Blue and Gold Health Executive Summary

Team 13

Phoebe Carrathers, Nathan Lou, Jenna Nguyen, Seita Yoshifusa

Manual Trend

We used the historical trends data to develop the manual trends. In order to construct the manual trends, we first reorganized the raw data using PivotTables into a form that displayed the yearly trends for different market types filtered by different service types. We then created line graphs depicting the movement of trends from 2014 to 2020 to identify the event trends. Upon identifying the event trends, we adjusted those values to compute the underlying trend. Ultimately, we employed the core trend unit tables to by inputting our resulting underlying trend and event trends to compute the respective manual trends for 2022.

Experience Trend

We used the 2021-2022 Claims Data to construct the experience trend. To find the event trend, we performed linear regression on the raw data to find predicted values for the second half of 2022. We regressed member months using the month and year as the independent variable. Utilization was regressed using member months as the independent variable because the number of claims is related to the number of people who are insured. Allowed dollars were regressed using utilization as the independent variable because the total cost of health services depends on the number of times that service was used.

Finding the underlying trend required accounting for certain irregularities during 2021 and 2022 and accounting for seasonality. For the experience trend, we divided January and February 2022 brand drug utilization by 1.05 to account for the 5% increase in flu vaccine rates compared to historical years. We multiplied the projected allowed dollars in the second half of 2022 for generic drugs and brand drugs by 0.93 and 0.98 respectively because of the expected 7% and 2% savings resulting from the Pharmacy Benefits Manager's renewed contract. To adjust for the deferred services due to fears seeking non-emergency medical care during the COVID pandemic, we divided utilization by one minus the estimated percent deferred for each service type that was affected. Finally, we divided all given values by their monthly seasonal factor, smoothing fluctuations and making linear regression more accurate.

Blending

We used the Limited Fluctuation Method, calculating the credibility factor, z, using the square root method, to blend the manual and experience trends together. We used 1,082 as the number of observations required to get full credibility since it is the most commonly used[1], producing a value of z equaling 0.9478 and giving about 95% weight to the experience trend over the manual trend. The results can be seen in Figure 1.

XGBoost Analysis and Recommendation

XGBoost, or Extreme Gradient Boosting, is an algorithm capable of predicting a target variable by bootstrapping, aggregating, and bagging a given dataset. Like any supervised machine learning model, we have to define the objective function and optimize it. The best optimization function is shown below.[2]

$$obj^* = -\frac{1}{2}\sum_{j=1}^{T}\frac{G_j^2}{H_j+\lambda} + \gamma T$$

XGBoost is highly efficient and fast to use, especially on large data like what we are given. Some of its strongest points include its high flexibility, ability to execute parallel processing and regularization. Nevertheless, the algorithm cannot perform well on sparse and unstructured data, as it is sensitive to outliers and often causes overfitting as a result. It also has trouble working with lots of noise, and so Random Forest is the best choice in terms of tuning and handling it. XGBoost is popular for its high accuracy, and there are criteria to best utilize this algorithm over the rest:

1. When one has a large number of observations in training data
2. When the number features are more than the number of observations in training data
3. When data has mixture numerical and categorical features, or purely numeric features
4. When the model performance metrics are to be considered

2022 ML Trends the 6 month pred_trend_all is greatly different from 3 months to 6 months (Figure 2). Although there are anticipated anomalies in the study, none would affect LG-2 and not LG-1. As a result, we cannot recommend using XGBoost. Instead, we recommend using Random Forest machine learning instead since it works much better than XGBoost when there is a lot of noise in the data.

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1 https://www.soa.org/492f2a/globalassets/assets/files/resources/tables-calcs-tools/credibility-methods-life-health-pensions.pdf

2 https://xgboost.readthedocs.io/en/stable/tutorials/model.html

Figures

Benefit Type	Market	Util/K	Unit Cost	PMPM
Ancillary	Individual	6.89%	14.50%	22.15%
	LG-1	4.30%	13.55%	18.76%
	LG-2	6.70%	15.25%	23.43%
	SG	4.02%	14.22%	18.92%
Brand	Individual	1.28%	16.41%	17.90%
	LG-1	-5.60%	11.95%	5.67%
	LG-2	-2.15%	8.80%	6.46%
	SG	-3.72%	12.68%	8.48%
Generic	Individual	5.20%	5.11%	10.58%
	LG-1	2.27%	4.09%	6.45%
	LG-2	4.03%	4.55%	8.78%
	SG	1.92%	4.04%	6.04%
IP	Individual	13.96%	-1.81%	11.88%
	LG-1	4.61%	2.61%	7.30%
	LG-2	5.40%	10.22%	16.19%
	SG	5.41%	-1.12%	4.23%
OP	Individual	15.51%	-2.79%	12.25%
	LG-1	10.55%	-2.36%	7.94%
	LG-2	10.55%	-1.19%	9.22%
	SG	7.31%	-2.97%	4.11%
Prof	Individual	8.82%	1.42%	9.99%
	LG-1	6.67%	1.11%	9.37%
	LG-2	8.48%	6.28%	34.35%
	SG	6.41%	0.39%	9.48%

Figure 1: Blended Manual Trend and Experience Trend

market	month	batch_size	learning rate	n_estimators	max_depth	min_samples_leaf	pred_trend_all
LG-1	3	100000	0.1	100	5	30	4.3%
SG	3	100000	0.1	100	5	30	6.4%
LG-2	3	100000	0.1	100	5	30	5.9%
Individual	3	100000	0.1	100	5	30	12.1%
LG-1	6	100000	0.1	100	5	30	4.0%
SG	6	100000	0.1	100	5	30	7.0%
LG-2	6	100000	0.1	100	5	30	9.4%
Individual	6	100000	0.1	100	5	30	11.0%

Figure 2: XGBoost Machine Learning Results