Model based segmentation of TV advertising scheduling patterns

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Abstract: This paper employs a model based classification for longitudinal data to identify typical scheduling patterns of TV sponsorship spots which is a type of TV advertisement.

Keywords: Classification; Longitudinal data; Segmentation.

1 Introduction

The advertising campaign is set according its goals and objectives. To ensure the highest efficiency of the campaign, the companies use different approaches to scheduling and timing the advertisements. There are different scheduling patterns identified to adjust the campaign timing according to the communication goals. The volume of advertising during the campaign may be continuous with steady (i.e. reminder advertising for matured products or building brand awareness), rising (i.e. to concentrate attention around a particular event) or falling (i.e. fade after initial launch of a new product) trend during the campaign. There are more scheduling pattern identified (i.e. flighting or pulsing) used for short and heavy advertising periods. The campaign length also reflects the nature of the communicated message and the goals of the campaign. For example longer campaigns (weeks or years) are often directed towards building the longer term effects of favorable brand image and strong brand loyalty

2 Data and research questions

In this paper, we concentrate on analysis of scheduling patters of so called TV sponsorship spots broadcasted in the Czech TV channels during 2011. The TV sponsorship is one possible type of the advertising campaign which can take many forms, i.e., TV billboards, sponsored trailers, injections, identifications, sponsorship reminders, break bumpers. Very often, the TV sponsorship comes before/after the broadcast (or within as a break bumper) and is mostly 10 or 15 seconds long. Other often used types are injections of various lengths (5 – 60 seconds).

Data for our analysis were gathered by the Mediaresearch company (`http://www.mediaresearch.eu`) which is the research agency conducting electronic monitoring of TV viewership in the Czech Republic. Data contain the broadcasting history of more than 5 000 unique TV sponsorship spots (*unique commercials*) that appeared during 2011 on one of 13 Czech TV channels that offer this type of advertisement.

Let us now introduce some notation. Let $Y_{i,t}$ be the number of broadcasting occurrences of the ith commercial ($i = 1, \ldots, N$) during week t ($t = 0, \ldots, T_i$) since its prime. Since only rarely (in less than 5% of cases), a particular commercial is being broadcasted longer than 16 weeks (4 months), we limit our analysis to data with $t \leq 16$. Our goal is to use the observed values of $\mathbf{Y}_i = \bigl(Y_{i,0}, \ldots, Y_{i,T_i}\bigr)^\top$ which characterize the scheduling history of the ith commercial to identify typical scheduling patterns of the TV sponsorship spots. This problem being often referred to as a problem of segmentation.

3 Model based segmentation

The observed values of the scheduling histories $\mathbf{Y}_i$ ($i = 1, \ldots, N$) might be viewed as longitudinal data and the problem of segmentation as a problem of classification based on the observed longitudinal profiles. To this end, a model based classification method of Komárek and Komárková (2013b) and a related contributed `R` (R Core Team, 2013) package `mixAK` (Komárek and Komárková, 2013a) might be exploited for this purpose.

As it is usual with model based classification, it is assumed that the scheduling history $\mathbf{Y}_i$ of the ith commercial is generated according to one of K models where K is the number of segments (groups). History generation according to the kth model ($k = 1, \ldots, K$) happens with an unknown probability w_k, where $0 < w_k < 1$, $\sum_{k=1}^{K} w_k$. In our particular application, the following (linear mixed) model is assumed for the scheduling history $\mathbf{Y}_i$ of the ith commercial provided it belongs to the kth segment:

$$\log(Y_{i,t}) = b_{i,0} + b_{i,1}\,t + b_{i,2}\,t^2 + \varepsilon_{i,t}, \qquad t = 0, \ldots, T_i,$$

where the random effect vector $\mathbf{b}_i = \bigl(b_{i,0}, b_{i,1}, b_{i,2}\bigr)^\top$ is assumed to follow a normal distribution with an unknown mean vector $\boldsymbol{\mu}_k = \bigl(\mu_{k,0}, \mu_{k,1}, \mu_{k,2}\bigr)^\top$ and an unknown covariance matrix $\mathbb{D}_k$. The random error vector $\boldsymbol{\varepsilon}_i = \bigl(\varepsilon_{i,1}, \ldots, \varepsilon_{i,T_i}\bigr)^\top$ is assumed to be independent of $\mathbf{b}_i$ and following a zero mean normal distribution with a diagonal covariance matrix with an unknown residual variance σ^2 being the same for all segments.

TABLE 1. Estimated characteristics of the scheduling patter segments.

Segment k	**Weight** w_k	**Intercept** $\mu_{k,0}$	**Linear term** $\mu_{k,1}$	**Quadratic term** $\mu_{k,2}$
1	0.192	1.297	-0.0277	0.00102
2	0.470	0.311	0.0497	-0.00267
3	0.282	2.231	-0.1065	0.00321
4	0.056	2.574	-0.6740	0.06130

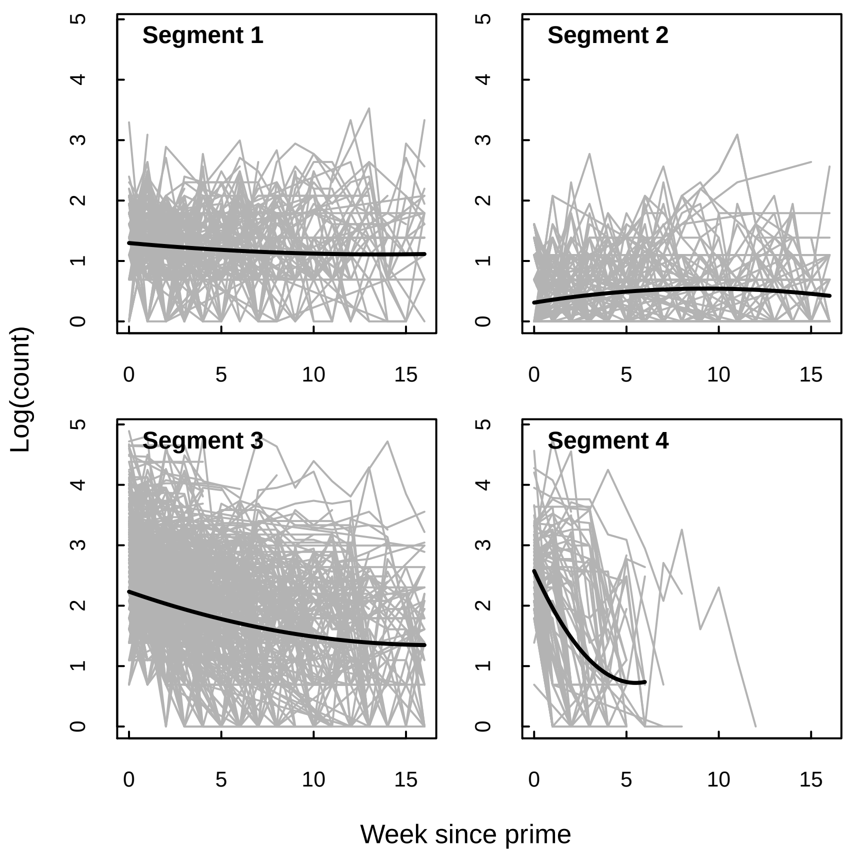

FIGURE 1. Observed (grey) and mean (black) evolution of the logarithmic number of broadcasted TV sponsorship in each of four segments.

In summary, the kth segment ($k = 1, \dots, K$) is characterized by the kth mean vector $\boldsymbol{\mu}_k$ and the kth covariance matrix $\mathbb{D}_k$. The mean vector determines the mean evolution of the logarithmic number of weekly broadcasting occurences of the kth segment whereas the covariance matrix the variability of the individual scheduling patterns around the mean pattern given by $\boldsymbol{\mu}_k$.
Komárek and Komárková (2013a) describe a Bayesian approach to estimation of unknown parameters and subsequent classification. They also suggest to use an approach based on penalized expected deviance (PED, Plummer, 2008) for selection of an optimal number of segments. Their methods have been applied to our application.

4 Results and discussion

The optimal number of segments according to PED is four, i.e., $K = 4$. Estimated segment weights and parameters of the segment specific patterns represented by the mean vectors $\boldsymbol{\mu}_1, \dots, \boldsymbol{\mu}_4$ are given in Table 1. Graphically, the segment specific patterns together with the observed histories for the individual creativities being classified in each patters are shown on Figure 1. More detailed discussion of results and results of more advanced analyses exploting also information on additional characteristics of each commercial (length, type of channel where broadcasted, ...) shall be postponed to a journal paper being in progress.

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References

Komárek, A. and Komárková, L. (2013a). Capabilities of `R` package `mixAK` for clustering based on multivariate continuous and discrete longitudinal data. *Submitted for publication,* preprint available from `http://msekce.karlin.mff.cuni.cz/~komarek/publication.html#mixAKclust`.

Komárek, A. and Komárková, L. (2013b). Clustering for multivariate continuous and discrete longitudinal data. *Annals of Applied Statistics*, **7**, 177 – 200.

Plummer, M. (2008). Penalized loss functions for Bayesian model comparison. *Biostatistics*, **9**, 523 – 539.

R Core Team (2013). *R: A Language and Environment for Statistical Computing*. Vienna: R Foundation for Statistical Computing. `http://www.R-project.org/`.