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Executive Summary

Objective

Insurance raters can follow two known rating algorithms, or raters, based on averaging a plan for a group of drivers or summing an individualized plan for each driver. There are several factors that go into determining which rating algorithm is appropriate to a company. This summary will explore the main components that will help the company decide a rating algorithm and whether it can be implemented globally or locally across their market jurisdiction.

Furthermore, in order to determine the credibility of such an algorithm, this summary will also aid in determining which the statistical significance of each component variable of the rater. Suggestions will be made addressing whether changes may be made to the variable groups in order to maintain a sound rater that also appeals to the younger aged market.

Driver Assignment vs Driver Averaging

We provide the data outputs for the rater based on driver assignment and the rater based on driver averaging. There are three polar profiles that are to be considered in this scenario.

		Assignment				Averaging			
		BI	PD	COMP	COLL	BI	PD	COMP	COLL
Profile 1	Vehicle 1	$168.12	$174.99	$324.56	$427.39	$207.57	$216.28	$396.79	$545.42
	Vehicle 2	$242.34	$250.44	$310.84	$359.65	$200.36	$206.93	$260.77	$291.32
	Vehicle 3	$177.00	$182.74	$306.35	$507.15	$218.82	$226.09	$374.27	$648.28
	Total	$3,431.57				$3,792.90			
Profile 2	Vehicle 1	$275.04	$272.39	$529.60	$1,016.69	$374.01	$370.28	$682.82	$1,514.63
	Vehicle 2	$420.20	$428.82	$337.20	$546.33	$319.73	$326.13	$277.48	$388.13
	Total	$3,826.27				$4,253.21			
Profile 3	Vehicle 1	$183.10	$207.30	$364.35	$435.07	$183.10	$207.30	$364.35	$435.07
	Total	$1,189.82				$1,189.82			

The following conclusions can be drawn about the two rating systems:

		Assignment		
	Vehicle Rate	Primary Driver	Class Factor	Avg Class Factor
Vehicle 1	$ 110.00	Driver 1	1.011	1.280
Vehicle 2	$ 100.00	Driver 2	1.578	1.280
Vehicle 3	$ 140.00	Driver 1	1.011	1.280
			$ 410.58	$ 448.11

Using a driver averaging rating system helps expedite the policy buying process. We believe this is great advantage over the driver assignment model but it is still important to consider some of the difficulties faced using an averaging system. Assuming the company was currently using a driver assignment model, transitioning to an driver averaging model will result in increased premiums for some policy holders while also resulting in some decreased premiums for others. In the first chart we see a case where the driver averaging model results in higher premiums for that household.

However, if that same household had Driver 2 assigned to a vehicle with a higher rate then the driver averaging model would result in lower premiums for that household. Despite, a driver average rating system requires less complicated rating algorithms. This means that a driver averaging rating system will streamline both the buying process for new policyholders and the rating system used. As a result, in order to provide the best step forward for the company, the actuarial analyst team at Bruins Mutual have determined that driver averaging is the optimal choice for rating insurance premiums.

		Assignment		
	Vehicle Rate	Primary Driver	Class Factor	Avg Class Factor
Vehicle 1	$ 110.00	Driver 1	1.011	1.280
Vehicle 2	$ 250.00	Driver 2	1.578	1.280
Vehicle 3	$ 140.00	Driver 1	1.011	1.280
			$ 647.33	$ 640.15

Adjustments to Factor Groups

A Generalized Linear Model (GLM) is a mathematical model that takes for input a set of variables in order to predict the outcome of another variable. The fact that premium raters include a set of variables makes it difficult to derive predictions using standard statistical methods; in this case, the generalized linear model is useful in determining the overall effect of each variable in the rater. When testing the variables through the GLM and significance test, it became evident that a couple variables' effects were not statistically significant; most notably the effect of a driver having zero years of prior driving experience. It is suggested more data be collected regarding the effect of driving experience in an attempt to create a more accurate rater. Also, it would be more beneficial to group having no years of driving experience with having 1 year of driving experience so as to have in place the factor: 0-1 years of driving experience. In addition it was also found that the 'Good Student' factor was insignificant. However, this has a miniscule effect on the rating process and could lead to customer dissatisfaction if removed. We suggest leaving this portion of the rater as is.

We consider it to be overall beneficial to keep all the current variable used by the rater. All current inputs appear to not only be relevant but imperative to having an accurate rater. However, We believe additional variable should be considered in the rating process. The main factor we would like to consider is a Mileage to Points Ratio. This would be a ratio of average mileage driven a month to the number of points a driver has accumulated over there driving history. This will provide deeper insight into the habits and driving style of our clients and allow us to adjust our premiums accordingly.
Since the company reported a dropping retention rate and an interest of expanding the market to younger drivers. The actuarial analysts at Bruins Mutual have determined that the following strategy should be taken to attract younger drivers the company could offer driving lessons to young drivers, and once they pass their exam we can offer a discounted policy. In addition to this a multi-car discount could ease parents into being more likely to buying their child a vehicle.

Conclusions

Premium raters may follow algorithms based on driver assignment and driver averaging. Due to the sensitivity of each factor, it was necessary to compare the data outputs of both raters on three different profiles. After considering the data, the optimal choice of rater is driver averaging, which should ideally be applied for each state individually. In order to maintain the effectiveness and be certain of the rater's credibility, a Generalized Linear Model was used to analyze the data of each variable. We suggest further investigating the statistical significance of the driving experience variable. In order to respond to dropping retention rate and market to younger drivers, we can attempt to draw in young driver from families already holding a policy with us as well as new drivers through a lesson program.