A Churn Model for Swiss Health Insurance from a Pricing Perspective

Lena Schuette *[1,2]

[1]Azenes AG and ETH Zurich

Abstract

The aim of the research was to investigate the use of churn models to predict the portfolio of insured in an actuarial pricing context. Usually these models are applied in a customer management setting to identify customers that are likely to leave and to prevent that. Applications in an actuarial pricing setting seem rare (see some references below).
We fit logistic regression, classification tree and gradient boosting machine models (BGM) to a large data set of a major swiss health insurer. Here, the actuarial premiums are implicitly based on an assumed portfolio structure, which is predicted by the churn model. We therefore develop a pricing loss function which measures the impact of the churn prediction error on the predicted profits and can be seen as a proxy for the error of the actuarial premium resulting from the error in the churn model. Each model?s performance is then compared with respect to the pricing loss function, the binomial deviance and the AUC. In addition, we introduced weights to a loss function of one of the models in order to incorporate the impact on the pricing loss.
As pricing is linked to setting a market premium, we aim to incorporate the impact of the insurer?s premium in a competitive market in the churn model. To do this, we include the insurer?s premium, premium changes and the premiums of the main competitors as explanatory variables. For logistic regression and gradient boosting machine, we then deduce an approximation of the premium sensitivity of the insured.
The main findings were the following:
All models and analyses made clear that premium differences to the competitor were the most important variables. So, no matter what churn model used, if it will be applied in a managed competition context similar to Swiss mandatory health insurance, this key information must be contained in the explanatory variables.
Theoretically, after integrating this information, the premium sensitivity can be derived, which can be used as a rule of thumb to understand premium change effects. In practice, the results seem sensible, however, they are easier obtained and understood in the logistic regression model than in the gradient boosting machine model.
When comparing different models, we found that the GBM achieved the highest AUC. It was the only model that was able to incorporate the non-linear relation of the premium differences and the churn probability. However, its pricing (net) loss was at best average.

*E-mail address: Lena.schuette@azenes.ch

The results for the classification trees were disappointing and showed that unbalanced data sets pose a severe problem for classification trees, if they are not adequately incorporated in the model.The logistic regression models yielded interesting results: The Naive Logit Regression model, which included all variables, was the most accurate in terms of AUC, and the Lasso Logit Regression model, which had a loss function modified by a penalty term, yielded a similar result with much less parameters.
In terms of net pricing loss, allowing the compensation of positive and negative technical results seem to make this measure more tolerant towards differences in the churn rate. In fact, the best result is achieved by the Logistic Regression where the loss function was modified by weights. Since the other two Logistic Regressions show particularly high losses, we conclude that: a) The right definition of the weights can indeed improve the pricing loss result, but b) one should be cautious when defining these weights as the "wrong" definition can lead to the opposite effect.Having said this, all other regression models do achieve better pricing net losses than the GBM.

Bringing together all these findings, we can conclude that application in a pricing context can lead to favor other churn models than in a customer management context:

- GBM is the most accurate one, but logistic regression models generally lead to smaller pricing losses
- GBM reflects the churn probability with respect to premium changes more accurately, but this makes it a priori more difficult to quantify and understand premium sensitivity in practice.

Keywords: Health Insurance, Actuarial Pricing, Machine Learning, Switching Behaviour, Churn Model, Premium Sensitivity, Loss Function, Pricing Loss

References

Daily-Amir, D., Albrecher, H., Bladt, M., Wagner, J. (2019): *On Market Share Drivers in the Swiss Mandatory Health Insurance Sector.* Risks, 7(4)

Huigevoort, C. (2015): *Customer churn prediction for an insurance company.* Master Thesis, Eindhoven University of Technology

Krikler, S., Dolberger, D., Eckel, J., (2004): *Method and tools for insurance price and revenue optimisation* Journal of Financial Services Marketing, 9(1), p. 68-79

Yeo, A.C., Smith, K.A., Willis, R.J., Brooks, M. (2002): *A mathematical programming approach to optimise insurance premium pricing within a data mining framework.* Journal of the Operational Research Society, 53(11), p. 1197-1203