OUTCOME EVALUATION IN HEALTHCARE: THE MULTILEVEL LOGISTIC CLUSTER WEIGHTED MODEL

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ABSTRACT: We show the multilevel logistic cluster-weigthted model and we make a comparison with the standard multilevel model when they are employed to provide an hospitals' ranking in order to evaluate the performance related to the 30-day mortality.

KEYWORDS: Expectation-Maximization algorithm, hierarchy, finite mixture models.

1 Introduction

Although measures of clinical outcomes were initially considered too complex and critical to be defined and measured, the growing desire for quality improvement in medical care has led to public reporting of providers' performance using league tables. A seminal paper by Goldstein & Spiegelhalter (1996) described multilevel models to provide hospital performance evaluations, where patients are nested into hospitals. Later on the statistical literature developed finite mixture models to account for heterogeneity in the response distribution, by splitting the population into a finite number of relatively homogeneous classes (McLachlan & Peel, 2000). Starting from this approach, the recent literature has proposed an extension of the mixture models to the multilevel setting to disentangle latent classes within the natural grouping in the data, such as schools and hospitals (Vermunt, 2005; Muthén & Asparouhov, 2009; Bartolucci *et al.* , 2011; Agasisti *et al.* , 2011).
The finite mixture models do not allow to describe the joint distribution of a random dependent variable Y and a random covariate X when also the distribution X is cluster specific. To this aim, Ingrassia *et al.* (2012) introduced the Cluster-Weighted Models (CWM), as a cluster weighted sum of the product

of the conditional distribution of Y given X, and the distribution of X. Both the conditional distribution and the density of X are clustered in groups and the overall sum is weighted by the proportional impact of the group on the observed population. Recently, Berta *et al.* (2016) extended CWM to the multilevel framework when Y is distributed as a Normal variable.
In Sec. 2 we propose another extension named Multilevel Logistic CWM (ML-CWM), and we show in Sec. 3 we present the data related to the application developed in Sec. 4 concerning the healthcare evaluation field. We apply this model to different hospital settings demonstrating how the evaluation of the hospital performance is affected by clusters of patients and how, avoiding this approach, different results can be obtained. In Sec. 5 we state some concluding remarks.

2 Multilevel Logistic Cluster Weighted Models

A cluster weighted framework allows to estimate the joint probability of $(\mathbf{X}, Y)$, a random vector of covariates $\mathbf{X}$ and a binary dependent variable Y. Suppose that $\mathbf{X}$ and Y are defined in some finite space $\Omega \subseteq \mathbb{R}^d \times \mathbb{R}$ and that Ω is partitioned into C clusters, say $\Omega_1, \ldots, \Omega_C$. Extending the CWMs to the multilevel framework allows to account for the fact that both the conditional distribution $Y|\mathbf{X}$ and the marginal distribution $\mathbf{X}$ depend on the C groups. In this way, the joint density of $(\mathbf{X}, Y)$ can be described by a mixture of conditional densities $p(Y|\mathbf{X}, \Omega_c)$ weighted on the marginal densities of $\phi(\mathbf{X}|\Omega_c)$ by the mixture's weights π_c.

In the following, we consider the observations related to just one covariate and one outcome (x_{ij}, y_{ij}) with $i = 1, ..., n_j$ and $j = 1, ...N$, where n_j is the number of patients i admitted to the hospital j. Based on this framework, and defining θ the vector of all model parameters, the MLCWM can be described by the joint probability which can be factorized as

$$p(x_{ij}, y_{ij}; \theta) = \sum_{c=1}^{C} \pi_c p(y_{ij}|x_{ij}; \xi_c) \phi(x_{ij}; \mu_c, \sigma_c^2),$$

where $\phi(x_{ij}; \mu_c, \sigma_c^2)$ is assumed to be Gaussian, with parameters μ_c and σ_c^2, and $p(y_{ij}|x_{ij}; \xi_c) = (1 - \pi_{ij})^{I(y_{ij}=0)} \pi_{ij}^{I(y_{ij}=1)}$ with I the indicator function and with π_{ij} linked to the covariates by a logit link with the following multilevel structure:

$$\text{logit}(\pi_{ij}|x_{ij}, C = c) = \alpha_{0c} + \beta_c x_{ij} + u_{cj},$$

where u_{cj} is the random coefficient for residuals at the hospital j level in the cluster c and it can be interpreted as the relative effectiveness of hospitals with respect to the outcome y_{ij}. The model parameters denoted by θ are estimated by the Expectaton-Maximization algorithm. Then, each patient can be assigned to one of the C clusters according to the maximum posterior probability

$$P(C_{ij} = c|x_{ij}, y_{ij}; \theta) = \frac{\pi_c p(y_{ij}|x_{ij}; \xi_c)\phi(x_{ij}; \mu_c, \sigma_c^2)}{\sum_{c=1}^{C} \pi_c p(y_{ij}|x_{ij}; \xi_c)\phi(x_{ij}; \mu_c, \sigma_c^2)}.$$

3 Data

We analyze an administrative dataset gathered from the Lombardy region (Italy), collecting information on patients admitted to 150 hospitals in 2014, including their demographic and clinical information. The outcome of interest is 30-day mortality, the most used proxy of quality in this research field. In order to test the ability of the model in identifying the clusters among patients within the context of effectiveness evaluation, we test the MLCWM on two different disciplines: cardiosurgery and medicine. Cardiosurgery is an highly specialized discipline admitting patients that need complex surgical intervention. It is characterized by a low level of mortality and a Diagnosis-Related Group (DRG) weight five times higher than medicine. Medicine wards admit older patients with lower complexity, but with an high level of mortality (15%). A number of selected patients characteristics describing sex and age, and measuring their severity by DRG weight and Elixhauser index (Elixhauser *et al.* , 1998) are included in the models as covariates. In particular DRG weight and Elixauser index are here considered as a proxy of patients' severity.

4 Results

Considering the hierarchical structure defined by cardiosurgery and medicine, we apply the proposed MLCWM to investigate whether there is evidence for further latent structures. We consider models with a number of different clusters and find that the optimal number of clusters according to the Bayesian Information Criterion (Schwarz, 1978) is two. We further compare the two models in order to verify whether the MLCWM help us to evaluate the hospitals in a different way, identifying clusters of patients and increasing our ability in disentangling the best and worst performer hospitals.

For sake of convenience, we show the results related to Cardiosurgery. Descriptive statistics, omitted in this short version, allow us to appreciate the clustering composition provided by the MLCWM. The latter indicates the presence of two latent groups where the main differences are due to the age (in cluster 2 the patients are younger) and to the risk of mortality. In Table 1 we show the estimated regression coefficients obtained with the multilevel model and those obtained with the two cluster components of the proposed model MLCWM. The effect for all the covariates included in the model is different between the two latent groups in terms of magnitude and also in terms of direction of the relationship between the covariate and the risk of mortality. This effect has also a consequence on the final league tables, presented in Figure 1 and in Figure 3. They show the hospital's estimated random coefficients under the multilevel model and the MLCWM, respectively. We notice in Figure 3 that the hospital coded as "030901" has a bad performance in both the first and second cluster of patients.

$\hat{\beta}$	Multilevel	MLCWM	
		C1	C2
Female	0.1785	0.6189	0.2277
Age	0.0517	-0.0032	0.0601
DRG Weight	-0.0038	0.4144	-0.0849
Comorbidities	0.2485	0.1833	0.3141

Table 1: *Estimates of the regression parameters related to the multilevel model (first column) and to cluster 1 of the MLCWM (second column, C1) and to cluster 2 of the MLCWM (third column, C2).*

5 Conclusions

The proposal can be adopted in order to identify latent clusters in the data, related to both the outcome and the risk-adjustment variables included in the analysis. These preliminary results shows that the proposed MLCWM points out two well-defined latent groups within the patients and, indeed, the model coefficients have different signs and magnitude for different groups. As well as the coefficients, the league tables of random effects show different patterns and this may have great implications for healthcare managers because by adopting a classic approach these effects could be masked and the final rankings of hospitals might be biased.

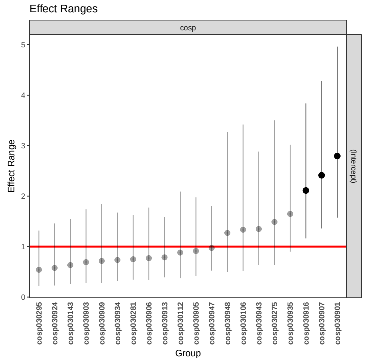
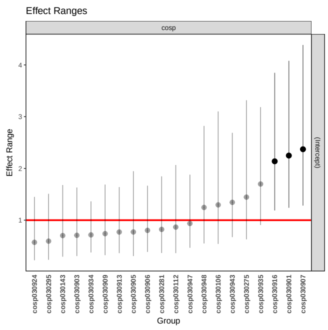
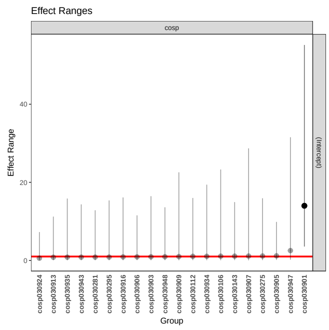


Figure 1: League Table for the Multilevel Model in Cardiosurgery



Cluster 1



Cluster 2

Figure 3: League Tables for the MLCWM in Cardiosurgery

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