2023 INTERNATIONAL CONGRESS OF ACTUARIES

BRIDGE TO TOMORROW

28 MAY – 1 JUNE 2023 · SYDNEY

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Multi-State Modelling of Customer Churn

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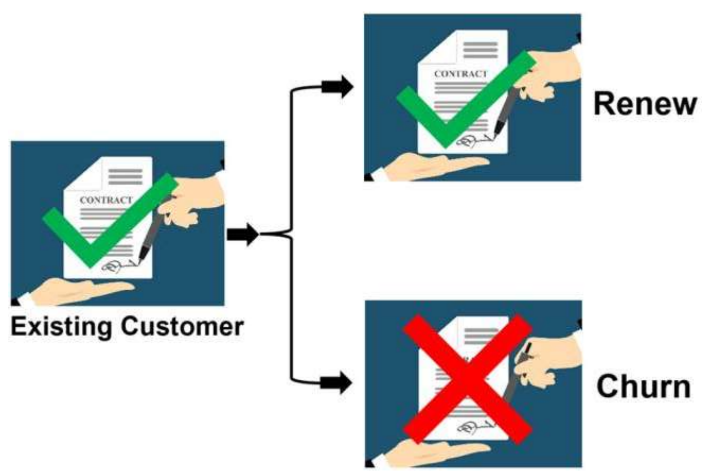
What is customer churn?

Customer churn (also known as customer attrition, dropout, turnover, or defection) refers to the non-renewal of existing customers for an insurance company.



Customer churn is an important problem in insurance

Problems

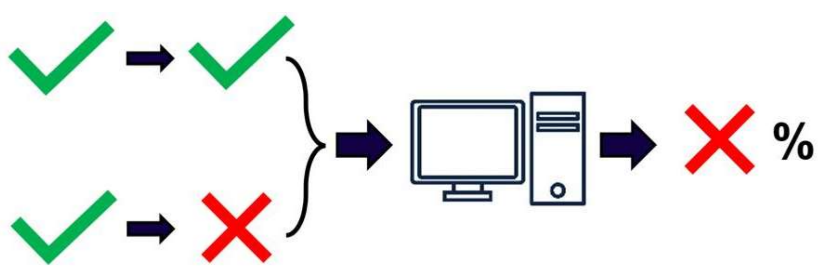
- Contracts are renewed periodically (monthly, quarterly, semi-annually, and annually);
- Substantial competition and diverse contracts in the market. For example, about 19 per cent of Australian small business owners switch commercial insurance providers every year (McKinsey, 2017).

Importance

- Keeping a current customer rather than acquiring a new one is often a more profitable strategy for a company.
- Long-term customers typically take up less of the company's resources compared to new customers.
- Customer churn analysis is related to the insurance pricing process in practice (price elasticity test).
- An insurance company's reputation is directly related to its customer loyalty.

Traditional customer churn analysis

Traditionally, customer churn analysis has focused on static models that utilise only a binary outcome (churn or renew) in one period.



- Binary logistic regression (BLR) and its variation.
- Tree-based methods, such as Random Forest (RF), Gradient Boosting Machine (GBM), and eXtreme Gradient Boosting (XGBoost).
- Support Vector Machine (SVM)
- Neural Networks.

Motivation of Multi-State Customer Churn Analysis

Diverse Contracts/Coverages

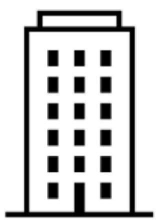
Policyholders can have multiple contracts with the same insurance company and have multiple coverages under a single bundled contract. For example,

- Multiple commercial contracts: building insurance + auto insurance + equipment insurance.
- Multiple coverages under an auto insurance: damage to your car from an accident + damage to other cars if you cause an accident.

Longitudinal Data

Real business relationships are multi-period, and policyholders may reside and transition between a wider range of states beyond that of the simply churn/renew throughout this relationship.

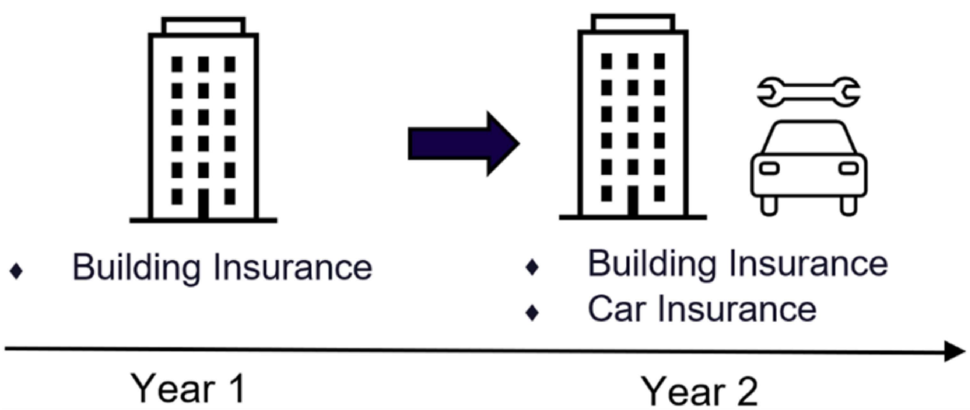
An Example of Multi-State Transition in Commercial Insurance



- Building Insurance

Year 1

An Example of Multi-State Transition in Commercial Insurance



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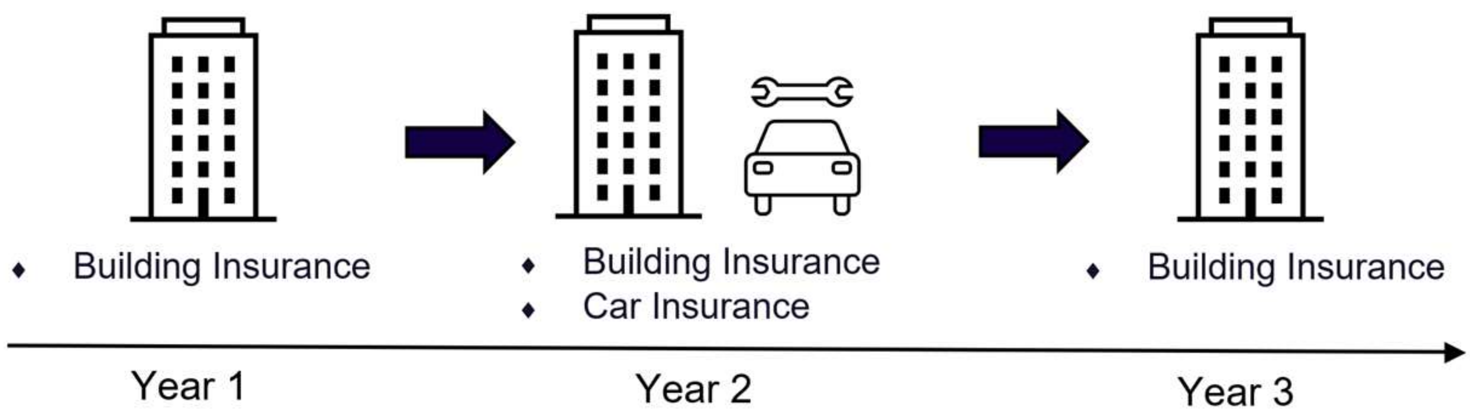
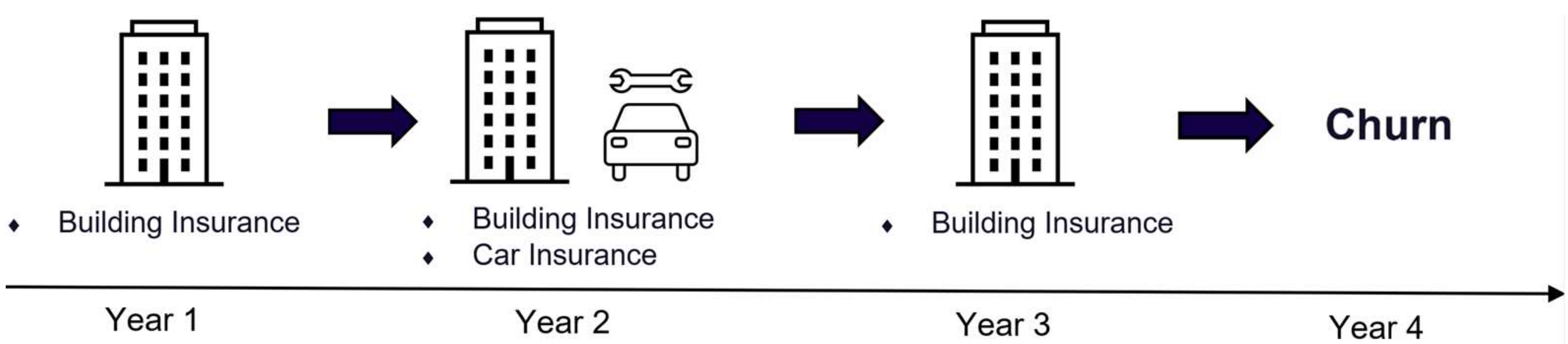


An Example of Multi-State Transition in Commercial Insurance



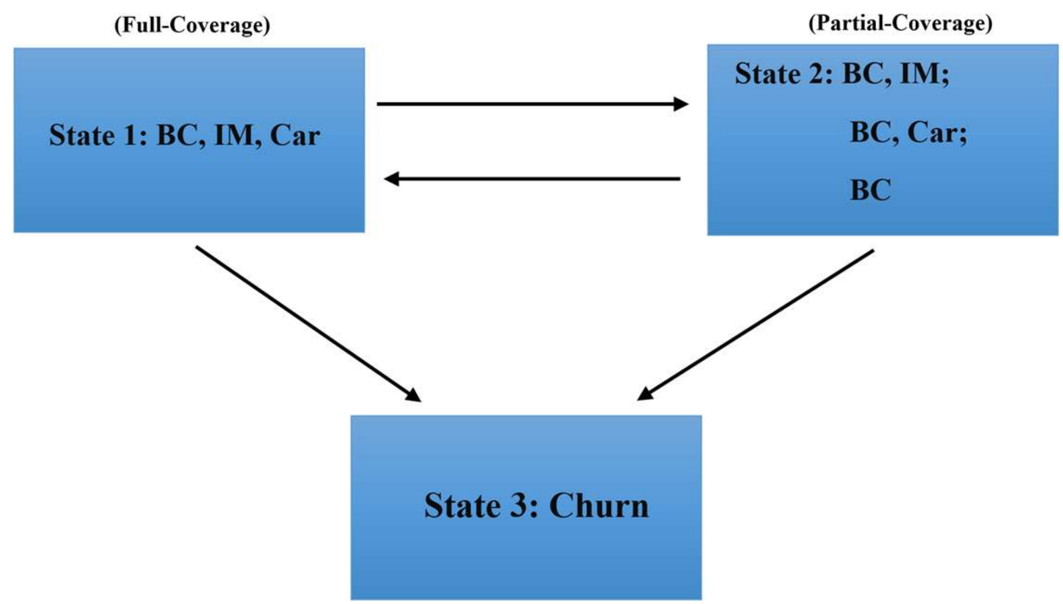
Multi-state customer churn analysis aims to model behaviour over a larger number of states (flexible definition of state based on research interests) and across multiple periods (thereby making use of readily available longitudinal data).

Application: Wisconsin Local Government Property Insurance Fund

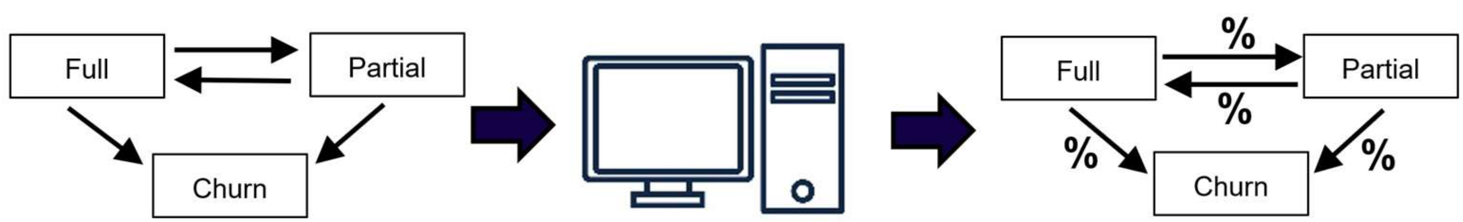
LGPIF

- LGPIF is administered by the Wisconsin Office of the Commissioner of Insurance, with its purpose being to make property insurance available for local government units

- LGPIF offers three coverages for policyholders to choose: building and content (**BC**), contractor's equipment (**IM**), and vehicles (**Car**).



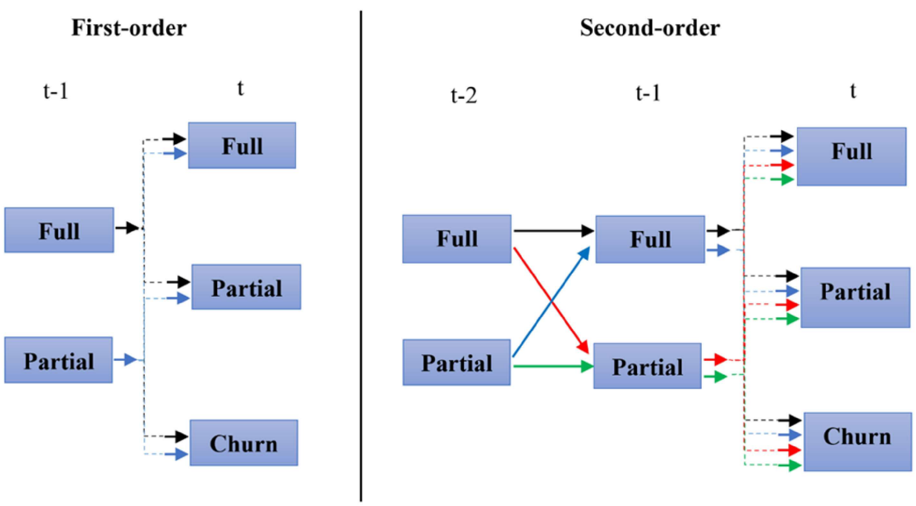
Methodology: Multi-State Models



Multi-state customer churn analysis focuses on dynamic models that utilize multi-class classification across multiple periods.

- Multinomial logistic regression (**MLR**): a natural extension of logistic regression to the case of categorical responses with more than two categories (good interpretability).
- Machine learning models: **GBM** and **SVM**.

Visualising First-Order and Second-Order Models for LGPIF Application



State 1: Full-Coverage; State 2: Partial-Coverage; State 3: Churn

Table 1: Second-order transition counts and empirical transition probabilities in per cent (in brackets) from 2006 to 2013.

State of origin $(t-2, t-1)$	State of destination (t): State 1 (full-coverage)	State 2 (partial-coverage)	State 3 (churn)
(NA, full)	416 (92.24%)	22 (4.88%)	13 (2.88%)
(full, full)	2098 (94.63%)	54 (2.44%)	65 (2.93%)
(partial, full)	38 (88.37%)	5 (11.63%)	0 (0.00%)
(NA, partial)	14 (1.72%)	780 (95.59%)	22 (2.70%)
(full, partial)	7 (9.33%)	63 (84.00%)	5 (6.67%)
(partial, partial)	27 (0.65%)	4015 (96.31%)	127 (3.05%)

First-Order MLR Model

$$P(y_{i,t} = s | y_{i,t-1} = r) = \frac{\exp\left(x_{i,t-1,r}^{\top} \beta_{rs}\right)}{\sum_{s'=1}^{Q} \exp\left(x_{i,t-1,r}^{\top} \beta_{rs'}\right)}$$

Second-Order MLR Model

$$P(y_{i,t} = s | y_{i,t-2} = q, y_{i,t-1} = r) = \frac{\exp\left(x_{i,t-1,qr}^{\top} \beta_{qrs}\right)}{\sum_{s'=1}^{Q} \exp\left(x_{i,t-1,qr}^{\top} \beta_{qrs'}\right)}$$

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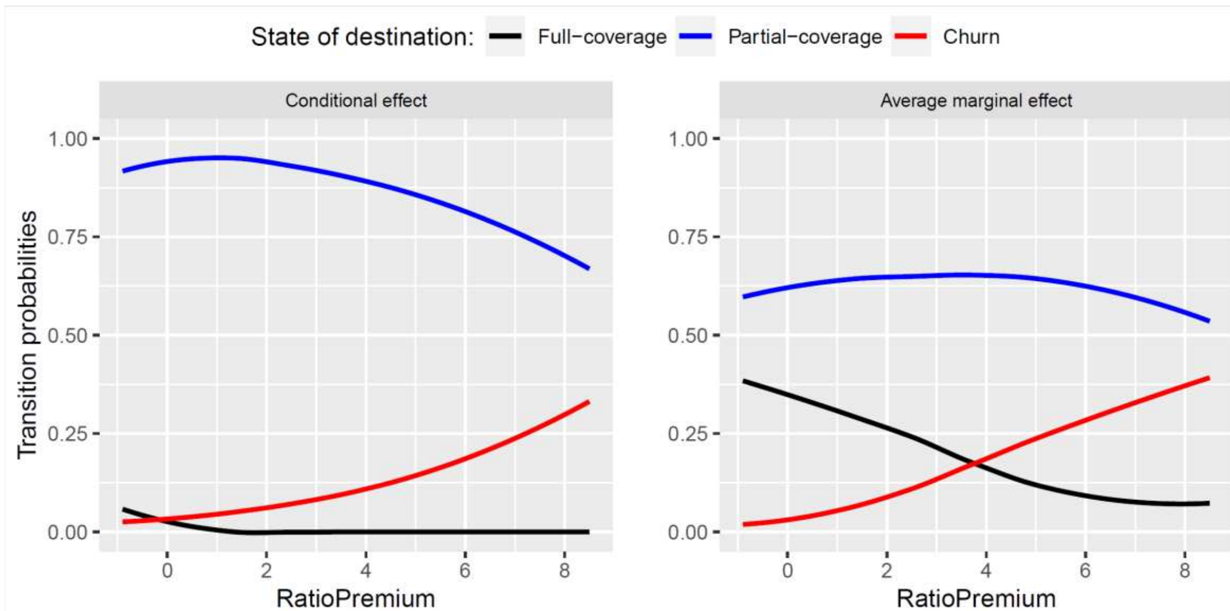
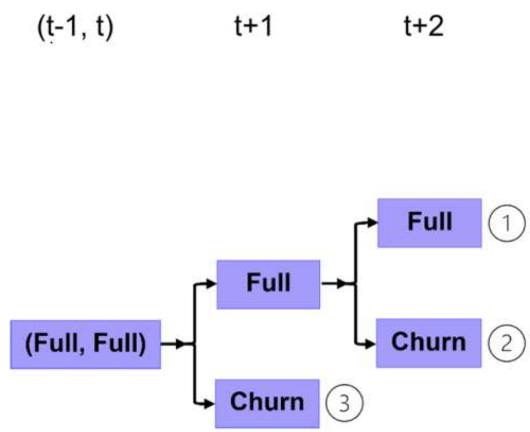
Managerial Implication 1: Visualising the Effects of Explanatory Variables



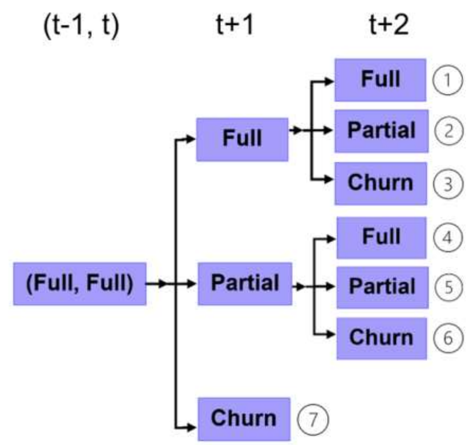
Conditional effect: varies a single variable while fixing all the other variables at some values for a policyholder.

Average marginal effect: varies a single variable for all policyholders and then averages effects among all policyholders.

Managerial Implication 2: Calculating Customer Lifetime Value



Traditional Customer Churn Analysis



Multi-State Customer Churn Analysis

Traditional customer churn analysis (second-order BLR)

Scenario	*Probability (per cent)*	*Expected present value*
(full, full)	92.60%	$2835.7
(full, churn)	3.63%	$81.8
(churn)	3.77%	$0.0
Sum	**100%**	**$2917.4**

Multi-state customer churn analysis (second-order MLR)

Scenario	*Probability (per cent)*	*Expected present value*
(full, full)	89.15%	$2730.3
(full, partial)	1.68%	$36.5
(full, churn)	3.58%	$80.7
(partial, full)	0.27%	$1.5
(partial, partial)	1.32%	$-4.1
(partial, churn)	0.20%	$-0.5
(churn)	3.80%	$0.0
Sum	**100%**	**$2844.5**

The difference of CLV is $72.9.

Out-of-Sample Predictive Performance

- Evaluation metrics: AUCs and Top-decile lift.
- The second-order MLR model has consistently strong out-of-sample predictive performance relative to several parametric models of different orders, and also compared to more non-parametric techniques such as support vector machines (SVMs) and gradient boosting machines (GBMs).

Thank You!