



On Subgrouping Continuous Processes in Discrete Time

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Recent years have witnessed a boom in the application of dynamic network models such as vector autoregression (VAR) models and their various flavors to the study of human behavior and psychology. VAR-type models have been invaluable in shedding light on idiographic dynamics in various areas such as affect (Wright et al., 2019) and neuroscience (Gates & Molenaar, 2012) and how they (mis-)align with nomothetic findings. These results have brought forth a new understanding of the importance of $N=1$ research for understanding individual dynamics. Commensurate to this rise in idiographic applications is an increased call for reconciling the person-specific domain with inferences obtained at the group-level. Several DT methodologies have been developed for identifying heterogeneous subgroups in intraindividual dynamics including approaches such as the subgroup group iterative multiple model estimation (S-GIMME; Gates & Molenaar, 2012) procedure and the subgrouped chain graphical VAR (scGVAR; Park et al., in press); however, some questions remain.

VAR-based approaches bear some limitations. For instance, potential inferential confounds may arise when time intervals vary within or across studies. These challenges may be ameliorated by fitting models in the continuous-time (CT) framework; however, a lexical gap exists in the literature due to the predominant usage of DT formulations in most contemporary dynamic network subgrouping methods. This work examines how various DT-based approaches such as S-GIMME and the scGVAR perform at identifying meaningful subgroups when applied to continuous processes. Specifically, we assessed the subgrouping accuracy and the quality of point-estimates from these two methods when applying them onto continuous

processes at various sampling intervals, Δt , in a Monte Carlo simulation.

We addressed two questions: (1) How accurate are DT subgrouping approaches across different Δt s and effect sizes? and (2) Do different Δt s and effect sizes correspond to reliable differences in the quality of point estimates? We simulated CT data from 4-variate Ornstein–Uhlenbeck models incorporating varying design factors including: the sampling interval, Δt , that continuous data were subsampled from ($\Delta t = 0.1$ s to $\Delta t = 10$ s), the degree of stability in the data-generating CT models, the separate between the subgroups, and the temporal sample size ranging from $T = 14$ to $T = 100$.

How accurate were DT subgrouping approaches across Δt s and effect size conditions?

Fairly accurate; results indicated that both approaches—S-GIMME and the scgVAR—performed well at identifying subgroups when sampling at intervals $\Delta t \geq 1.0$ as assessed by an Adjusted Rand Index ≥ 0.75 across stability configurations as well as high and low separation conditions (Figure 1). Even when sample sizes were as few as $T = 14$ measurements per subject, both algorithms had acceptable performance when successive measurements were spaced sufficiently apart to capture critical dynamics of a system.

Do different Δt s and effect sizes correspond to differences in the quality of point estimates?

Yes, decreased biases were generally observed in all parameters with increase in Δt , even though greater variability in parameter estimates was observed with S-GIMME under large $\Delta t = 10$ and small total number of time points ($T = 14$). Reasons for differences in the two approaches, caveats, decisions that can drive subgrouping results, and potential future extensions are discussed.

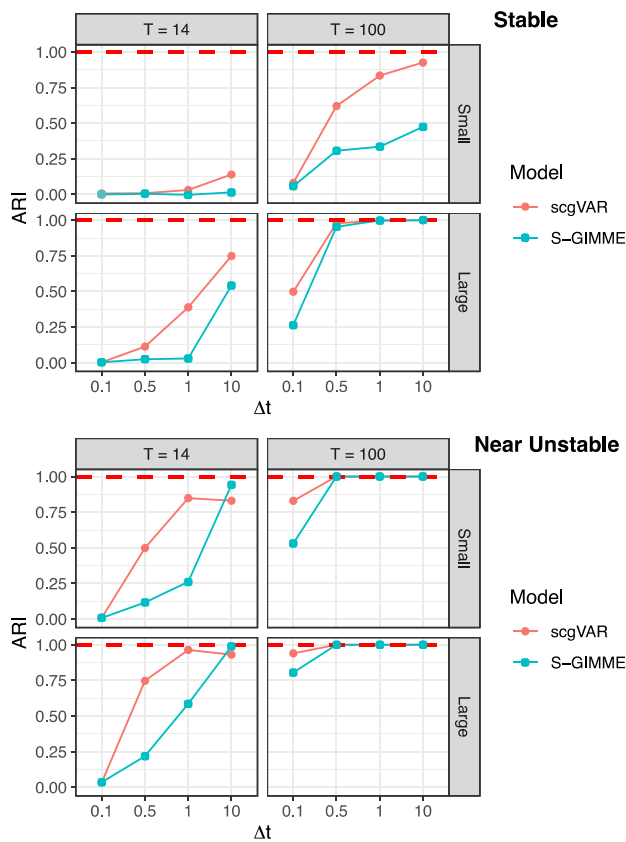


Figure 1. Adjusted Rand index (ARI) values across the Monte Carlo simulation conditions. $ARI \geq 0.75$ are considered acceptable recovery of subgroup membership. Greater separation between groups was associated with higher ARI values alongside greater Δt . Nearly unstable systems were more differentiable than stable systems at smaller Δt intervals.

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References

- Gates, K. M., & Molenaar, P. C. (2012). Group search algorithm recovers effective connectivity maps for individuals in homogeneous and heterogeneous samples. *NeuroImage*, 63(1), 310–319.
- Park, J. J., Fischer, Z., Chow, S., Epskamp, S., & Molenaar, P. C. (Under Review). Subgrouping with chain graphical VAR models. *Multivariate Behavioral Research*.
- Wright, A. G. C., Gates, K. M., Arizmendi, C., Lane, S. T., Woods, W. C., & Edershile, E. A. (2019). Focusing personality assessment on the person: Modeling general, shared, and person specific processes in personality and psychopathology. *Psychological Assessment*, 31(4), 502–515. <https://doi.org/10.1037/pas0000617>