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Forecasting the Number of Customers Visiting Restaurants Using Machine Learning and Statistical Method

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Abstract. In this paper, it is proposed the forecasting of the number of customers visiting restaurants using machine learning and statistical method. There are some researches on forecasting the number of customers visiting restaurants. Since the beginning of last year, the number of customers visiting restaurants has plummeted due to COVID-19. A machine learning-based approach can be applied to forecast something including stable trends. Therefore, in this paper, machine learning that incorporates the moving average method is proposed to reflect the latest fluctuation trend. Furthermore, a forecasting method using deep learning is proposed to improve forecasting accuracy. In the method using deep learning, the analysis results on the normalization of training data and the contribution of meteorological data to the forecasting accuracy are described. It was found that the introduction of the moving average into the explanatory variables is effective when the trend of the number of customers visiting fluctuates rapidly. It was also found that normalization for each year of training data is effective when the annual average number of customers visiting restaurants increases or decreases monotonically.

Keywords: Forecasting Customers Visiting, Machine Learning, Deep learning.

1 Introduction

The GDP of the service industry accounts for more than 70% of that of Japan. The productivity of the service industry is lower than that of the manufacturing industry. In order to improve the productivity of the service industry, it is important to improve "efficiency" and "customer satisfaction and service quality" at the same time by using engineering methods. The goal of our research is to improve a store management method by optimizing employee job arrangements and cooking material orders based on accurate forecasts of the number of customers visiting restaurants. In our research up to last year, we made forecasts using machine learning and statistical method [1][2]. Since the beginning of last year, the number of customers visiting restaurants has

plummeted due to COVID-19. A machine learning-based approach can be applied to forecast something including stable trends. In this paper, machine learning that incorporates the moving average (MA) method is proposed in order to reflect the latest fluctuation trend in the forecast for 2020, when the number of customers visiting the restaurant has dropped sharply affected by the COVID-19. Furthermore, a forecasting method using deep learning is proposed to improve forecasting accuracy. In deep learning, we also analyzed the normalization method of training data and the effect of the presence or absence of meteorological data.

2 Forecasting Method

In this paper, "Gradient Boosting Regression (GBR) [3]", "Bayesian Linear Regression (Bayesian) [4]", "Boosted Decision Tree Regression (Boosted) [5]", "Decision Forest Regression (Decision) [6]", " Random Forest Regression (RFR) [7]", and " Stepwise Method [8]" are used as machine learning and statistical method. In addition, "Simple Recurrent Neural Network (RNN) " and "long short-term memory (LSTM) " are used as deep learning methods [9].

3 Forecasting the number of customers visiting restaurants

3.1 Target data

Using the customers visiting data of four stores from restaurant chain A of the joint research, the number of customers visiting was forecasted. Table 1 shows the period of training data set and test data set. The number of customers visiting restaurants was forecasted by machine learning incorporating the MA method using the training data set for the past four years. In order to compare the forecasting accuracy with and without the influence of COVID-19, we compared the forecasting results using the training dataset from 2018/5/1 to 2019/4/30 and 2019/5/1 to 2020/4/30. In deep learning, two-year, three-year, and four-year training data were used to compare the forecasting accuracy depending on the amount of training data.

Table 1. Training data set and test data set

Method	Data set	Period	From	To
Machine learning	Training data set	Four years	2014/5/1	2018/4/30
		Four years	2015/5/1	2019/4/30
	Test data set	Year 2018	2018/5/1	2019/4/30
		Year 2019	2019/5/1	2020/4/30
Deep learning	Training data set	Four years	2014/5/1	2018/4/30
		Three years	2015/5/1	2018/4/30
		Two years	2016/5/1	2018/4/30
	Test data set	Year 2018	2018/5/1	2019/4/30

Table 2 shows the explanatory variables used for the forecasting. The meteorological data used was the data from the Japan Meteorological Agency's observation station closest to the location of each store. From our last year's research [10], we obtained the result that meteorological data do not affect the forecasting accuracy in machine learning, thus those data were excluded from explanatory variables. On the other hand, in deep learning, the effect on the forecasting accuracy of the presence or absence of meteorological data was analyzed.

Table 2. Explanatory variable

Category	Explanatory variable	Definition
Month	January	Jan/1-Jan/31
	February	Feb/1-Feb/28
	March	Mar/1-Mar/31
	April	Apr/1-Apr/30
	May	May/1-May/31
	June	Jun/1-Jun/30
	July	Jul/1-Jul/31
	August	Aug/1-Aug/31
	September	Sep/1-Sep/30
	October	Oct/1-Oct/31
	November	Nov/1-Nov/30
	December	Dec/1-Dec/31
The day of the week	Monday	Weekday and the next day is weekday
	Tuesday	Weekday and the next day is weekday
	Wednesday	Weekday and the next day is weekday
	Thursday	Weekday and the next day is weekday
	Friday	Weekday and the next day is weekday
	Saturday	Even if the target day is a holiday it is Saturday.
	Sunday	Sunday and the next day is weekday
		Even if the target day is a holiday it is Sunday.
	Sunday during holidays	Sunday and the next day is holiday
		Even if the target day is a holiday it is Sunday.
	Holiday	Holiday and the nextday is weekday
Holiday during holidays	Holiday and the nextday is holiday	
Before holiday	Weekday and the next day is holiday	
Lastday during holidays	The last day of three or more consecutive holidays	
5 day pitch week	First week	1st day - 5th day
	Second week	6th day - 10th day
	Third week	11th day - 15th day
	Fourth week	16th day - 20th day
	Fifth week	21th day - 25th day
	Sixth week	26th day - Last of the month
Event	January 1st	January 1st
	January 2nd	January 2nd
	January 3rd	January 3rd
	Year-end	Dec/29-Dec/31
	End of year party	Weekday of December
	Christmas eve	December 24th
	Coming-of-age day	Second Monday in January
	Setsubun	February 2nd
	Obon	Aug/13-Aug/15
	New year's party	Weekday till the coming-of-age day except Jan/1-Jan/3
Farewell party	Weekday in March	
Welcome party	Weekday in April	
Meteorology	Average wind speed	Average wind speed per day (m/s)
	Maximum wind speed	Maximum wind speed per day (m/s)
	Highest temperature	Highest temperature in a day (°C)
	Lowest temperature	Lowest temperature in a day (°C)
	Amount of precipitation	Amount of precipitation in a day (mm)
	Maximum precipitation	Maximum amount of precipitation in ten minutes (mm)
	Maximum instantaneous wind speed	Maximum instantaneous wind speed in a day (m/s)
Moving average	Simple moving average	Simple moving average value

The forecasting accuracy α , that is a ratio of the number of forecasted customers to that of actual customers, is calculated using the equations (1) and (2). The reasons for excluding reserved customers in equation (1) are as follows. Since many of the reserved customers of restaurant chain A are for business use such as social gatherings associated with business trips, factors related to reserved customers are not included in the explanatory variables.

- p_i : Actual number of customers visiting without reservation on i -th day
 e_i : Forecasted number of customers visiting without reservation on i -th day
 α_i : Forecasting accuracy without reservation on i -th day
 N : Forecasting period

$$\alpha_i = \frac{p_i - |p_i - e_i|}{p_i} \quad (1)$$

$$\alpha = \frac{\sum_{i=1}^N \alpha_i}{N} \quad (2)$$

3.2 Order of MA

The relationship between the order of MA and the forecasting accuracy value was investigated to find the best order of MA. Using visitor data from 2014/5/1 to 2018/4/30, we forecasted the number of visitors visiting the four stores using only MA. In doing so, the order of MA was varied from 2 to 31. Figure 1 shows the forecasting accuracy. There was no significant change in forecasting accuracy for all four stores for 7 or higher of the order of MA. Figures 2 and 3 show the actual number of customers visiting over the four years and the forecasting results when the order of MA is set to 7, 14, 21, and 28 at store A. As the order of MA increased, the forecasting results tended to become smoother. Based on the above, and from the perspective of reflecting the weekly trend the next day, the order of MA was set to 7 in the following research.

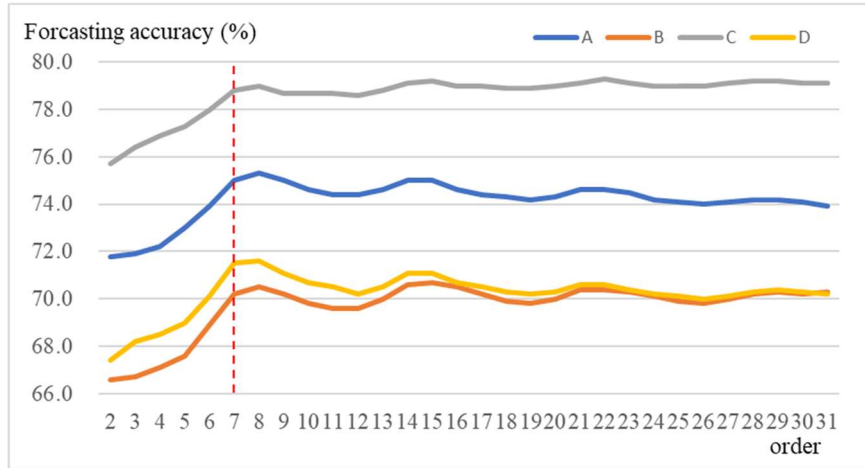


Fig. 1. Forecasting accuracy using MA

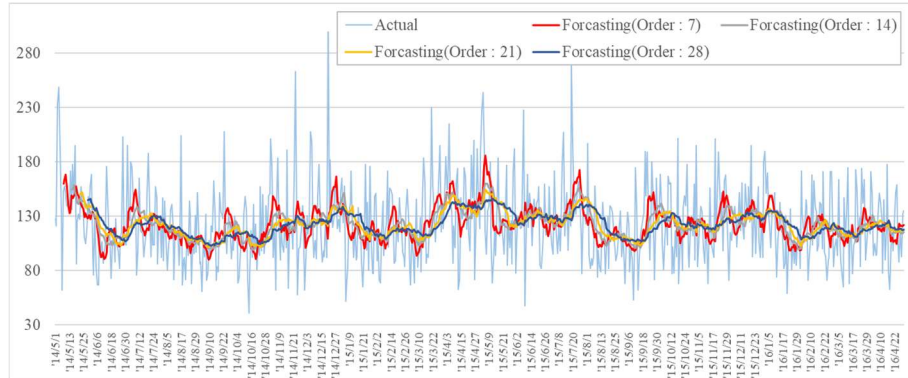


Fig. 2. Forecasting results and actual result (2014/5 – 2016/4)

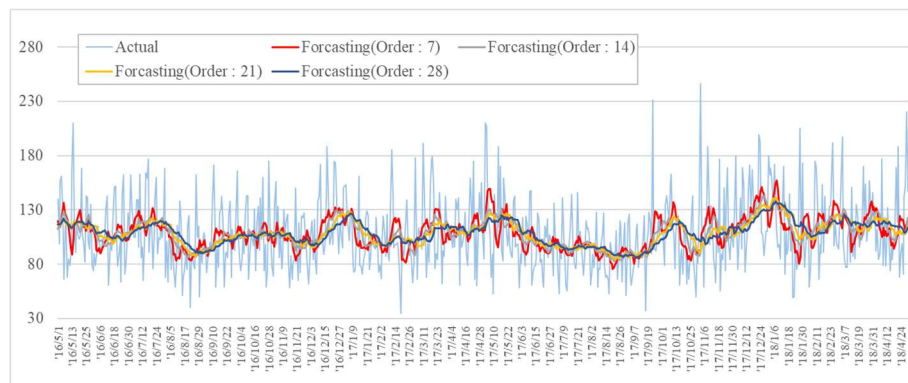


Fig. 3. Forecasting results and actual result (2016/5 – 2018/4)

3.3 Forecasting results of machine learning

Table 3 shows the forecasting accuracy using machine learning. With the MA method, the method with the highest forecasting accuracy in 2018 was different for each store. In 2019, the stepwise method was the highest except for store B. Without the MA method, the forecasting accuracy of the Decision method was the highest in 2018 except for store A. In 2019, the Boosted method was the highest except for store D. Comparing with and without the MA method, the forecasting accuracy was higher with the MA method. This tendency was remarkable in 2019, which was affected by COVID-2019.

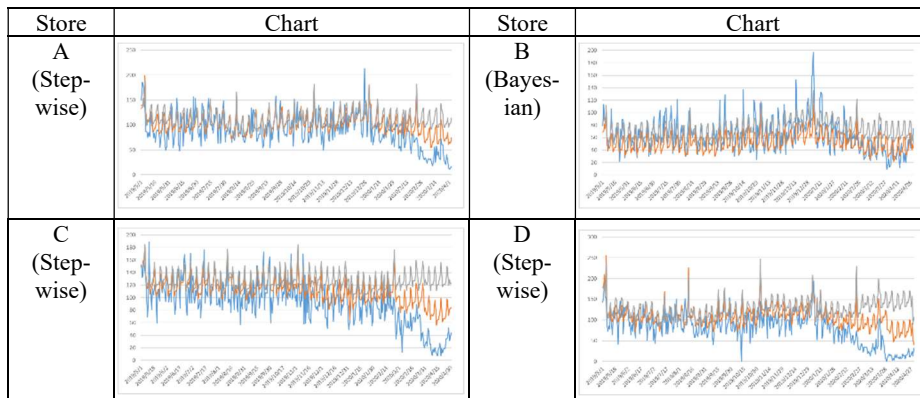
Table 3. Forecasting accuracy using machine learning

:better result between 'with MA' and 'without MA'

Store	Year	MA	GBR	Bayesian	Boosted	Decision	RFR	Stepwise
A	2018	with	79.10%	78.27%	66.08%	77.12%	78.39%	78.89%
		without	77.86%	75.67%	72.16%	74.57%	75.67%	75.83%
	2019	with	65.17%	68.50%	66.60%	66.56%	66.02%	68.95%
		without	63.92%	63.39%	68.44%	65.21%	61.86%	63.66%
B	2018	with	76.03%	76.72%	74.62%	76.57%	74.03%	76.88%
		without	74.33%	73.15%	74.58%	76.15%	71.97%	72.92%
	2019	with	65.78%	73.76%	57.06%	66.47%	64.40%	72.96%
		without	65.28%	64.86%	67.11%	66.46%	65.47%	65.20%
C	2018	with	79.02%	79.59%	76.71%	78.27%	78.57%	79.56%
		without	74.57%	74.17%	74.03%	76.50%	74.18%	74.29%
	2019	with	66.05%	67.99%	63.70%	64.19%	65.00%	68.24%
		without	57.48%	57.84%	65.92%	64.26%	58.12%	57.79%
D	2018	with	53.00%	37.27%	52.77%	55.03%	55.21%	34.04%
		without	64.62%	44.40%	68.89%	70.05%	50.10%	39.22%
	2019	with	57.81%	58.34%	53.76%	58.51%	57.89%	58.65%
		without	50.23%	49.97%	41.38%	56.67%	51.38%	49.59%

Figure 4 shows the transition in the actual customers visiting values and the forecasting values for the most accurate method in Table 3 for each store. Since January 2020, which was affected by the COVID-2019, the forecasting method with MA was able to follow the sharp decrease in the actual visiting. This is probably because the latest trend information could be reflected in the forecast by MA. However, since the forecast period is short (4 months), consideration will be given based on the forecast results for a longer period.

— : Actual — : Forecasting (with MA) — : Forecasting (without MA)

**Fig. 4.** Forecasting results using machine learning

3.4 Forecasting results of deep learning

Table 4 compares the accuracy of the forecast using the training data normalized for all years (all years) and the training data normalized for each year (each year). At stores, C and D, the forecasting accuracy of both RNN and LSTM using the training data normalized for each year was higher. On the other hand, at store A, there were many cases where the forecasting accuracy using normalized data for all years was high. At store B, there was no significant tendency. Table 5 shows the average number of customers visiting per day compared to 2014. At stores, C and D, the average number of customers visiting per day has decreased almost monotonically, and 2018, which is the forecast target, has decreased by more than 20% compared to 2014. Furthermore, this is also considered to be the reason why the forecasting accuracy is higher when the training data of the last 2 years is used than the 4 years that the number of training data is more.

Table 4. Forecasting accuracy using deep learning comparing normalization

Store	Traing data	With meteorological data				Without meteorological data			
		RNN		LSTM		RNN		LSTM	
		All year	Each year	All year	Each year	All year	Each year	All year	Each year
A	four	76.90%	65.77%	75.20%	75.18%	81.05%	72.58%	73.90%	73.84%
	three	80.67%	67.52%	73.00%	68.31%	75.40%	67.65%	73.90%	66.26%
	two	68.96%	69.41%	70.95%	70.55%	69.10%	76.14%	70.11%	70.96%
B	four	65.99%	58.28%	63.73%	57.48%	64.10%	63.75%	63.52%	57.73%
	three	75.16%	74.44%	71.81%	74.44%	71.50%	72.48%	71.68%	71.76%
	two	72.04%	63.27%	69.86%	72.25%	69.22%	70.63%	69.03%	71.36%
C	four	29.95%	70.24%	41.81%	71.39%	63.44%	74.27%	40.34%	70.20%
	three	64.77%	74.43%	65.69%	72.95%	68.21%	76.47%	64.44%	72.36%
	two	69.86%	74.65%	70.57%	72.33%	75.04%	67.77%	70.40%	72.53%
D	four	36.17%	69.25%	25.52%	71.54%	15.89%	62.73%	18.89%	70.71%
	three	53.57%	75.94%	54.53%	73.33%	34.50%	74.66%	55.05%	73.06%
	two	65.24%	66.21%	73.02%	73.87%	63.89%	64.99%	72.98%	74.28%

Table 5. The average number of customers visiting per day

Year	Store			
	A	B	C	D
2014	100.0%	100.0%	100.0%	100.0%
2015	100.7%	104.9%	84.9%	101.5%
2016	87.8%	87.6%	78.8%	94.7%
2017	89.4%	84.8%	76.5%	86.6%
2018	86.5%	85.8%	71.6%	79.5%

Table 6 compares the accuracy of the forecast using the training data including meteorological data (with data) and not (without data). In the forecasting using RNN, the accuracy of the forecasting using the training data with the meteorological data was higher at store D and was lower at stores A and C. At store B, there was no significant tendency. In forecasting using LSTM, the accuracy of the forecasting using the training data with the meteorological data was higher. Since the tendency is different between RNN and LSTM, more detailed analysis and tuning will be performed in the future.

Table 6. Forecasting accuracy using deep learning comparing meteorological data

Store	Traing data	All year				Each year			
		RNN		LSTM		RNN		LSTM	
		With data	Wiout data	With data	Wiout data	With data	Wiout data	With data	Wiout data
A	four	76.90%	81.05%	75.20%	73.90%	65.77%	72.58%	75.18%	73.84%
	three	80.67%	75.40%	73.00%	73.90%	67.52%	67.65%	68.31%	66.26%
	two	68.96%	69.10%	70.95%	70.11%	69.41%	76.14%	70.55%	70.96%
B	four	65.99%	64.10%	63.73%	63.52%	58.28%	63.75%	57.48%	57.73%
	three	75.16%	71.50%	71.81%	71.68%	74.44%	72.48%	74.44%	71.76%
	two	72.04%	69.22%	69.86%	69.03%	63.27%	70.63%	72.25%	71.36%
C	four	29.95%	63.44%	41.81%	40.34%	70.24%	74.27%	71.39%	70.20%
	three	64.77%	68.21%	65.69%	64.44%	74.43%	76.47%	72.95%	72.36%
	two	69.86%	75.04%	70.57%	70.40%	74.65%	67.77%	72.33%	72.53%
D	four	36.17%	15.89%	25.52%	18.89%	69.25%	62.73%	71.54%	70.71%
	three	53.57%	34.50%	54.53%	55.05%	75.94%	74.66%	73.33%	73.06%
	two	65.24%	63.89%	73.02%	72.98%	66.21%	64.99%	73.87%	74.28%

3.5 Comparison of machine learning and deep learning

Table 7 shows the comparison of machine learning and deep learning. In order to compare the difference in forecasting accuracy between machine learning and deep learning, it is necessary to make the conditions other than the method the same. Therefore, among the forecasts for 2018 with training data of 4 years, without meteorological data as explanatory variables, and with MA data as explanatory variables, we compared the forecasting results of the most accurate methods for both machine learning and deep learning. The forecasting accuracy of deep learning was high in stores A and D, and that of machine learning was high in stores B and C. From this, it is unclear which machine learning and deep learning are better for forecasting the number of customers visiting. However, deep learning is at the beginning of the research, and we plan to adjust the parameters in the future.

Table 7. Comparison of machine learning and deep learning

Store	Machine learning	Deep learning	
		RNN	LSTM
A	79.10%	81.05%	73.90%
B	76.88%	64.10%	63.52%
C	79.59%	74.27%	70.20%
D	55.21%	62.73%	70.71%

4 Conclusion

In this paper, it is proposed the forecasting of the number of customers visiting restaurants using machine learning and statistical method. The following results were obtained.

- (1) The MA is effective when the trend of the number of customers visiting fluctuates rapidly. However, since the forecast period is short (4 months), consideration will be given based on the forecast results for a longer period.
- (2) Normalization for each year of training data is effective when the annual average number of customers visiting increases or decreases monotonically.
- (3) Depending on the location of the store, the meteorological data may affect the forecasting accuracy.

We will proceed with research on deep learning in forecasting the number of customers visiting, aiming to improve the forecasting accuracy.

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