
[6] Hyndman, R. J., & Koehler, A. B. (2006). Another Look at Measures of Forecast Accuracy.
[7] Gans, N., Koole, G., & Mandelbaum, A. (2003). Telephone call centers.
[8] Brown, L., Gans, N., Mandelbaum, A., Sakov, A., Shen, H., Zeltyn, S., & Zhao, L. (2005). Statistical analysis of a telephone call center.
[9] Ibrahim, R., L'Ecuyer, P., Shen, H., & Huang, J. (2016). Modeling and forecasting call center arrivals: A literature survey and review. International Journal of Forecasting.
[10] Aldor-Noiman, S., Feigin, P. D., & Mandelbaum, A. (2009). Workload forecasting for a call center: Methodology and a case study. Annals of Applied Statistics.
[11] Shen, H., & Huang, J. Z. (2008). Forecasting time series of inhomogeneous Poisson processes with application to call center workforce management. Annals of Applied Statistics.