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Bayesian statistic model for nurse call data considering time-series, individual patient variabilities and massive zero-count call data

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***Abstract*— Analysis of nurse calls is important to evaluate nursing management, because nurse calls reflect the fundamental demand of patients. However, the nurse call data include time-series properties and individual patient variabilities. In addition, the calls do not necessarily follow the common single distributions such as normal and Poisson distribution. These characteristics of the nurse call data cause the difficulty of applying traditional frequent statistics. To resolve this problem, we introduced Bayesian statistics and proposed a model including three elements: 1) transition, which represents time-series change of nurse calls, 2) random effect, which handles individual patient variabilities, and 3) zero inflated Poisson distribution, which is suitable for nurse call data including massive zero data. To evaluate the model, nurse call dataset containing total 3324 patients in orthopedics ward was used and the differences of nurse calls between the patients who had undergone orthopedics surgery and those who had undergone other surgeries were analyzed. The result in comparing all combinations of elements suggested that our model including all elements was the most fitting model to the dataset. In addition, the model could detect longer duration of nurse call difference existence than the other models. These results indicated that our proposed model based on Bayesian statistics may contribute to analyzing nurse call dataset.**

I. INTRODUCTION

The nurse call system is an inevitable system equipped in the general hospital because the patients can easily notify their needs of assistance or emergency using the system. Thus, the number of nurse calls can become an indicator of nursing in a hospital. Indeed, we have been analyzing the nurse call data to investigate ward status[1]. The previous researches utilize a total number of nurse calls as an indicator of quality of nursing cares directly[2][3]. However, the number of nurse calls may reflect not only nursing management, such as nursing round for patients and administrative structure, but also patients' body conditions, such as recovery or suffering from disease. Thus, development of statistical analysis method for nurse calls may provide new information to evaluate both total status of a ward and individual patients status.

The statistical analysis of nurse calls using traditional frequent-based statistics is difficult, especially time-series data. The nurse call data include several issues that block introduction of traditional statistics. In other words, since the nurse calls change hourly and daily after patient's admission, the analysis method should treat with this time-series change. The number of nurse calls may depend on not only patients' body condition but also personality (i.e. while some patients never hesitate to call nurses, some patients do), which can result in wide variability of the nurse calls. Besides, the number of nurse calls is not necessarily observed as a normal or Poisson distributions because some patients never call nurses in particular duration due to their severe conditions, which lead to massive zero-count call data. The analysis method should handle these issues.

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In order to analyze nurse call data with these problems, we introduce Bayesian statistics. Bayesian statistics require pre-designed statistic model but permit complicated model based on various probabilistic distributions. However, there are no research on how to construct the statistic model to dataset like nurse calls. Thus, to explore the statistical model for nurse calls is required. The models that should be explored are 1) how to model time-series change, 2) how to model individual patient variabilities according to patients' personalities, and 3) how to model observation of nurse calls.

As a target for analysis of nurse call data, we analyzed the change of the number of nurse calls after surgery in orthopedics ward because almost 80% of patients claim the pain after surgery in the ward[4][5]. In addition, the pain after surgery depends on the type of surgeries[6]. The pain may decrease gradually after surgery, which results in the decrease in the number of nurse calls. Thus, investigating time-series change and difference of nurse calls among surgery types is an interesting analysis target. The detection of time-series change and differences may support assessing the current status of patients in the ward and suggest some cues for change of nursing system and introduction of new cares for pain management. This analysis contains not only issues related to nurse call data but also multiple comparison problem. In order to detect differences on days, traditional statistics supplies multiple comparison analysis. However, this comparison fundamentally contains the occurrence of the alpha error problem, which cause over-estimation of the difference between two groups. On the contrary to the traditional statistics, since Bayesian statistic estimates distribution model parameters directly from dataset, Bayesian statistics does not cause this problem. In this point of view, analysis target is suitable to confirm effectiveness of our model. Thus, our research purpose is to explore what Bayesian model is suitable for nurse calls data containing individual difference.

II. Bayesian statistic model for nurse calls

Firstly, a simple model was constructed. The statistic model assumes 1) the daily nurse call changes after surgery independently, 2) there is no consideration of individual variability per patient, and 3) the daily nurse calls are observed as Poisson distribution. The model is denoted as follows.

$$X_d^{(g1)} \sim Uniform() \tag{1}$$
$$X_d^{(g2)} \sim Uniform() \tag{2}$$
$$log(m) = \begin{cases} X_d^{(g1)} + s_v \\ X_d^{(g2)} + s_v \end{cases} \tag{3}$$
$$Y \sim Poisson(m) \tag{4}$$

X_d represents the number of nurse calls at day d. $g1$, and $g2$ mean individual groups. s_v was variance of observation. Eq. 1 and Eq. 2 represents that all means of daily nurse calls are derived from non-informative prior. In other words, the equations represent that the number of nurse calls on a day is independent from the number of nurse calls on the other days or other groups. Eq. 3 shows that log is used for link function for mean m of Poisson distribution. This is the same as link function in general linear model. The fact that the same s_v was used for every patient data in both group 1 and group 2 is equivalent to hypothesis that all patients has the same variability of daily nurse calls. s_v is was derived by non-informative prior. Eq. 4 shows each observed daily nurse call Y is generated by Poisson distribution with the mean value m of Eq. 3.

A. Transition Model

As a simple introduction of time sequence model, we consider the model that the nurse call on the previous day affects the nurse call on the current day. In this model, the Eq. 1 and Eq. 2 are replaced by the following equations.

$$X_d^{(g1)} \sim Normal(X_{d-1}^{(g1)}, s_d) \tag{5}$$
$$X_d^{(g2)} \sim Normal(X_{d-1}^{(g2)}, s_d) \tag{6}$$

where s_d is common variance among the groups and transition of nurse calls. The variance is derived from non-informative prior. The normal distribution is used for transition representation. This equation is regarded as consideration of 1-order differential. In this paper, this model is called '1-order'.

In order to express that the nurse calls depends on nurse calls on previous consecutive days more smoothly than '1-order' model, the second-order differential model is also considered as follows.

$$X_d^{(g1)} \sim Normal(2X_{d-1}^{(g1)} - X_{d-2}^{(g1)}, s_d) \tag{7}$$
$$X_d^{(g2)} \sim Normal(2X_{d-1}^{(g2)} - X_{d-2}^{(g2)}, s_d) \tag{8}$$

In this case, the nurse calls at the day was decided from previous two days and smoothly connected based on gradient between previous days. In this paper, this model is called '2-order'.

B. Patient Model

Nurse call dataset includes multiple entries of one patient. The variability of daily nurse calls depends on the uniform variability in the basic model. It is known that repetitive entries distort the statistical result. Thus, traditionally, the linear mixed model is often utilized to treat with this problem by introducing a random effect variable, which includes all variability related to individual patients. In Bayesian statistics, the hierarchical Bayes model can handle this problem. To introduce nurse call variabilities based on individual patients, the following equation is inserted.

$$r_i \sim Normal(0, s_r) \tag{9}$$

r_i represents that individual variability of patient i. This variability is generated from normal distribution with 0 mean and variance s_r. s_r is generated from non-informative prior. And then, Eq. 3 is modified as follows by introducing r_i.

$$log(m) = \begin{cases} X_d^{(g1)} + r_i + s_v \\ X_d^{(g2)} + r_i + s_v \end{cases} \tag{10}$$

In the equation, individual variabilities are added in both group 1 and group 2 model. This addition adjusts the difference of tendency to call nurses.

C. Observation Model

The nurse calls are finally observed as Poisson distribution. This observation model represents that all patients call the nurses the same way. However, the patients who need no assistance from nurses or the patients with serious condition never call nurses during a day. This tendency does not depend on patient's personality related to nurse calls. This ratio of zero-count nurse calls in dataset is not so few. Inclusion of zero-count nurse calls distorts total distribution of nurse calls. It is known that zero inflated Poisson (ZIP) distribution fits this distribution well. Thus, ZIP distribution is introduced instead of usual Poisson distribution. In this case, Eq. 4 is replaced as follows using combination of Bernoulli and Poisson distributions.

$$Y \sim \begin{cases} B(0|q) \\ +B(1|q)Poisson(y=0|m) \quad (if \quad y=0) \\ B(1|q)Poisson(y|m) \quad (if \quad y>0) \end{cases} \tag{11}$$

where q indicates that possibility of zero-count nurse call occurrence. B is Bernoulli distribution.

D. Implementation

For estimating parameters of the model from dataset, Markov chain Monte Carlo (MCMC) method is usually utilized. For the implementation, Stan* was used. Since there is no model of the difference between the two groups per day explicitly, $X_d^{(diff)}$, difference of $X_d^{(g1)}$ and $X_d^{(g2)}$, was also calculated simultaneously to confirm significant daily differences between two groups. The number of sampling for estimation was 5000.

*https://mc-stan.org/

TABLE I: WAIC, LOO, and mean with credible interval on day 1 and 6 after surgery among models

transition model	patient model	observation model	WAIC	LOO	difference on day 1 2.5%	50%	97.5%	difference on day 6 2.5%	50%	97.5%
no	no	Poisson	72.47	53.51	0.56	0.64	0.73	-0.00	0.07	0.14
1-order	no	Poisson	72.47	53.53	1.85	2.07	2.30	-0.01	0.22	0.43
2-order	no	Poisson	72.50	53.50	1.86	2.07	2.30	-0.01	0.22	0.43
no	random effect	Poisson	11.54	14.35	1.54	1.85	2.08	0.53	0.74	0.90
1-order	random effect	Poisson	11.51	14.99	1.55	1.81	2.10	0.54	0.72	0.91
2-order	random effect	Poisson	11.54	15.03	1.50	1.78	2.07	0.50	0.71	0.90
no	no	ZIP	56.91	46.59	0.22	0.25	0.28	-0.05	-0.00	0.04
1-order	no	ZIP	56.80	46.10	0.30	0.35	0.39	-0.09	-0.01	0.06
2-order	no	ZIP	57.00	46.23	0.29	0.33	0.38	-0.07	-0.01	0.06
no	random effect	ZIP	10.54	14.09	0.30	0.35	0.40	0.08	0.14	0.19
1-order	random effect	ZIP	10.61	13.73	0.28	0.32	0.39	0.07	0.11	0.18
2-order	random effect	ZIP	10.54	14.04	0.27	0.33	0.39	0.08	0.13	0.19

III. Model Evaluation Experiment

A. Dataset

The database in a university hospital in Japan was used for analysis. This research was approved by the ethical committee of medical department of the University of Tokyo. The duration of data records was from Apr. 1st 2014 to Oct. 31th 2017. The final dataset was created by integrating several database in the hospital. The single record in the dataset included anonymized patient ID, days from surgery (day0 means surgery day), the number of nurse calls in a day, surgery type which a patient have undergone (0: other surgery and 1: orthopedics surgery). Total number of patients in the dataset was 3329.

The target analysis is to investigate how differently the number of nurse calls changes between patients who have undergone orthopedics surgery (g1) and those who have undergone other surgery (g2). Duration of d was defined from 0 to 14, according to hospitalization duration (mean $\pm$ standard deviation: 14 $\pm$ 11 days and median: 13 days). In the duration, sufficient data samples and nurse calls exists (i.e., as approaching discharge day, the number of calls become zero)

B. Evaluation method

To compare the fitness of the statistical models to dataset, two indicators were used: the widely applicable information criterion (WAIC)[7] and Leave-one-out (LOO)[8]. WAIC is more widely applicable than Bayesian information criteria and Akaike information criteria, which are commonly utilized for the evaluation of linear models due to their limitation of target distributions. Thus, the WAIC is often utilized for Bayesian statistical modeling to evaluate how the model represents the dataset without complexity. Lower WAIC value represents that the statistic model fits well to the dataset considering penalty of model complexity. LOO validation is often utilized to evaluate how the model fits the dataset in machine learning. In LOO validation, how single out-of-sample predicted value fits a single data sample is calculated over all combinations of partitioned samples. The same concept was introduced into MCMC samples and the calculation method of LOO value was developed[8]. The LOO values were often utilized for the evaluation of MCMC-estimated statistic model. The Lower LOO value represents the good model fitting as WAIC.

C. Result and discussion

Table I represents the WAIC, LOO, and means with 95% credible intervals on days 1 and 6 after surgery in each model. The differences between $X^{(g1)}$ and $X^{(g2)}$ in each model were shown in Fig. 1.

The result demonstrated that the model consisting of 2-order, random effect and ZIP was the most suitable model for the nurse call dataset. The difference among transition models was small. The transition model was expected to capture the nurse call data property that the nurse calls after surgery depends on the number of the previous nurse calls because the nurse calls decrease gradually according to recover from surgery. However, since the patients are continuously monitored and intensively cared after surgery, the treatment and care might have a big effect for the number of nurse calls rather the body condition on the previous days. In deed, the number of nurse calls on 1 and 2 days before surgery was total different from the number after surgery. Thus, in this ward, the patient condition might change daily according to not previous tendency about nurse calls but body conditions and cares. This might result in a slight difference among transitional models.

All models including random effect decreased the differences. The raw nurse call data usually includes the individual tendency whether the patients often call nurses or not. This tendency might increase the apparent differences of nurse calls, but adjustment of individual patient variabilities might reveal fundamental differences between the two groups. Interestingly, introduction of ZIP reduced credible intervals on all days after surgery. This suggested that ZIP was more suitable to model the nurse calls than Poisson distribution. Changes of WAIC and LOO by introducing ZIP demonstrates smaller than those by introducing random effect, which demonstrating that introduction of random effect was more important to model the nurse calls statistically.

Curiously, the basic model, which only includes Poisson, scored bad WAIC and LOO values, but differences with credible intervals were better than 1-order and 2-order models including the transition models without random effect and ZIP. In these cases, the introduction of the transition model forced to fit the dataset into the transitional model, which might distort the estimated differences.

The X and difference values of the model including only Poisson and the model including 2-order transition

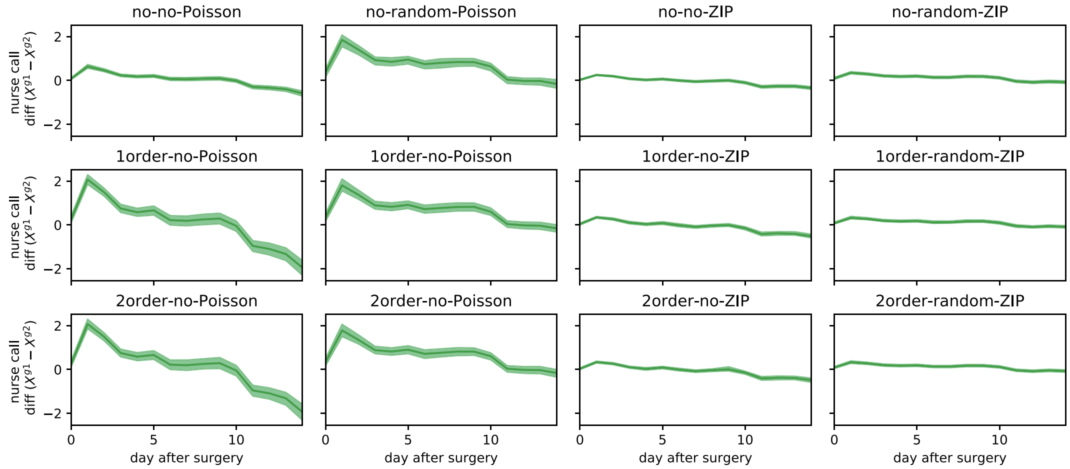

Fig. 1: Differences of nurse calls after surgery among statistic models

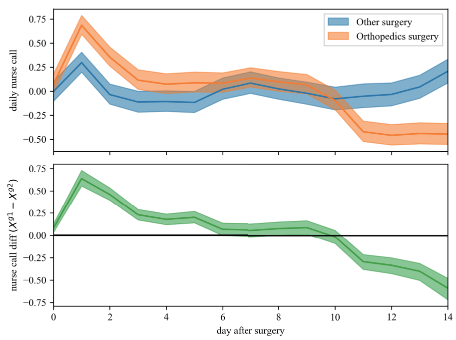

Fig. 2: Plot of X values and difference on the plane model

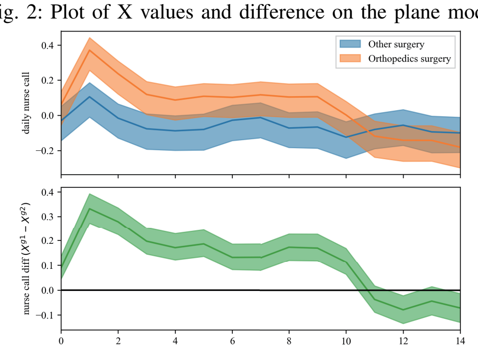

Fig. 3: Plot of X values and differences on the model using 1-order transition and Zero Inflated Poisson

model, random effect and ZIP are shown in Fig. 2 and 3, respectively. The days when the differences with 95% credible intervals were over zero represents the existence of significant difference between two groups in the frequent statistics. In the model including only the Poisson model, the difference itself was larger than the model including all condition, but the model only detected 5 days differences between two groups. On the other hand, the well-fit model, including all conditions, indicated that the differences continued until 10 days after surgery, and the differences between 4 and 10 days were similar. This demonstrated that the differences of surgeries affected the nurse calls continuously until 10 days after surgery, which might be not detected using only traditional analysis method. In other words, our approach, using Bayesian statistics and the model including transition model, random effect and ZIP, is effective to analyze the complicated nurse call dataset that contains time-series property, individual patient variability, and particular observation model. This also suggests that our approach might be useful for another medical dataset similar to nurse calls.

IV. Conclusion

In this paper, we proposed the Bayesian statistical model for comparison analysis of time-series nurse calls data. The proposed model contains that transition model, random effect, and ZIP. The experiment results using real nurse call dataset demonstrated that the model including 2-order transition, random effect and ZIP most fitted the dataset. While the transition model only slightly improved the model fitting to the dataset, random effect, which consideration of individual patient variabilities, drastically improved the fitting of the model to the data. In the future, we try to develop a more complicated model to adjust other parameters such as age, sex and their activity of daily living (ADL).

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