2nd special issue on robust analysis of complex data

When we embarked to invite submissions for this 2nd special issue on robust analysis of complex data, we did so with the following call:

Nowadays we are often confronted with large data sets in high dimensions. These new types of data have led to the emergence and use of complex models such as graphical models, models for complex correlation structures and models for functional data for instance. These complex structures pose many challenges. Specifically, when many measurements on several variables are recorded, it becomes more likely that not all of these measurements are recorded with high accuracy. This may result in data of uneven quality that contains gross errors and other anomalies that need to be taken into account. Therefore, there is a need for robust procedures that can reliably analyze large data sets containing outliers and other data contamination. This special issue will focus mainly on computationally efficient, robust procedures to analyze such complex data sets. This call resulted in 37 submissions, from which five high quality papers have been selected for inclusion in this special issue. We greatly acknowledge the help of the CSDA co-editors to handle these papers and we thank all anonymous referees for their valuable comments, honest opinions and constructive suggestions.

[Dhaene and Zhu \(2017\)](#) study the robustness properties of median-based estimators for the AR(1) coefficient in different types of additive outliers scenarios for panel data when the number of time-points is growing to infinity while the number of observed panels is fixed. They do so through showing that the influence function is bounded when outliers occur independently over time or are patched additive, i.e. they occur in random sequences of length k .

[Bali and Boente \(2017\)](#) consider robust principal component estimation of several populations of functional data. They adapt methods from one population functional data, instead of estimating the covariance operator for each of the populations

separately, [Bali and Boente \(2017\)](#) propose to use robust projection-pursuit estimators for the common directions under a common principal component model instead. The benefit is that considerably fewer parameters need to be estimated. A particular highlight of the article is that [Bali and Boente \(2017\)](#) extend the definition of a functional common principal component model to the situation in which the covariance operator does not exist or when the underlying distribution is not elliptical, and show how this still ensures Fisher-consistency.

[Chiancone et al. \(2017\)](#) show how to robustify Sliced Inverse Regression (SIR), which has been shown in [Cook \(2007\)](#) to correspond to the maximum likelihood of an inverse regression model with Gaussian errors, by extending its inverse regression formulation to non-Gaussian errors with heavy tailed distributions. In contrast to alternative robust versions of SIR, [Chiancone et al. \(2017\)](#) do not replace the standard SIR estimators by robust versions but achieve robustness through focussing on the intrinsic characterisation of SIR by working with multivariate t -distributions where estimation of parameters can still be achieved through maximum likelihood estimation via the EM algorithm.

[He et al. \(2017\)](#) investigate the estimation of high dimensional copula graphical model by simultaneous testing whether or not in high-dimensional Gaussian graphical models the i th component of a p -variate multivariate normal distributed random

variable is conditionally independent of the j th component, given all remaining variables. The false discovery rate is used to

measure performance and robustness is gained by exploiting nonparametric rank-based tests. The procedure requires that

p regression equations are solved, which is done with the Lasso or Dantzig selector [Candes and Tao \(2007\)](#).

[Maruotti and Punzo \(2017\)](#) use flexible hidden Markov regression models to analyze heterogeneous longitudinal multivariate responses which may depend on several fixed covariates. To provide robustness against outlying responses, the

standard multivariate Gaussian distribution for the outcome vectors can be replaced by either a multivariate t -distribution or a multivariate contaminated Gaussian distribution. This is one of the first contributions providing a robust method to analyze these complex data.

As is the nature of publishing, what is eventually selected is to a high degree independent of competing submissions, yet it is striking that the five selected papers by 'chance' cover the entire range of what was sketched in the original call and more—it is encouraging to see robustness at play in a very different sense.

Since the first special issue on robust analysis of complex data was published in CSDA ([Croux et al., 2013](#)) four years ago, the journal continued to attract a considerable body of work on different aspects of robustness in complex data analysis. These include [Alfons et al. \(2016\)](#), [Cui et al. \(2016\)](#), [Hämäläinen \(2016\)](#), [Kirschstein et al. \(2016\)](#), [Martinez and Gray \(2016\)](#), [Salibián-Barrera et al. \(2016\)](#) and [Tarr et al. \(2016\)](#), the seven articles in a special issue on advances in data mining and robust statistics as well as articles in regular issues such as [Atkinson et al. \(2016\)](#), [Boente and Pardo-Fernández \(2016\)](#), [Chee and Wang \(2016\)](#), [Cheng \(2016\)](#), [García-Escudero et al. \(2016\)](#), [Gutiérrez et al. \(2016\)](#), [Huang et al. \(2016\)](#), [Leung et al. \(2016\)](#), [Li et al. \(2016\)](#), [Mount et al. \(2016\)](#), [Xiang et al. \(2016\)](#), [Aeberhard et al. \(2017\)](#), [Agostinelli et al. \(2017\)](#), [Bianco and Spano \(2017\)](#), [Kaffine and Davis \(2017\)](#), [Maronna and Yohai \(2017\)](#), [Moradi Rekabdarkolae et al. \(2016\)](#), [Serfling and Wijesuriya](#)

(2017) and Song et al. (2017), to just focus on publications since 2016.

We encourage all readers to continue to choose CSDA as one of their main outlets to share their latest achievements in the various important areas of robust statistics.

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Samuel Mueller *

University of Sydney, Australia

E-mail address: samuel.mueller@sydney.edu.au.

Graciela Boente

Universidad Buenos Aires, Argentina

E-mail address: gboente@dm.uba.ar.

Christophe Croux

KU Leuven, Belgium

E-mail address: christophe.croux@econ.kuleuven.be.

Juan Romo

Universidad Carlos III de Madrid, Spain

E-mail address: romo@est-econ.uc3m.es.

Stefan Van Aelst

Ghent University, Belgium

E-mail address: stefan.vanaelst@ugent.be.

*Corresponding editor.