MOX–Report No. 12/2012

Hospital clustering in the treatment of acute myocardial infarction patients via a Bayesian semiparametric approach

Guglielmi, A.; Ieva, F.; Paganoni, A.M.; Ruggeri, F.

MOX, Dipartimento di Matematica "F. Brioschi"
Politecnico di Milano, Via Bonardi 9 - 20133 Milano (Italy)

mox@mate.polimi.it http://mox.polimi.it

Hospital clustering in the treatment of acute myocardial infarction patients via a Bayesian semiparametric approach

Alessandra Guglielmi[a], Francesca Ieva[a], Anna Maria Paganoni[a] and Fabrizio Ruggeri[b]

January 31, 2012

[a] Dipartimento di Matematica "F. Brioschi"
Politecnico di Milano
via Bonardi 9, 20133 Milano, Italy
alessandra.guglielmi@polimi.it
francesca.ieva@mail.polimi.it.it
anna.paganoni@polimi.it
[b] CNR IMATI
Via Bassini 15, 20133 Milano, Italy
fabrizio@mi.imati.cnr.it

Abstract

In this work, we develop Bayes rules for several families of loss functions for hospital report cards under a Bayesian semiparametric hierarchical model. Moreover, we present some robustness analysis with respect to the choice of the loss function, focusing on the number of hospitals our procedure identifies as "unacceptably performing". The analysis is carried out on a case study dataset arising from MOMI^2 (Month MOnitoring Myocardial Infarction in MIlan) survey on patients admitted with ST-Elevation Myocardial Infarction to the hospitals of Milan Cardiological Network. The major aim of this work is the ranking of the health care providers performances, together with the assessment of the role of patients' and providers' characteristics on survival outcome.
Keywords: Semiparametric Bayesian hierarchical models, Provider profiling, Decision analysis, Cardiovascular health care research.
AMS Subject Classification: 62F15, 62P10, 62J12

1 Introduction

Performance indicators have recently received increasing attention; they are mainly used with the aim of assessing quality in health care research [1, 2, 7, 13, 14, 15, 16]. In this work, we suitably model the survival outcome of patients affected by a specific disease in different clinical structures; the aim is to point out similar behaviours among groups of hospitals and then classify them according to some acceptability criteria. In general, provider profiling of health care structures is obtained producing report cards comparing their global outcomes or performances of their doctors. These cards have mainly two goals:

- to provide information that can help individual consumers (i.e. patients) making a decision,
- to identify hospitals that require investments in quality improvement initiatives.

Here we are interested not only in the point estimation of the mortality rate, but also to decide whether investing in quality improvement initiatives for each hospital with “unacceptable performances”. The paper presents Bayes rules under several families of loss functions for hospital report cards. In particular, we adopt a Bayesian semiparametric hierarchical model in this case, since it is known that they are more flexible than “traditional” Bayesian parametric models. Moreover, we did some robustness analysis with respect to the choice of the loss function, focusing on the number of hospitals our procedure identifies as “unacceptably performing”.

Our aim is to profile health care providers in our regional district, i.e. Regione Lombardia. Indeed, the health governance of Regione Lombardia is very sensitive to cardiovascular issues, as proved by the huge amount of social and scientific projects concerning these syndromes, which were promoted and developed during the last years. Details on some of the most important clinical and scientific local projects can be found in [3]. The data we have analyzed in our application come from a survey called MOMI^2, which is a retrospective longitudinal clinical survey on a particular type of infarction called STEMI (STsegment Elevation Myocardial Infarction). STEMI has very high incidence all over the world and it causes approximately 700 events each month only in our district. These cases are mainly treated through the surgical practice of primary angioplasty (a collapsed balloon is inserted through a catheter in the obstructed vessel, and then inflated, so that the blood flow is restored). It is well known [5, 6] that within this pathology, the more prompt the intervention is, the more effective the therapy is; for this reason the main process indicators used to evaluate hospitals performances are in-hospital treatment times. The MOMI^2 survey consists of six time periods data collection in the hospitals belonging to the cardiological network of the milanese urban area. It contains 841 statistical units, and, for each patient, personal data, mode of admission, symptoms and process indicators, reperfusion therapy and outcomes have been collected. After each collection, all the hospital performances (in terms of patients survivals) were evaluated; moreover, a feedback was given to providers (especially those with “unacceptable performances”) in order to let them improve their performances.

The article is organized as follows: in Section 2 we present the statistical method used to support decisions in this health care context, while Section 3 shows how the proposed model and method have been applied to data coming from MOMI^2 survey. Finally conclusions and open problems are discussed in Section 4.

2 Statistical support to decision-making in health-care policy

Even in a perfect risk-adjustment framework, random errors will be present. Therefore, when classifying hospital performances as “acceptable” or not, some mistakes could occur, so that some hospitals could be misclassified. Anyway, different players in the health care context would pay different costs on misclassification errors. By *False Positive* we mean the hospital that truly had acceptable performances but was classified as “unacceptably performing”, and by *False Negative* the hospital that truly had unacceptable performances but was classified as “acceptably performing”. Then a health care consumer would be presumably willing to pay a higher charge for decisions that minimize false negatives, whereas hospitals might pay a higher cost for information that minimizes false positives. On the other hand, the same argument could be used to target hospitals for quality improvement: false positives would yield unneeded investments in quality improvement, but false negatives would lead to loose opportunities in improving the hospital quality. According to its plans, any health care government could be interested in minimizing false positives and/or false negatives.

In order to provide support to decision-making in this context, we carry out the statistical analysis in the following way: firstly we estimate the in-hospital survival rates after fitting a Bayesian semiparametric generalized linear mixed-effects model, in particular modelling the random effect parameters via a Dirichlet process; then we develop Bayes decision rules in order to minimize the expected loss arising from misclassification errors, comparing four different loss functions for hospital report cards.

We fit a Bayesian generalized mixed-effects model for binary data. For unit (patient) $i = 1, \ldots, n_j$, in group (hospital) $j = 1, \ldots, J$, let Y_{ij} be a Bernoulli random variable with mean p_{ij}, i.e.

$$Y_{ij}|p_{ij} \overset{ind}{\sim} Be(p_{ij}).$$

The p_{ij}s are modelled through a logit regression of the form

$$logit(p_{ij}) = \log \frac{p_{ij}}{1-p_{ij}} = \gamma_0 + \sum_{h=1}^{p} \gamma_h x_{ijh} + \sum_{l=1}^{J} b_l z_{jl} \tag{1}$$

where $z_{il} = 1$ if $i = l$ and 0 otherwise. In this model, $\boldsymbol{\gamma} = (\gamma_0, \ldots, \gamma_p)$ represents the $(p+1)$-dimensional vector of the fixed effects, $\mathbf{x}_{ij}$ is the vector of patient covariates and $\mathbf{b} = (b_1, \ldots, b_J)$ is the vector of the additive random-effects parameters of the grouping factor. According to [12], we assume a nonparametric prior for $b_1, \ldots, b_J$, namely the b_js will be i.i.d. according a Dirichlet process (see [4]), to include robustness to miss-specification of the prior at this stage, since it is known that the regression parameters can be sensitive to the standard assumption of normality of the random effects; the prior for $\boldsymbol{\gamma}$ is parametric. Prior details will be given in Section 3. Model (1) is a generalized linear mixed model with $p+1$ regression coefficients and one random effect. In [9] the same model was fitted on a different dataset to classify hospitals taking advantage of the in-built clustering property of the Dirichlet process prior. Here we use Bayesian estimates to address a new decision problem concerning hospitals' performances.

Bayesian inferences are based on the posterior distribution, i.e. the conditional distribution of the parameters vector, given the data. Once the posterior distribution has been computed, suitable loss functions can be defined in order to *a posteriori* weigh the decision of wrongly classifying the hospital as having acceptable or unacceptable performances. The random intercepts of model (1), i.e. $\gamma_0 + b_1, \gamma_0 + b_2, \ldots, \gamma_0 + b_J$ represent the hospital performances quantifying the contribution to the model after patients' covariates adjustment. Let us denote by β_j the sum of γ_0 and b_j. The class of loss functions we are going to assume is then

$$L(\beta_j, d) = c_I \cdot f_1(\beta_j) \cdot d \cdot \mathbb{I}(\beta_j > \beta_t) + c_{II} \cdot f_2(\beta_j) \cdot (1-d) \cdot \mathbb{I}(\beta_j < \beta_t), \quad (2)$$

where d is the decision to take ($d = 1$ means that the hospital has "unacceptable performances", $d = 0$ stand for "acceptable performances"), c_I is the weight assigned to the cost $f_1(\beta_j)$, occurring for a false positive, c_{II} is the weight assigned to cost $f_2(\beta_j)$, occurring for a false negative and β_t is defined as $\log(p_t/(1-p_t))$, being p_t a reference value for survival probabilities.

Without loss of generality, we can assume a proportional penalization, i.e. $f_2(\beta_j) = k \cdot f_1(\beta_j)$, taking k as the ratio c_{II}/c_I. In this sense, the parameter k quantifies our beliefs on cost, being greater than 1 if we credit that accepting a *false negative* should cost more than rejecting a true negative and less than 1 otherwise. An acceptable performance is then defined comparing the posterior expected losses associated with the decision that the hospital had "acceptable performances"

$$R(\mathbf{y}, d=0) = E_\pi\left(L(\beta_j, d=0)|\mathbf{y}\right) = \int f_2(\beta_j)\mathbb{I}(\beta_j < \beta_t)\Pi(\beta_j|\mathbf{y})d\beta_j$$

and the decision that the hospital had "unacceptable performances"

$$R(\mathbf{y}, d=1) = E_\pi\left(L(\beta_j, d=1)|\mathbf{y}\right) = \int f_1(\beta_j)\mathbb{I}(\beta_j > \beta_t)\Pi(\beta_j|\mathbf{y})d\beta_j.$$

In short, we classify an hospital as being "acceptable" (or with "acceptable performances") if the risk associated with the decision $d = 0$ is less than the risk associated with the decision $d = 1$, i.e. if $R(\mathbf{y}, d = 0) < R(\mathbf{y}, d = 1)$.

Within this setting, four different loss functions (2) will be considered in the next section, to address the decision problem, namely

$$\begin{aligned}
\textbf{0/1 Loss} &\;:\\
L(\beta_j, d) &= d \cdot \mathbb{I}(\beta_j > \beta_t) + k \cdot (1-d) \cdot \mathbb{I}(\beta_j < \beta_t),\\
\textbf{Absolute Loss} &\;:\\
L(\beta_j, d) &= |\beta_j - \beta_t| \cdot d \cdot \mathbb{I}(\beta_j > \beta_t) + k \cdot |\beta_j - \beta_t| \cdot (1-d) \cdot \mathbb{I}(\beta_j < \beta_t),\\
\textbf{Squared Loss} &\;:\\
L(\beta_j, d) &= (\beta_j - \beta_t)^2 \cdot d \cdot \mathbb{I}(\beta_j > \beta_t) + k \cdot (\beta_j - \beta_t)^2 \cdot (1-d) \cdot \mathbb{I}(\beta_j < \beta_t),
\end{aligned}$$

LINEX Loss :

$$L(\beta_j, d) = l(\beta_j - \beta_t) \cdot d \cdot \mathbb{I}(\beta_j > \beta_t) + k \cdot l(\beta_j - \beta_t) \cdot (1-d) \cdot \mathbb{I}(\beta_j < \beta_t).$$

For instance, this means that, to recover the 0/1 loss function above, the functions $f_i(\beta_j),\ i = 1, 2$ in (2) are both constant, $f_i(\beta_j) = |\beta_j - \beta_t|, i = 1, 2$ for the Absolute Loss case, $f_i(\beta_j) = (\beta_j - \beta_t)^2,\ i = 1, 2$ for the Squared Loss case and $f_i(\beta_j) = l(\beta_j - \beta_t) = \exp\{a \cdot (\beta_j - \beta_t)\} - a \cdot (\beta_j - \beta_t) - 1,\ i = 1, 2$ to obtain the LINEX Loss function. Note that all the loss functions but the last one are symmetric, and the parameter k is used to introduce an asymmetry in weighting the misclassification error costs.

3 Application to MOMI^2 data

In this section we apply the model and the method proposed in Section 2 to 536 patients of MOMI^2 data underwent to PTCA treatment. For this sample, 17 hospitals of admission are involved, and a in-hospital survival rate of 95% is observed. Among all possible covariates (mode of admission, clinical appearance, demographic features, time process indicators, hospital organization etc.) available in the survey, only age and killip class (which quantifies the severity of infarction on a scale ranging from 1 to 4) have been selected as being statistically significant. The killip class is binary here, i.e. the killip covariate is equal to 1 for the two more severe classes and equal to 0 otherwise. Moreover we considered the total ischemic time (namely Onset to Balloon time or briefly OB) in the logarithmic scale too, because of clinical best practice and know-how. The choice of the covariates and the link function was suggested in [10], according to frequentist selection procedures and clinical best-practice, and confirmed in [8] using Bayesian tools.

Summing up, the model (1) we considered for our dataset is

$$logit(\mathbb{E}[Y_{ij}|b_j]) = logit(p_{ij}) = \gamma_0 + \gamma_1 \cdot age_i + \gamma_2 \cdot \log(OB)_i + \gamma_3 \cdot killip_i + b_j \tag{3}$$

for patient i $(i = 1, \ldots, 536)$ in hospital j $(j = 1, \ldots, 17)$. As far as the prior is concerned, we assume

$$\begin{gathered} \gamma \perp \mathbf{b} \qquad \gamma \sim \mathcal{N}_4(\mathbf{0}, 100 \cdot \mathbb{I}_4) \\ b_1, \ldots b_J | G \overset{iid}{\sim} G \qquad G|\alpha, G_0 \sim Dir(\alpha G_0) \\ G_0|\sigma \sim \mathcal{N}(0, \sigma^2) \quad \sigma \sim Unif(0, 10) \quad \alpha \sim Unif(0, 30). \end{gathered} \tag{4}$$

See details in [9]. The estimated posterior expected number of distinct values among the b_js, computed on 5000 iterations of Markov chain, is close to 7. In Table 1 the performances of different loss functions for different values of k and different threshold β_t are reported. The different values of p_t we considered (that determine the β_t values), were fixed in a range of values close to the empirical survival probability, in order to stress the resolution power of different loss in detecting unacceptable performances. Of course, when increasing the threshold p_t (and therefore β_t), more hospitals will be labelled as unacceptable. The tuning depend on the sensitivity

Table 1: Providers labelled as "unacceptable", under (3)-(4), for different loss functions and different values of the threshold.

Loss	$k = 0.5$ $p_t = 0.96$ $\beta_t = 3.178$	$k = 1$ $p_t = 0.96$ $\beta_t = 3.178$	$k = 2$ $p_t = 0.96$ $\beta_t = 3.178$
0/1	None	None	None
Absolute	None	None	None
Squared	None	None	9
LINEX	None	None	9
Loss	$k = 0.5$ $p_t = 0.97$ $\beta_t = 3.476$	$k = 1$ $p_t = 0.97$ $\beta_t = 3.476$	$k = 2$ $p_t = 0.97$ $\beta_t = 3.476$
0/1	None	9	3,5,9,10
Absolute	None	9	3,5,9,10
Squared	9	9	3,5,9,10
LINEX	9	3,5,9,10	3,5,9,10
Loss	$k = 0.5$ $p_t = 0.98$ $\beta_t = 3.892$	$k = 1$ $p_t = 0.98$ $\beta_t = 3.892$	$k = 2$ $p_t = 0.98$ $\beta_t = 3.892$
0/1	3,5,9,10	All	All
Absolute	2,3,4,5,9,10, 13,15	1,2,3,4,5,6,7,8,9,10, 11,13,14,15,16,17	All
Squared	2,3,4,5,9,10, 13,15	1,2,3,4,5,6,7,8,9, 10,13,14,15,17	All
LINEX	2,3,4,5,6,7,8,9, 10,13,15,17	All	All

required by the analysis. The parameter a of the LINEX loss is set to be equal to -1. Some comments are due, observing results of the Table 1. Firstly, as mentioned before, k describes the different approach to evaluating misclassification errors. For example, people in charge with health care government might be more interest in penalizing useless investments in quality improvements, choosing a value less than 1 for k. On the other hand, patients admitted to hospitals are more interested in minimizing the risk of wrongly declaring as "acceptably performing" providers that truly behave "worse" than the gold standards; therefore, they would probably choose a value greater than 1 for k. Moreover, when fixing the loss functions among the four proposed here, and k equal to $0.5, 1$ or 2, as the threshold β_t increases, we obtain the same "implicit ranking" of providers:

$$9, 3, 5, 10, 2, 4, 13, 15, 6, 7, 8, 17, 1, 14, 16$$

(i.e. hospital 9 was classified as "unacceptable" even with small values of β_t, then, when increasing β_t, hospital 3 was classified as "unacceptable", etc.). This result is in agreement with the provider profiling pointed out also in [7]. On the other hand, Figure 1 shows the number of hospitals labelled as "unacceptable" as k increases, for a fixed value of the threshold β_t, under the Squared and the LINEX Loss functions.

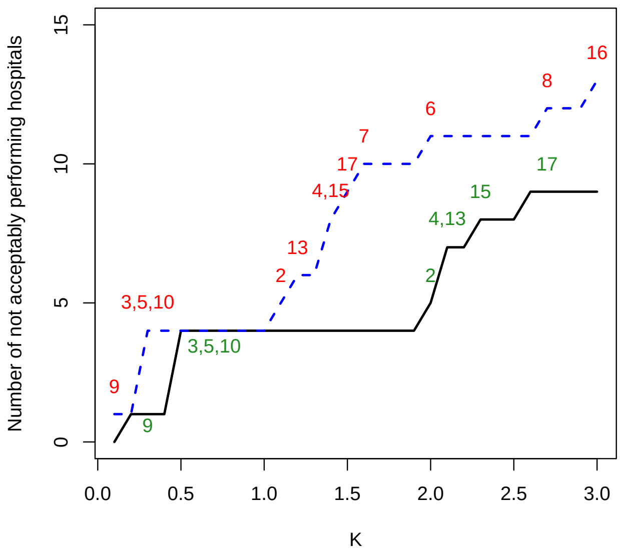

Figure 1: Number of hospitals labelled as "unacceptable" as a function of k, under the Squared Loss function (solid black) and the LINEX Loss function (dotted blue). The threshold parameter β_t is 3.6635.

Of course, the choice of the most suitable loss function is problem-driven: in our case, it seems reasonable to consider an asymmetric loss in order to penalize departures from threshold in different ways. For this reason we suggest the LINEX Loss with $k \neq 1$.

4 Conclusions and further developments

In this work we considered data coming from a retrospective survey on STEMI to show an example of Operational Research applied to Regione Lombardia health care policy. Using a logit model, we represented the survival outcome by patient's covariates and process indicators, comparing results of different loss functions on decisions about provider's performances. In doing so, information coming from clinical registries was used to make the hospital network more effective, improving the overall health-care process and pointing out groups of hospitals with similar behaviour, as it is required by the health-care decision makers of Regione Lombardia.

Actually, we are working on the extension of this paradigm to the whole Regional district, having designed and activated a new registry, called STEMI Archive (see [11]), for all patients with STEMI diagnosis admitted to any hospital in Regione Lombardia. The analysis applied here to this sort of decision problems is relatively simple and effective. We believe that this approach could be considered by people in charge of the health-care governance in order to support decision-making in the clinical context.

References

[1] Austin, P.C.: Bayes rules for optimally using Bayesian hierarchical regression models in provider profiling to identify high-mortality hospitals. BMC Medical Research Methodology, 8–30 (2008)

[2] Austin, P.C., Lawrence, J.B.: Optimal Bayesian probability levels for hospital report cards. Health Service and Outcomes Research Method **8**, 80–97 (2008)

[3] Barbieri, P., Grieco, N., Ieva, F., Paganoni, A.M., Secchi, P.: Exploitation, integration and statistical analysis of Public Health Database and STEMI archive in Lombardia Region. In: Complex data modeling and computationally intensive statistical methods, pp. 41-56. Springer, Contribution to Statistics (2010)

[4] Ferguson, T.S.: A Bayesian analysis of some nonparametric problems. Annals of Statistics **1**, 209–230 (1973)

[5] Gersh, B.J., Stone, G.W., White, H.D., Holmes, D.R.: Pharmacological Facilitation of Primary Percutaneous Coronary Intervention for Acute Myocardial Infarction: Is the Slope of the Curve the Shape of the Future? Journal of American Medical Association **293**, 8, 979–986 (2005).

[6] Giugliano, R.P., Braunwald, E.: Selecting the Best Reperfusion Strategy in ST-Elevation Myocardial Infarction Its All a Matter of Time. Circulation. **108**, 2828–2830 (2003)

[7] Grieco, N., Ieva, F., Paganoni, A.M.: Performance assessment using mixed effects models: a case study on coronary patient care, IMA Journal of Management Mathematics, *In press* (2011)

[8] Guglielmi, A., Ieva, F., Paganoni, A.M., Ruggeri, F.: A Bayesian random-effects model for survival probabilities after acute myocardial infarction. Chilean Journal of Statistics, *Accepted* (2012)

[9] Guglielmi, A., Ieva, F., Paganoni, A.M., Ruggeri, F.: Process indicators and outcome measures in the treatment of Acute Myocardial Infarction patients. In: Faltin, F., Kenett, R. and Ruggeri, F. (eds.) Statistical Methods in Healthcare. Wiley (2012)

[10] Ieva, F., Paganoni, A.M.: Multilevel models for clinical registers concerning STEMI patients in a complex urban reality: a statistical analysis of MOMI^2 survey. Communications in Applied and Industrial Mathematics **1**, 1, 128–147 (2010)

[11] Direzione Generale Sanità – Regione Lombardia: Patologie cardiocerebrovascolari: Interventi di Prevenzione, Diagnosi e Cura, Decreto N^o 20592, 11/02/2005, (2005).

[12] Kleinman, K.P., Ibrahim, J.G.: A semi-parametric Bayesian approach to generalized linear mixed models. Statistics in Medicine **17**, 25792596 (1998)

[13] Normand, S.T., Glickman, M.E., Gatsonis, C.A.: Statistical methods for profiling providers of medical care: issues and applications. Journal of the American Statistical Association, **92**, 803–814 (1997)

[14] Normand, S.T., Shahian, D.M.: Statistical and Clinical Aspects of Hospital Outcomes Profiling. Statistical Science **22**, 2, 206-226 (2007)

[15] Ohlssen, D.I., Sharples, L.D., Spiegelhalter, D.J.: A hierarchical modelling framework for identifying unusual performance in health care providers. Journal of the Royal Statistical Society: Series A (Statistics in Society) **170**, 4, 865-890 (2007)

[16] Racz, J., Sedransk, J.: Bayesian and Frequentist Methods for Provider Profiling Using Risk-Adjusted Assessments of Medical Outcomes. Journal of the American Statistical Association **105**, 489, 48–58 (2010).

MOX Technical Reports, last issues

Dipartimento di Matematica "F. Brioschi",
Politecnico di Milano, Via Bonardi 9 - 20133 Milano (Italy)

12/2012 GUGLIELMI, A.; IEVA, F.; PAGANONI, A.M.; RUGGERI, F.
Hospital clustering in the treatment of acute myocardial infarction patients via a Bayesian semiparametric approach

11/2012 BONNEMAIN, J.; FAGGIANO, E.; QUARTERONI A.; DEPARIS S.
A Patient-Specific Framework for the Analysis of the Haemodynamics in Patients with Ventricular Assist Device

10/2012 LASSILA, T.; MANZONI, A.; QUARTERONI, A.; ROZZA, G.
Boundary control and shape optimization for the robust design of bypass anastomoses under uncertainty

09/2012 MAURI, L.; PEROTTO, S.; VENEZIANI, A.
Adaptive geometrical multiscale modeling for hydrodynamic problems

08/2012 SANGALLI, L.M.; RAMSAY, J.O.; RAMSAY, T.O.
Spatial Spline Regression Models

07/2012 PEROTTO, S; ZILIO, A.
Hierarchical model reduction: three different approaches

06/2012 MICHELETTI, S.; PEROTTO, S.
Anisotropic recovery-based a posteriori error estimators for advection-diffusion-reaction problems

05/2012 AMBROSI, D; ARIOLI, G; KOCH, H.
A homoclinic solution for excitation waves on a contractile substratum

04/2012 TUMOLO, G.; BONAVENTURA, L.; RESTELLI, M.
A semi-implicit, semi-Lagrangian, p-adaptive Discontinuous Galerkin method for the shallow water equations

03/2012 FUMAGALLI, A.; SCOTTI, A.
A reduced model for flow and transport in fractured porous media with non-matching grids