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Research Article

Time Series Cleaning Methods for Hospital Emergency Admissions

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ABSTRACT

Due to the nature of hospital emergency services, density cannot be easily estimated. It is one of the important issues that should be planned for emergency service managers to have sufficient resources continuously in services that develop suddenly, and emergency interventions are made for human life. Effective and efficient management and planning of limited resources are important not only for hospital administrators but also for people who will receive service from emergency services. In this situation, estimating the number of people who will request service in the emergency service with the least error is of great importance in terms of resource management and the operations carried out in the emergency services. The density of patients coming to the emergency department may vary according to the season, special dates, and even time zones during the day. The aim of the study is to show that more successful results will be obtained because of processing the time series by considering the country and area-specific features instead of the traditional approach. In this paper, the patient admission dataset of the public hospital emergency service in Turkey was used. Data cleaning and arranging operations were carried out by considering the official and religious special days of Turkey and the time periods during the day. The data set is first handled holistically, and its performances are measured by making predictions with the LSTM (Long Short Term Memory) model. Then, to examine the effect of time zones, performance values were calculated separately by dividing each day into 3 equal time zones. Finally, to investigate the effect of triage areas on the total density, the model performance was measured by dividing the data forming each time zone into 3 different triage areas in 3 equal time periods. Three stages were applied both on the raw data set and on the data created by extracting the official, religious holidays, and weekend data specific to Turkey. According to the MAPE (Mean Absolute Percentage Error) and RMSE (Root Mean Square Error) results, more successful results are obtained thanks to the cleaning and editing processes. Thanks to the study, it is thought that the data sets used for demand forecasting studies in the health sector will produce results closer to reality by determining and standardizing the purification criteria in this way.

1. Introduction

Emergency services, unlike polyclinics, provides basic care support to patients and accepts patients in 24 hours a day, 7 days a week [1]. In general, patients may come to the emergency services due to a sudden onset of illness, an undiagnosed illness or sudden injury. As in every field, resources are limited in the field of health. In this case, hospital managers must perform effective and efficient resource management and planning processes to meet the needs. Personnel needs in emergency services are generally met by a doctor and nurses on duty, regardless of their specialty, in 8-hour shifts. This brings additional workload for duty personnel such as doctors and nurses. Patients who apply to the emergency departments of hospitals operating in Turkey are first

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determined by the diagnostic desk to which triage area they will follow [1]. In some countries in Europe, triage categorization is made over 5 colors. Red, orange, yellow, green, and blue colors indicate urgent, very urgent, urgent, standard, and non-emergency situations, respectively [2]. Three colors are used for triage categorization in Turkey. Category 1 (red), category 2 (yellow), category 3 (green) means immediate intervention, intervention within one hour at the latest, and intervention within three hours at the latest, respectively. In this way, it is aimed to use human and logistic resources correctly and effectively and to intervene quickly to patients. Today, the increase in people's expectations from the health system leads to a lack of capacity and resources, which in turn reduces their satisfaction with the service provided. In order to minimize such negative situations and to perform resource management in the most effective way, it has become important to dynamically adjust resources according to short-term forecasts. There are some factors having effects on the time series. These factors, time series components, are named as trend (T), regular fluctuations (M), irregular fluctuations. Trend shows the main tendency of the time series in the long run [3]. Regular fluctuations are fluctuations having both cyclical and periodicity properties [4]. Clinics may be out of service in case of special days (official-religious holidays), disasters, or epidemics that vary according to countries. The number of applications to the emergency department may increase in such cases. It causes a decrease in the performance of estimator models due to the effect of such irregular fluctuations on the time series.

In this study, it is aimed to reveal the effects of the above-mentioned conditions on time series forecasting performances. First, LSTM (Long Short Term Memory) model performance was measured on the raw data. Then, raw data was edited by extracting daily data for the weekend and holidays in 2015. Performance of LSTM was measured again on edited data. In addition, using the edited data, performance measurement was made with the LSTM model by dividing a day into three 8-hour slices and 3 different triage situations. In this study, the contribution of modifications made in the raw datasets used for forecasting of the hospital emergency service units was aimed to be revealed by comparing the model performance obtained because of the statistical metrics.

This study is divided in 6 sections. Basic information about the research subject is given in the introduction section. In the literature review section, studies on traditional time series models and the LSTM model based on deep learning are introduced. In the material and method section, it is detailed the modifications performed on the data set used in the study, the LSTM model used and the performance criteria. In the findings section, the performance on modified data sets of LSTM model is given. In the fifth part, evaluation and conclusion part, the performance of the LSTM on the data preparation method are evaluated. In the last section, future studies, the limitations of this study and recommendation for future studies are shared.

2. Literature Review

Time series are in demand in a very wide area in daily life, from stock market to transportation, from telecommunication to energy sector. Time series are frequently used in decision-making mechanisms as they make it easier for us to make predictions for the future on management issues such as investment, planning and optimization. In the transportation sector, models have been developed using time series for calculating the transportation times of vehicles, especially in metropolitans that have transportation problems due to traffic density, for planning urban transportation vehicles [5] [6]. There are lots of studies on changes and fluctuations on time series data sets, especially in areas such as seasonal electricity consumption [4], [7], natural gas consumption [8], [9], [10] economy [11] and food [12]. Box-Jenkins (ARIMA- Autoregressive Integrated Moving Average) models (AR-Autoregression, MA- Moving average, ARMA-Autoregressive moving average) [13] have been used in many fields such as furniture [14], finance [15], energy [16], food [17] for discrete and linear time series datasets. In the healthcare field, in addition to the emergency department density estimation [18] [19], covid-19 [20], the number of calls to the 112-emergency call center [21], the average cost per prescription [22], the need for medical supplies [23], serum set consumption [24], Electrocardiogram (ECG) signal analyzes [25] and hospital disaster preparedness [26] have also been used for estimation purposes. LSTM (Long Short Time Memory) with recent success in deep learning approaches [27] [28] [29] has been used in many fields such as [30] financial [31], energy [32], health [33] [34] [35] [36]. In addition, the LSTM shows high performance in areas such as handwriting recognition [37] [38], translation [39]. It produces more successful results than traditional/statistical models in predictions made using time series [40].

3. Material and Method

3.1 Dataset

The data set used in the study consists of information of patients who applied to emergency services of public hospital operating in Turkey between 01.01.2015 and 31.12.2015 in yearly, monthly, daily, hourly, minutely, and secondly. Triage sections which the patients they were referred are also included in dataset (Table 1).

Table 1 Emergency service data set sample

Examination	Triage Epicrisis Entry Date	Triage Information
Green field examination	1/1/2015 0:17	GREEN
Green field examination	1/2/2015 19:49	GREEN
Green field examination	1/2/2015 21:35	GREEN
Green field examination	1/2/2015 22:16	GREEN

First, the raw data set was grouped to show the total number of patients who applied in one day (Data Set-1). Secondly, weekends, public and religious holidays were excluded and grouped in the same way (Data Set-2). Finally, for both data sets, a day was divided into three equal time periods (shifts) and grouped daily for each time period (Data Set-3 and Data Set-4). Finally, for both data sets, a day was divided into three equal time periods (shifts) and grouped daily for each time period (Data Set-3 and Data Set-4). While creating Data Set-2, all weekend holidays of 2015 were excluded from the dataset. At the same time, only the days covering the Feast of Sacrifice were extracted from the data set. Only public holidays are excluded. The aim here is that official holidays are limited to one day and other religious holidays do not have a dominant effect on the data. At the same time, it was aimed to keep sufficient data to reach realistic results.

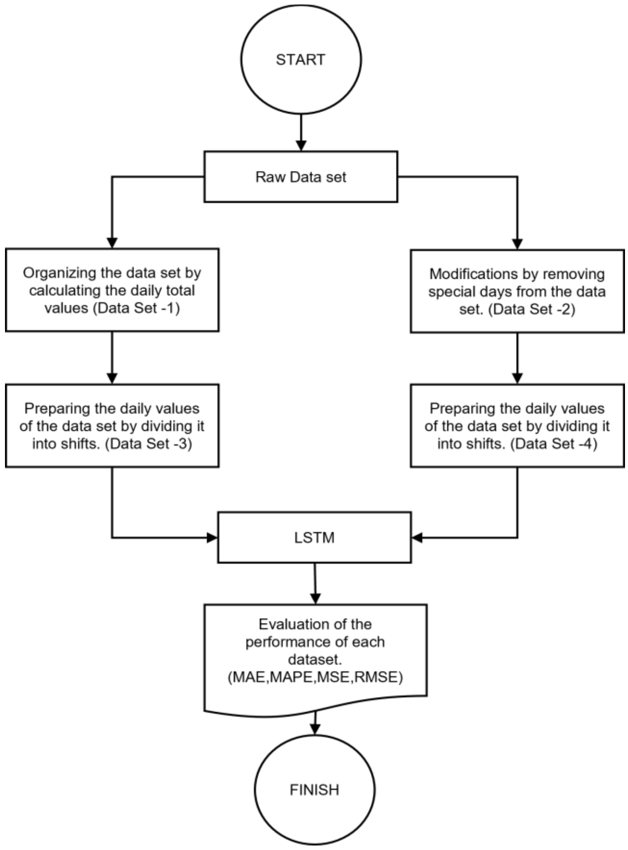

Figure 1 Data preparation and make regression process steps

3.2 LSTM (Long Short-Term Memory) Model

The LTSM was introduced to the literature by Sepp Hochreiter and Jurgen Schmidhuber in 1997 [41]. Later, the model took its current form [42] with some innovations and regulations such as adding the forget gate [43] and the activation function [44]. Since LSTM can learn long-term trends with its memory that can hold historical data, sequential or time series performs well [22]. Equations of input, output, forget gates and memory cells using in basic LSTM architecture are shown in Equations 1, 2, 3, 4, 5 and 6, respectively [45].

$$i_t = \sigma(W_{ix}x_t + W_{hh}h_{t-1} + W_{ic}c_{t-1} + b_i) \quad (1)$$
$$f_t = \sigma(W_{fx}x_t + W_{hh}h_{t-1} + W_{fc}c_{t-1} + b_f) \quad (2)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot g(W_{cx}x_t + W_{hh}h_{t-1} + W_{cc}c_{t-1} + b_i) \quad (3)$$
$$o_t = \sigma(W_{ox}x_t + W_{hh}h_{t-1} + W_{oc}c_{t-1} + b_o) \quad (4)$$
$$h_t = o_t \odot h(c_t) \quad (5)$$
$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (6)$$

i, f, o, c, w and σ(x) represents input gate, forget gate, output gate, cell activation vector, weight matrix and sigmoid function respectively (Eq. 6). The ⊙ symbol represents the scalar product of two vectors or metrics.

3.3 Performance Measurements

Some statistics are used on the estimation results produced by the models to measure the model performance and to determine which of the generated models produces better results. In the performance evaluation of the estimation results of the model, MAPE (Mean Absolute Percentage Error), and RMSE (Root Mean Squared Error) equations are used. As the MAPE (Eq. 7), and RMSE (Eq. 8) results get closer to 0, it indicates that the model performs well, and on the contrary, the model performs poorly. Choosing which evaluation metric to use may vary depending on the problem. For regression problems, RMSE and MAPE are the most used performance evaluation tools [46]– [48].

For example, Results can be classified according to MAPE value. Results and its classifications are given below as:

it means "very good" if the result less than 10%,

it means "good" if the result is between 10% and 20%,

it means "moderate" if the result is between 20% and 50%,

it means "false" or "incorrect" if the result is more than 50% [49].

$$MAPE = \left(\frac{1}{n}\sum_{t=1}^{n}\frac{|Y_t - \hat{Y}_t|}{Y_t}\right) * 100 \qquad (7)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2} \qquad (8)$$

In the above equations Y, $\hat{Y}$ and n indicate the actual value, predicted value, and total number of values, respectively.

4. Experimental Results

Same LSTM (Long Short-Term Memory) model trained and tested on each dataset created. Python was used as programming language. In this study, very simple LSTM model was used. LSTM model architecture consists of 3 layers in total: LSTM with 10 units, drop out and dense layers. Sigmoid function was used as an activation function. Some training data parameters are as follows: 10 batch size,100 epochs, Adam optimizer and binary cross entropy as lost function. If the training loss of the model did not change during the 10 epochs, the model training process was stopped. Dataset was split into 70% as training and 30% as a testing.

Data Set-1 and Data Set-3 consist of 365 daily data, for Data Set-2 and Data Set-4 consist of 257 daily data after subtracting holidays. LSTM performance results on 4 data set are shown in Table 2.

```
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 10)                640
_________________________________________________________________
dropout (Dropout)            (None, 10)                0
_________________________________________________________________
dense (Dense)                (None, 1)                 11
=================================================================
```

Figure 1 LSTM architecture

Table 2 Datasets total values

Datasets		MAPE	RMSE
Data Set-1		0.207	22.884
Data Set-2		0.157	15.661
Data Set-3	**00.00-08.00**	0.529	5.031
	08.00-16.00	0.33	13.96
	16.00-00.00	0.163	11.164
Data Set-4	**00.00-08.00**	0.513	4.864
	08.00-16.00	0.28	10.531
	16.00-00.00	0.147	9.28

Considering the results shown in Table 3, if the raw data set (Data Set-1) is used without any modification, the MAPE (Mean Absolute Percentage Error) value is 20% and the RMSE (Root Mean Squared Error) value is 22.88. In this case, performance can be described as "medium". It is seen that the MAPE and RMSE results of the Data Set-2, which was modified by subtracting the determined days, are 15% and 15.66, respectively. According to the results, Data Set-2 performance can be considered in the "good" category. There is a difference of about 5% between the two dataset performances.

Table 3 Performance results according to triage of Data Set-1 and Data Set-2

Triage Group	Data Set-1		Data Set-2	
	MAPE	RMSE	MAPE	RMSE
Red	-	0.419	-	0.393
Yellow	0.658	6.783	0.756	6.911
Green	0.223	21.739	0.159	15.177
Sum	0.207	22.884	0.157	15.661

Data Set-3 and Data Set-4 were obtained by separating Data Set-1 and Data Set-2 values according to 8-hour time periods and triage sections, respectively. Performance results for Data Set-3 and Dataset-4 are shown in Table 4 and Table 5, respectively.

Table 4 Performance results according to triage of Data Set-3

		Red	Yellow	Green	Sum
00.00-08.00	MAPE	-	-	0.527	0.529
	RMSE	0.193	2.034	4.023	5.031
08.00-16.00	MAPE	-	-	0.552	0.330
	RMSE	0.350	4.335	14.249	13.960
16.00-00.00	MAPE	-	0.919	0.185	0.163
	RMSE	0.151	3.804	11.098	11.164

MAPE value in Table-4 and Table5 couldn't be calculated for the "Yellow Triage" between 00.00-08.00 and 08.00-16.00 and for all time periods "Red Triage". The reason for this is that in the MAPE equation (Equation 8) if actual value is 0, division by zero cannot be performed. Model performance on Dataset-2 is seen as 2% more performant in general. When the "Green Triage" field MAPE and RMSE values are examined, it is seen that model performs much better.

Table 5 Performance results according to triage of Data Set-4

		Red	Yellow	Green	Sum
00.00-08.00	MAPE	-	-	0.539	0.513
	RMSE	0.201	1.889	4.050	4.864
08.00-16.00	MAPE	-	-	0.392	0.280
	RMSE	0.300	3.999	9.038	10.531
16.00-00.00	MAPE	-	0.929	0.150	0.147
	RMSE	0.177	3.816	8.663	9.280

5. Conclusions

Time series are frequently used in the field of economics and data cleaning forms [50]–[53] prepared by considering many factors such as trends and seasonal effects are used and constantly improved. However, in the health sector, where many disciplines work intertwined and coordinated, there are some studies [19] that focus on seasonal effects in the field of emergency service demand forecasting, but there are not enough studies on triage or time zones in general. In the study, it has been shown that cleaning methods on time series data sets contribute positively to the performance of the model, as well as the selection of the methods or methods to be applied on the time series. As stated in the study, emergency service admission criteria may vary according to country. Researchers can work on creating cleaning and purification forms by country in future studies. In addition, future works can be focused on to help determine general and special criteria in emergency patient admission procedures.

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