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

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Abstract

The use of 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 12.1 year 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). In a seminal review of the literature, Piquero (2008) identified over 80 studies that have used these statistical techniques.

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; the highest posterior probability suggests the class to which the person belongs. Finally, decisions about the optimal number of trajectory 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 (Helie, 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).

In addition, the effect of <u>length of follow-up</u> on the nature and pattern of trajectory groups (Nagin & Tremblay, 2005; Piquero, 2008; 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. For example, only 25% of the high rate chronic offenders in the 7 – 72 years model were identified as high rate chronic offenders in the 7 - 70 years model. Only 38% of the moderate-rate chronic offenders from the 7 – 32 years model remained in this group in the 7 – 70 years model. By comparison, 57% of the classic desisters in the 7 – 32 years model were identified as classic desisters in the 7 – 70 years model.

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), and (2) use CVE rather than BIC 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.

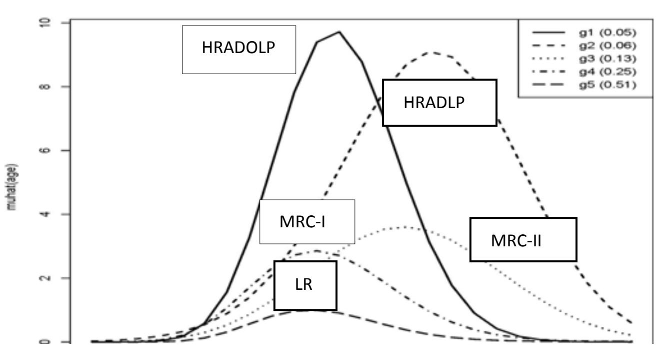
Early childhood/adolescent and adult official criminal records were obtained from three government ministries and from predisposition reports (PDRs) available from client files.

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:

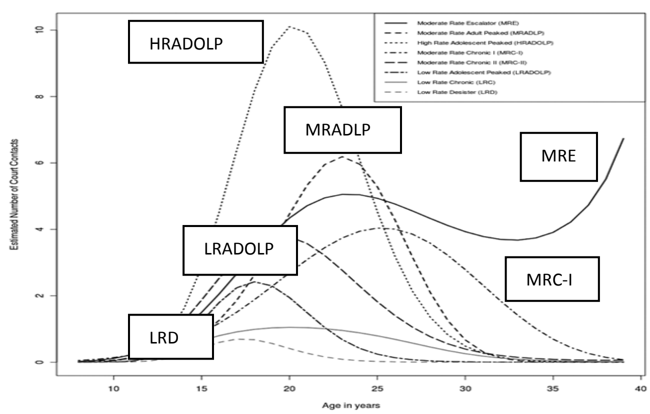
Ngr	llike	AIC	BIC	CV
1	-11613.042	23236.08	23271.85	1.1644799
2	-9782.644	19587.29	19665.98	0.9638853
3	-9330.680	18695.36	18816.97	0.9450418
4	-9140.214	18326.43	18490.96	0.8974869
***5**	-9014.186	18086.37	18293.83	**0.8765911**
6	-8921.572	17913.14	18163.53	0.9130521
7	-8845.171	17772.34	18065.65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



In this model, the CVE is minimized for the 5-group model. The BIC continues to decrease up to the 8-group model.

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 this model, the CVE is minimized for the 8-group model. Once again, the BIC continues to decrease up to the 9-group model.

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

- 63.2% (12/19) of the High Rate Adolescence Peaked (HRADOLP) group remained in the HRADOLP group; 21.1% (4/19) moved to the Moderate Rate Chronic-II (MRC-II) group;
- 54.4% (106/195) of the Low Rate (LR) group became the Low Rate Desister (LRD) group and 34.9% (68/195) became the Low Rate Chronic (LRC) group, essentially splitting into a desister group and a chronic group; 9.2% (18/195) became the Low Rate Adolescence Peaked (LRADOLP) group;

- The Moderate Rate Chronic-I (MRC-I) group showed low stability, with 45.2% (42/93) of this group becoming the Low Rate Adolescence Peaked (LRADOLP) group (although the shapes of the two trajectories look very similar); the remaining members of the MRC-I group were split equally between the MRC-II (25.8%; 24/93) and LRC (25.8%; 24/93) groups;

- The High Rate Adult Peaked (HRADLP) and MRC-II groups also showed low stability; 0.0% of the HRADLP group remained in a HRADLP group; 42.9% (9/21) became the Moderate Rate Escalator (MRE) group, 28.6% (6/21) became the HRADOLP group, and 23.8% (5/21) became the Moderate Rate Adolescence Peaked (MRADOLP) group.

- Only 34.0% (17/50) of the MRC-II group remained in the MRC-II group; 32.0% (16/50) became the MRC-I group, and 18.0% (9/50) became the MRADOLP group;

- The HRADLP and MRC-II 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 HRADOLP 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, with, generally, the more chronic groups at initial follow-up showing the least stability.

Longer follow-up periods appear to yield important information about the chronicity of offending even among individuals following a low rate trajectory.

Last, the CVE performed better than the BIC in identifying the optimal models.

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