Trajectories of Criminal Activity in a Sample of 378 Adjudicated Ontario Youth

David. M. Day,[1] Jason. D. Nielsen[2], Ashley K. Ward[1], Ye Sun[3], Jeffrey S. Rosenthal[4], Irene Bevc[5], Thierry Duchesne[6], & Lianne Rossman[4]

[1]Ryerson University; [2]Carleton University, [3]University Health Network, [4]University of Toronto, [5]Hincks-Dellcrest Centre, [6]Université Laval

RYERSON UNIVERSITY

Abstract

Group-based trajectory analysis has yielded important insights into the nature and pattern of offending over the life span. Particularly important is research on the progression of criminal activity across major developmental periods such as adolescence to adulthood and early adulthood to mid-adulthood and beyond. The purpose of this study was to: (1) compare the criminal trajectories of our sample of 378 juvenile offenders generated for a *M* = 12.1-year follow-up period, from age 15 to 27 years (on average), with the criminal trajectories generated for a *M* = 18.7 year follow-up period, from age 15 to 34 years (on average); and (2) apply cross-validation (CV) to determine the optimal number of groups as an alternative to the Bayesian Information Criterion (BIC), which is known to be problematic The trajectory analyses found that a 5-group model best fit the initial follow-up data and an 8-group model best fit the extended follow-up data. Trajectory groups with shorter trajectory lengths at the initial follow-up were more stable over the two follow-up periods than groups with longer trajectory lengths. Last, CV performed better than the BIC in finding the optimal models.

Introduction

- Since its advent about 15 years ago, the criminology and psychology fields have widely embraced group-based trajectory analysis (GBTA) (Piquero, 2008).
- GBTA is a specialized application of finite mixture modeling that aims to parcel out underlying (unobserved) heterogeneity of within-individual trajectories of behaviour into discrete subgroups or latent classes of common pathways. GBTA allows the researcher to identify clusters of individuals whose rate of criminal activity is statistically similar as it unfolds over time. Its value is that it is able to describe the inherent heterogeneity in the nature and pattern of criminal offending *across* individuals as the course of their behaviour is charted over time *within* individuals.
- Following estimation of the model parameters, each individual is assigned to a trajectory group based on the posterior probabilities associated with each latent class. Decisions about the optimal number of groups that best represent the data are conventionally based on the Bayesian Information Criterion (BIC) (Nagin, 2005). However, the BIC is known to be problematic; thus, we propose the use of cross-validation (CV) (Hélie, 2006; Stone, 1974) as an alternative. The cross-validation error (CVE) methodology provides a fair, objective, and unambiguous means of assessing the number of groups and avoids the limitations, ambiguities, and subjectivity that may arise with the BIC (Day et al., 2007; Nielsen et al.,2011).
- The effect of length of follow-up on the nature and pattern of trajectory groups (Nagin & Tremblay, 2005; Tremblay & Odgers, 2010) has received scant attention in the literature. This is an important issue as examining changes in trajectory group attributes over different follow-up lengths may shed light on the dynamic nature of criminal offending over the life span.
- Using the Gluecks' (1950) data, Eggleston et al. (2004) compared trajectory groups for four follow-up lengths, 18, 25, 38, and 63 years, from age 7 years up to age 70 years. They found that longer follow-up periods yielded more trajectory groups, ranging from 4 to 6. Length of follow-up also had differential effects on trajectory group membership. High rate and moderate rate groups showed the greatest instability across follow-up periods and groups with shorter trajectory lengths were less affected.
- The aims of the present study were to (1) compare the trajectory groups of a sample of 378 juvenile offenders whose criminal trajectories were followed for *M* = 12.1 years (range = 5.8 – 22.8 years) and then for *M* = 18.7 years (range = 12.3 – 29.3 years), extending the initial follow-up period by *M* = 6.5 years, and (2) use CVE for model selection.

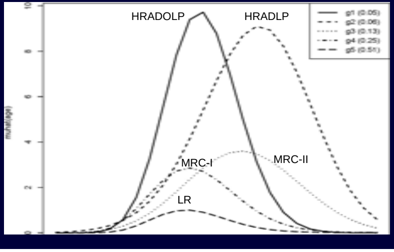
Method

- The sample comprised 378 juvenile offenders who had been sentenced between 1985 and 1996 to one of two open custody facilities in Toronto.
- Early childhood/adolescent and adult official criminal records were obtained from three government ministries and from predisposition reports (PDRs) available from client files.
- For comparison, trajectory analyses were performed using *crimCV*, a software program we developed for our research (Nielsen et al., 2011), that generates CVE, BIC, and AIC values. Specifically, we used a zero-inflated Poisson ZIP(tau) model, with controls for time-at-risk and age at offence (rather than adjudication), to model the data.
- Smaller CVE, BIC, and AIC values indicate the model that best fit the data.

Results

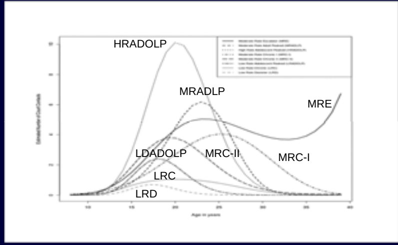
Results for initial trajectory analysis for *M* = 12.1 year follow-up:

ngr	llike	AIC	BIC	CV
1	-11613.042	23236.08	23271.85	1.1644799
2	-9782.644	19587.29	19665.98	0.9638853
3	-9330.680	18695.36	18816.97	0.9450418
4	-9140.214	18326.43	18490.96	0.8974869
***5**	-9014.186	18086.37	18293.83	**0.8765911**
6	-8921.572	17913.14	18163.53	0.9130521
7	-8845.171	17772.34	18065.65	0.8962775
8	-8794.504	17683.01	**18019.24**	0.8872718



Results for extended trajectory analysis for *M* = 18.7 year follow-up:

ngr	llike	AIC	BIC	CV
1	-13967.63	27945.26	27982.26	1.0902792
2	-11929.40	23880.81	23962.22	0.9128347
3	-11424.68	22883.37	23009.18	0.9592355
4	-11191.28	22428.55	22598.77	0.9052791
5	-11016.19	22090.37	22304.99	0.8535441
6	-10886.30	21842.61	22101.63	0.8334242
7	-10805.59	21693.18	21996.60	0.8261734
***8**	-10732.58	21559.16	21906.99	**0.8123785**
9	-10684.54	21475.08	**21867.31**	0.8240060



In terms of changes in trajectory group membership across follow-up lengths:

- 63.2% (12/19) of the HRADOLP group remained in the HRADOLP group;
- 54.4% (106/195) of the LR group became the LRD group and 34.9% (68/195) became the LRC group, essentially splitting into a desister group and a chronic group;
- 45.2% (42/93) of the MRC-I group became the LRADOLP group; the remaining MRC-I group was split equally between the MRC-II (25.8%) and LRC (25.8%; 24/93) groups;
- The HRADLP and MRC-II groups also showed low stability; these groups also had the longest trajectory lengths in the initial analysis, at 12.4 and 13.2 years, respectively, compared with 6.0 and 9.7 years for the LR and HRADLOP groups, respectively.

Discussion

- The larger number of groups yielded by the longer follow-up period was expected (Eggleston et al., 2004; Tremblay & Odgers, 2010).
- Follow-up length had differential effects on the stability of the trajectory groups across the two follow-up periods. Longer follow-up periods yield important information about the chronicity of offending even among individuals following a low rate trajectory.
- CVE performed better than the BIC in identifying the optimal models.

Acknowledgements: Funding for this research was provided by the National Crime Prevention Centre (NCPC), the Ministry of Children and Youth Services (MCYS), The Hincks-Dellcrest Centre, Ryerson University, the Samuel Rogers Memorial Trust, and the Natural Sciences and Engineering Research Council (NSERC).