

Event History Analysis for Debt Collection Portfolios

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Consumer debt sales

- **Debt type:** e.g. delinquent credit card payments and personal loans
- **Major players:**
 - Debt sellers: major banks and credit lenders
 - Debt buyers: debt purchase and collection companies
- **Transaction method:** closed tenders / public auctions
- **Contract types:** *one-off inventory sales* and *forward-flow agreements*
- **Portfolio composition:** *arrangement* and *general*
- **Portfolio price:** a fraction of debt face value

Data sample

- 6,000⁺ credit card accounts from 24 sequentially enrolled arrangement portfolios in the years 2002 and 2003.
 - each account having
 - details of the customer (*account information*)
 - dates and amounts of payments made to the debt recovery company (*transaction details*)
 - records of all contacts made between account customer and the debt recovery company (*action records*)
- all up until Dec 2006.

A typical debt portfolio collection process

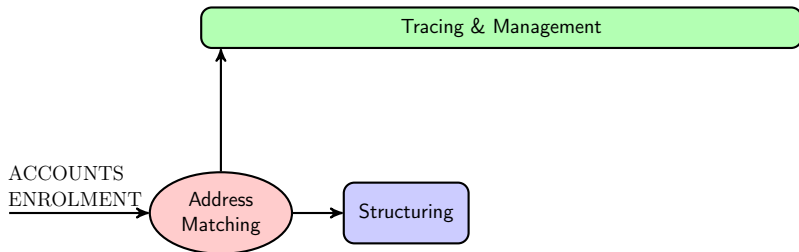
ACCOUNTS
ENROLMENT



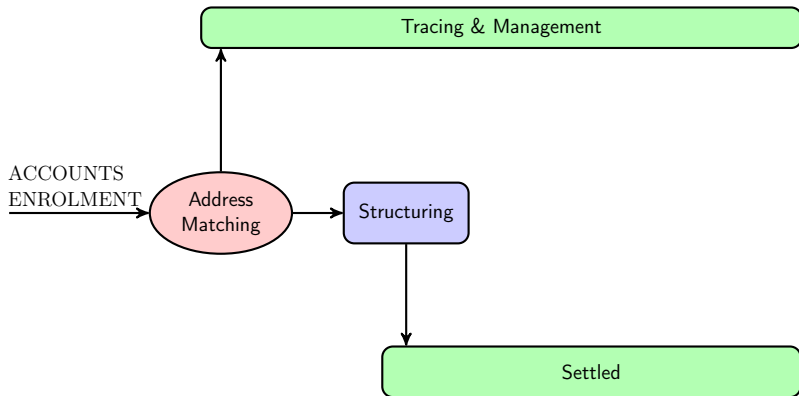
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graph LR; A[ACCOUNTS ENROLMENT] --> B((Address Matching));
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Address
Matching

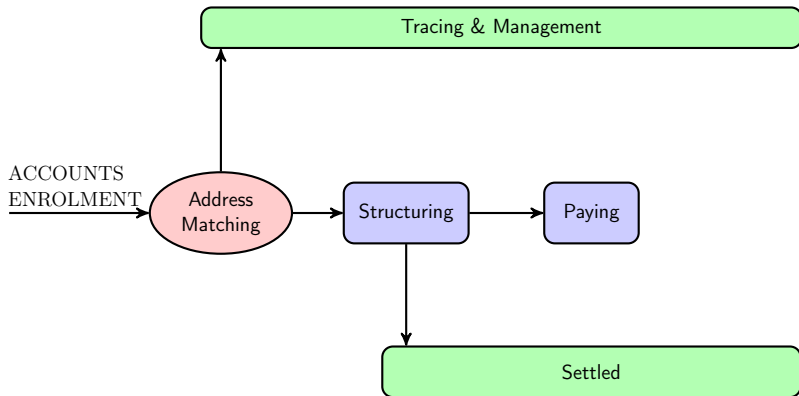
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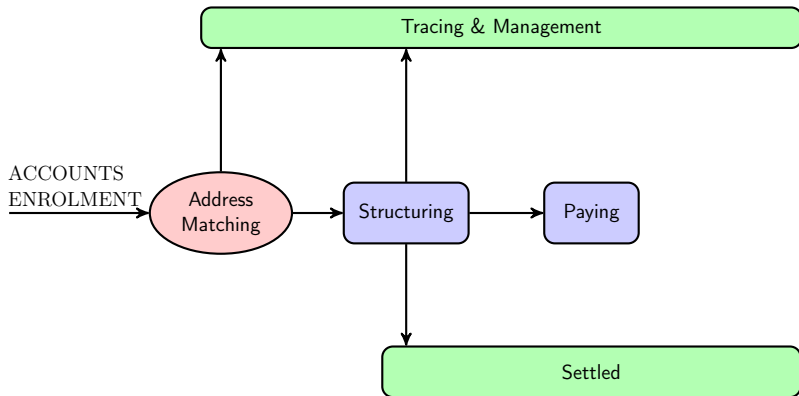
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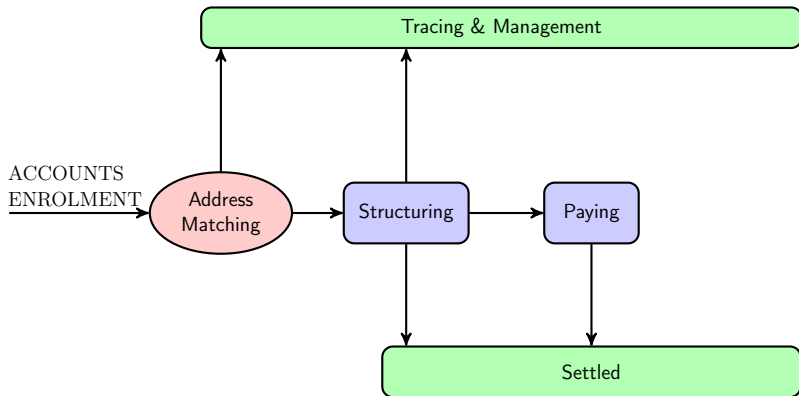
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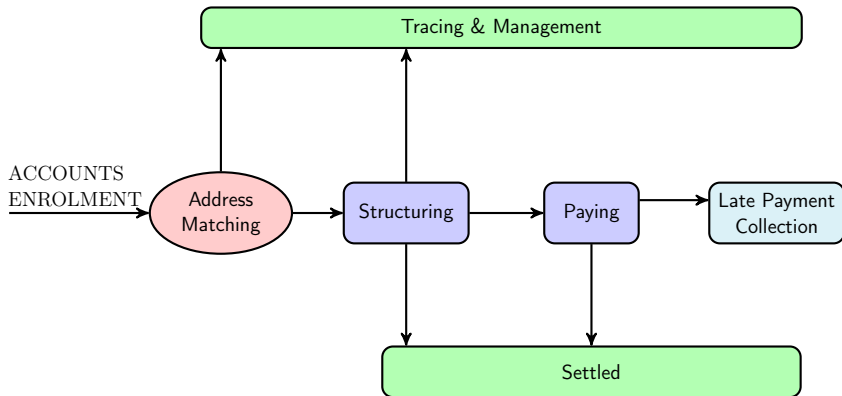
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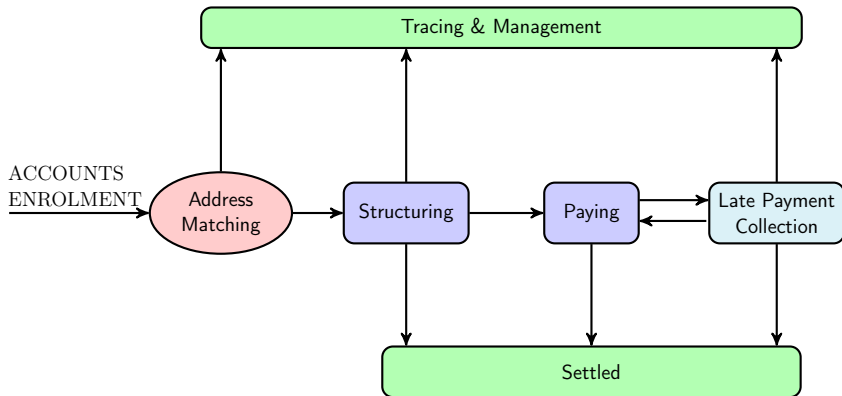
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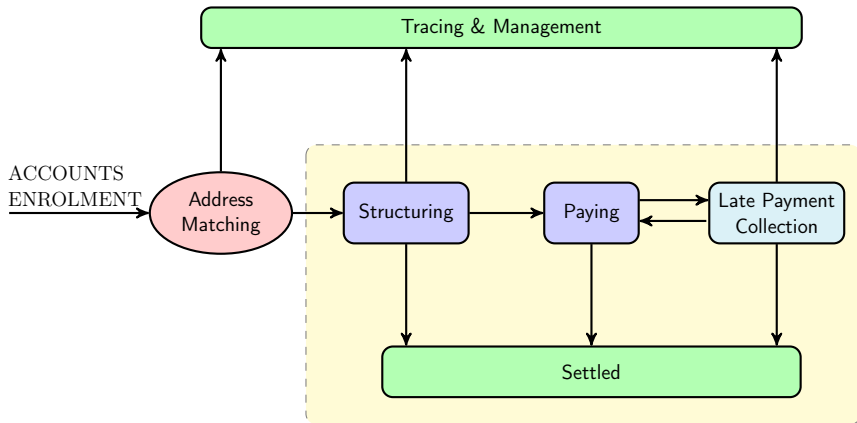
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Multi-state models : Formulation

State structure specifies the states and the possible transitions between states.

For a given data set,

- The state structure is **NOT** unique;
- Selecting a good state structure makes the data analysis more approachable.

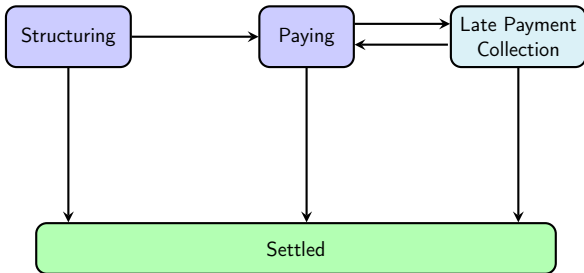
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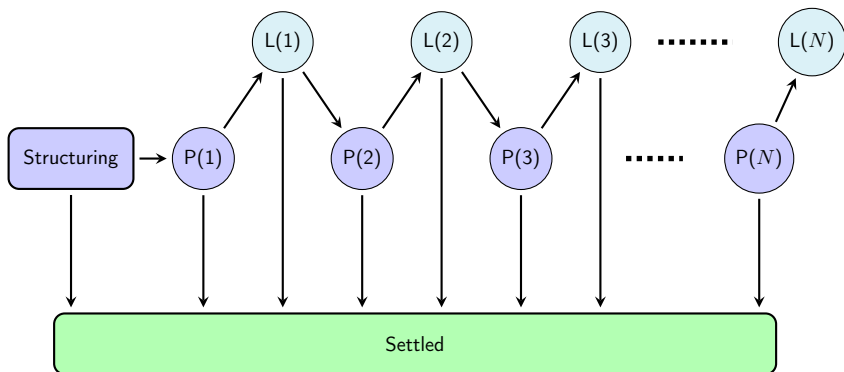
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The initial formulation



The *unfolded* formulation



Possible factors

For each *Paying state* $P(i)$ or *Late-payment-collection state* $L(i)$ ($i = 1, \dots, N$), we have a list of possible factors to be tested in the regression models:

- **Background variables:** Age, Gender, Balance, Debt grade, Type of credit card, etc.
- **Performance variables:** Times of earlier transitions, Number of contacts made in earlier states, etc.

Regression models

For each $P(i)$ or $L(i)$ ($i = 1, \dots, N$) state, we have a **competing risks model**:

The risk of proceeding to next P or L state
VS.
The risk of settlement.

Regression models

Regression models for the sub-distribution hazard:

- Cox regression model:

$$h_k(t|\mathbf{X}) = h_{k,0}(t) \exp(\beta_k^T \mathbf{X}) \quad k = 1, 2$$

- Cox regression model with time-dependent covariates:

$$h_k(t|\mathbf{X}(t)) = h_{k,0}(t) \exp(\beta_k^T \mathbf{X}(t))$$

- Aalen Additive regression model:

$$h_k(t|\mathbf{X}(t)) = Y(t)(\alpha_k(t)^T \mathbf{X}(t))$$

Regression models

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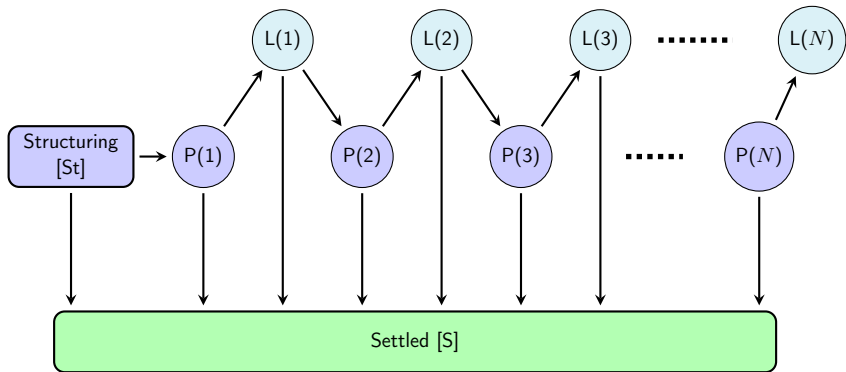
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The *unfolded* model



Results: Stepwise variable selection

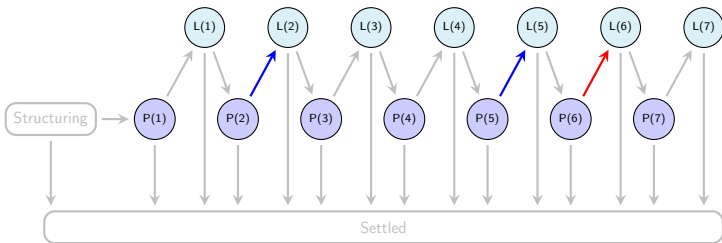
	P1L1	P2L2	P3L3	P4L4	P5L5	P6L6
StP1 time	0.09	0.10				
P1L1 time		-0.24	-0.11			
L1P2 time		0.38				
P2L2 time			-0.34	-0.16		-0.38
L2P3 time						
P3L3 time				-0.31		
L3P4 time						
P4L4 time					-0.24	
L4P5 time						
P5L5 time						-0.004
L5P6 time						

	P1L1	P2L2	P3L3	P4L4	P5L5	P6L6
# actions in St	0.11	0.06			-0.16	
# actions in P1		0.09				
# actions in L1		-0.26		-0.21		-0.59
# actions in P2			0.11			
# actions in L2						
# actions in P3						
# actions in L3						
# actions in P4						
# actions in L4						
# actions in P5						
# actions in L5						

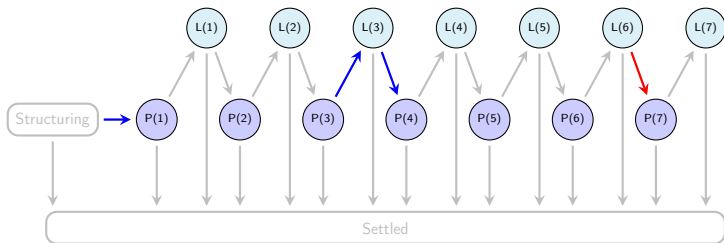
	L1P2	L2P3	L3P4	L4P5	L5P6	L6P7
StP1 time	-0.19					-1.47
P1L1 time	0.05		0.10			
L1P2 time		-0.30	-0.40			
P2L2 time		0.17				
L2P3 time			-0.32			
P3L3 time			0.12	0.33		1.00
L3P4 time				-0.80		3.43
P4L4 time				0.21		
L4P5 time						
P5L5 time					1.00	
L5P6 time						
P6L6 time						

	L1P2	L2P3	L3P4	L4P5	L5P6	L6P7
£ leaving-St payment	-0.08					
£ leaving-L1 payment		-0.22			-1.09	
£ leaving-L2 payment			-0.29		1.70	
£ leaving-L3 payment				-0.25		
£ leaving-L4 payment						
£ leaving-L5 payment						

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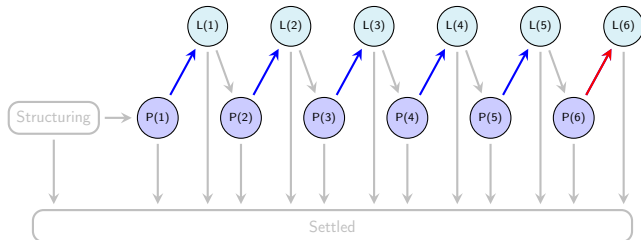
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Tailored stepwise variable selection

To facilitate the interpretation of covariate effects, we

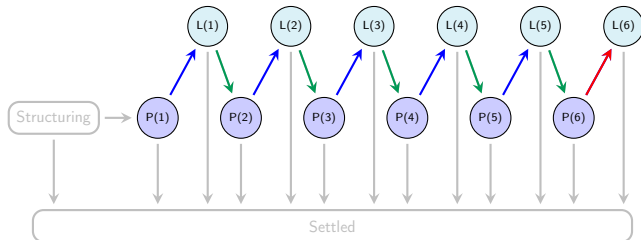
- only allow the p th lag of covariate x to be considered in the selection procedure when lags $1, 2, \dots, p - 1$ are also included in the model.



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Results: Tailored stepwise variable selection

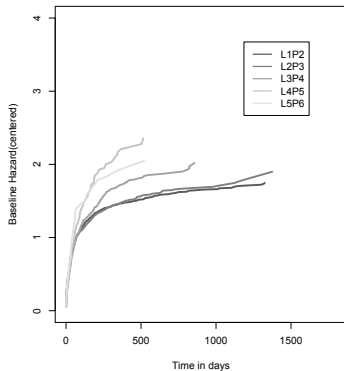
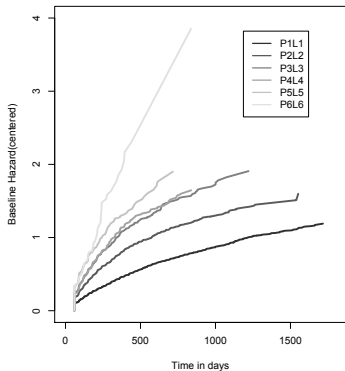
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Baseline hazards



Summary

In conclusion, we

- proposed a multi-state framework for the debt collection process,
- explored a state structure which allows us to add performance variables into regression models, and
- implemented a tailored variable selection algorithm to achieve improved interpretability of regression results.

Thank you!