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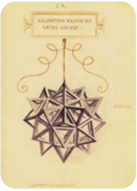

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NETWORK-BASED SEMI-SUPERVISED CLUSTERING OF TIME SERIES DATA

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ABSTRACT: Semisupervised clustering extends standard clustering methods to the semisupervised setting, in some cases considering situations when clusters are associated with a given outcome variable that acts as a "noisy surrogate", that is a good proxy of the unknown clustering structure. A novel approach to semisupervised clustering associated with an outcome variable named network-based semisupervised clustering (NeSSC) has been recently introduced (Frigau *et al.*, 2021). It combines an initialization, a training and an agglomeration phase. In the initialization and training a matrix of pairwise affinity of the instances is estimated by a classifier. In the agglomeration phase the matrix of pairwise affinity is transformed into a complex network, in which a community detection algorithm searches the underlying community structure. Thus, a partition of the instances into clusters highly homogeneous in terms of the outcome is obtained. A particular specification of NeSSC, called Community Detection Trees (Co-De Tree), uses classification or regression trees as classifiers and the Louvain, Label propagation and Walktrap as possible community detection algorithm. NeSSC is based on an ad-hoc defined stopping criterion and a criterion for the choice of the optimal partition of the original data. In this presentation, we provide a new specification of the NeSSC algorithm that allows us to perform clustering of time series data. This specification is based on the integration between Co-De Tree and the Atheoretical Regression Tree (ART) approach introduced by (Cappelli *et al.*, 2013; Cappelli *et al.*, 2015). ART exploits the concept of contiguous partitions within the framework of Least Squares Regression Trees using as a single covariate an arbitrary sequence of completely ordered numbers $K = 1,2,\ldots,i,\ldots,N$. Tree-regressing the response variable Y on this artificial covariate resorts to create and check at any node h all possible binary contiguous partitions of the $Y_i \in h$. These splits are the only ones that need to be checked to detect the binary partition that minimizes the sum of squares and, indeed, they are generated by using K as covariate. In other words, for the

contiguity property the best split lays in K (or in its subintervals after the split of the root note has taken place) and the tree algorithm, based on the classical "reduction in impurity" splitting criterion is forced to identify it. In general, the use of K as covariate enables ART to generate G different groups having different means. The effectiveness of the proposed NeSSC-ART combined approach for time series clustering is demonstrated on simulated and real data

KEYWORDS: network-based semisupervised clustering, community detection trees, atheoretical regression tree.

References

CAPPELLI, C, D'URSO, P, & DI IORIO, F. 2013. Change point analysis of imprecise time series. *Fuzzi Sets and Systems*, **225**, 23–38.

CAPPELLI, C, D'URSO, P, & DI IORIO, F. 2015. Regime change analysis of interval-valued time series with an application to PM10. *Chemiometrics and Intelligent Laboratory System*, **146**, 337–346.

FRIGAU, L, CONTU, G, MOLA, F, & CONVERSANO, C. 2021. *NNetwork-based semisupervised clustering*. Vol. 37.