Analysis in Medicare Provider Utilization and Payment Data

From the Prospectives of Average Difference between Submitted and Charged Medicare Amount from Physician in California

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[1] Picture reference: https://seniortubs.com/cost/medicare-and-medicaid-coverage

Introduction

With the growth of older population, the need for Medicare is increasing. It is important to understand how Medicare works and what factors would contribute to the difference in Medicare. Medicare is the federal health insurance program for people who are 65 or older, specific younger people with disabilities, and people with End-Stage Renal Disease (permanent kidney failure requiring dialysis or a transplantIn this analysis [1]. For Medicare beneficiaries, Medicare has different types of plans, beneficiaries would choose the plan based on their need. For providers, there are several options provided for charging medicare patients [2]. Generally, Medicare has established a standard allowed payment for each procedure, if the amount of payment physicians submitted to the Medicare exceed the allowed amount, most of the time, physicians/ providers need to cover these extra expense (sometimes beneficiaries are required to pay the extra expense if they are out-of-network or if they opt to certain private plan). Therefore, in this analysis, I would like to focus on Average Medicare Difference (AMD), which is the difference that providers, private insurance, or beneficiaries possibly need to afford. AMD is difference between Average Medicare Allowed Amount established by Medicare and Average Submitted Charged Amount filed by providers.

To encourage providers to accept assignment with Medicare for all their patients and become participating providers, there are several incentives providing to participating providers. For example, Medicare payment rates for participating providers are approximately 5% or higher than the rates paid to non-participating providers. In addition, participating providers may receive Medicare's reimbursement amount directly from Medicare compared to non-participating providers, who generally bill their Medicare patients according to their charges and may not receive payment from Medicare. Also, participating providers will have electronic access to Medicare beneficiaries insurance status and make them easy to file claims to get beneficiaries coinsurance [2].

Formula for medicare is complicated and may depend on case by case. From the prospective of providers, it requires planning and strategies to choose optimal options to reduce the cost and maximize profit based on their entities, service, and pursuit. I would use statistical method and machine learning to investigate what factors would influence the difference between average Medicare submitted amount and average amount physicians charged in the provider type of Neurosurgery, Cardiac surgery, Vascular surgery, Nurse Anesthetist (CRNA), and Thoracic Surgery, in the state of California.

Data Preprocessing

Data Set Information and Subset

The data set contains roughly 10 million samples and 26 features. After dissecting the data set into the State of California, The dataset became 700 thousands samples. Several features have been removed before preprocessing because they are not factors that I am interested in looking into based on domain knowledge and I would like to reduce potential noises from the data.

Missing Value Imputation

Missing value would be one of the important issue to be dealt during data preprocessing steps. Generally, there will be multiple strategy to deal with missing value, including imputation by mean, median, mode, and probability distribution of the data. Here, after removing unimportant features, only feature of Gender of the Provider has missing value. The result showed that gender in male accounts for almost 74% of the data, it is unlikely that missing value missed at random. Generally, more information should be looked into to before removing missing value, yet missing values account less 20% of the feature (missing at 6%), therefore these missing values were just removed without further imputation.

Correlations Among Features

To determine the degree of relationships exist between two variables, correlation matrix was performed. the matrix showed that Average Submitted Charged Amount, Average Medicare Allowed Amount, Average Medicare Payment Amount, and Average Medicare Standardized Amount have relatively higher positive correlation to Average Medicare Difference, with correlation coefficient of 0.98, 0.71, 0.7, and 0.7 respectively [Figure 1].

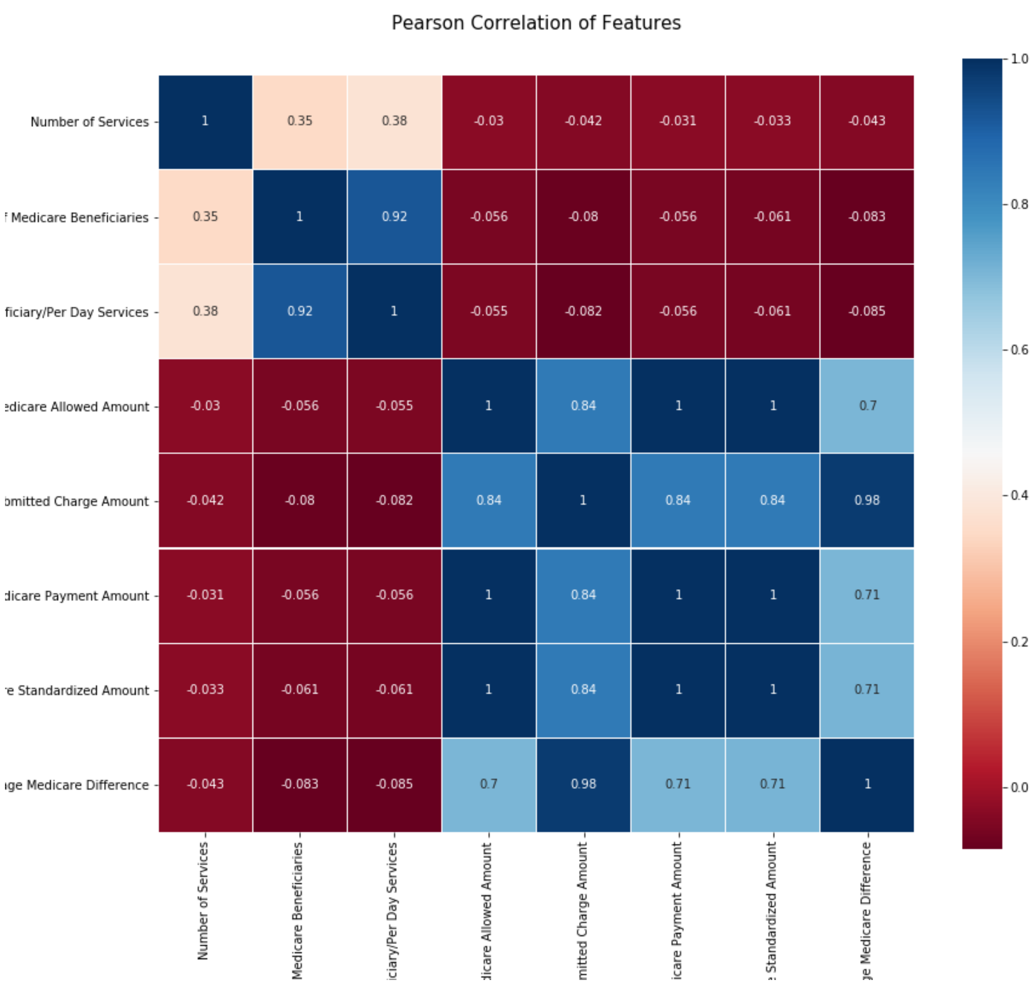

Figure 1. Correlation Matrix

Converting Categorical Variables into Dummy Variables

All the categorial variables in the dataset have been converted dummy variables because I am going to apply the dataset to regression models. Keep noted that our question is " predicting Average Medicare difference", which our target variable is numerical and a regression model should be built. Converting categorical variables into dummies would allow us to build a regression model without too much hurdles. In addition, dummies improves efficiency by saving space and computational complexity.

Top 5 Highest Average Medicare Difference in Providers

Average Medicare Difference (AMD) is referred to the difference between Average Medicare Allowed Amount (AMAA) and Average Submitted Charge Amount (ASCA). The top 5 providers that have highest AMD are: Thoracic Surgery, Neurosurgery, Cardiac Surgery, Vascular Surgery, and CRNA. Among all, Thoracic Surgery has the highest AMD, with $1192 USD per beneficiary [Table 1].

Table 1. Top 5 Highest Average Medicare Difference in Providers

Provider Type	Average Medicare Difference
Thoracic Surgery	$1193
Neurosurgery	$1149
Cardiac Surgery	$1146
Vascular Surgery	$1042
CRNA	$883

Average Medicare Difference by City and Zip Code

It is also interesting to see if AMD differs among cities or zip code. The result showed that City of San Diego (zip code 92093) has the highest AMD, with roughly $17248 USD per beneficiary [Table 2].

Table 2. Average Medicare Difference by City and Zip Code

City of the Provider	Zip Code of the Provider	Average Medicare Difference
San Diego	92093	$17248
Long Beach	90803	$6280
West Hills	91307	$4544
Willits	95490	$4190
Marina Del Rey	90292	$3934

Top Procedures in Provider Type

In Thoracic Surgery, heart surgery has the highest AMD, with $17248 USD per beneficiary. In Neurosurgery, the procedure of repair of bulging of blood vessel (aneurysm) in brain has the highest AMD, with $11521 USD per beneficiary. In Cardiac Surgery, the procedure of insertion of vena cava filter by endovascular approach (including radiological supervision and interpretation) has the highest AMD, with $30758 USD per beneficiary. In Vascular Surgery, the procedure of removal of plaque and insertion of stents into artery in one leg, endovascular, accessed through the skin or open procedure, has the highest AMD, with $23740 USD. Lastly, in CRNA, the procedure of anesthesia for procedure on heart and great blood vessels on heart-lung machine, age 1 year or older, or re-operation more than 1 month after original procedure, has the highest AMD, with $5002 per beneficiary [Table 3].

The information behind these numbers indicate that any of these procedures involved would be expected to have larger difference between the amount that physician actually charged and submitted and the amount that Medicare generally allows. The difference would be expected to be paid by either the provider or beneficiary according to In-Network or Out-of-Network. More information should be provided to land a conclusion.

Table 3. Top Procedures in Provider Type

Provider Type	Procedure	Average Medicare Difference
Thoracic Surgery	Heart Surgery	$17248
Neurosurgery	Repair of Bulging of Blood Vessel in Brain	$11521
Cardiac Surgery	Insertion of Vena Cava Filter by Endovascular Approach	$30758
Vascular Surgery	Removal of Plaque and Insertion of Stent into Artery	$23740
CRNA	Anesthesia for Procedure on Heart and Great Blood Vessels	$5002

Training Dataset and Testing Dataset

The dataset was split into training dataset and testing dataset at ratio of 4:1.

Regression Models

Baseline Model: Linear Regression

A linear regression model was built as a baseline model. The result of the model showed a R-squared, an indicator of how good the model fit to the data, is -2.56. Here, the coefficient R-squared is defined as (1 - u/v), where u is the residual sum of squares ((y_true - y_pred) ** 2).sum() and v is the total sum of squares ((y_true - y_true.mean()) ** 2).sum(). The number was negative because the model is arbitrarily worse, and the Mean Squared Error is unreasonably high (1.0xE19). The model performs awful and linear model may not be a good tool to predict the data because the data might not be linear separable. Thus, other models are built to improve the performance

Elastic Net Regressor

Elastic Net is a combination of Lasso Regression(l1) and Ridge Regression (l2). To prevent overfitting of the model, l1 and l2 norms are penalized based on parameter λ. Some of coefficients of unimportant variables would shrink to zero by shrinking the beta coefficient. Alpha mediates the amount of penalty applied to the data, if alpha equals to zero, then we have a ridge regression, if alpha equals to one, then we have a lasso regression.

After 10-fold cross validation, the optimal parameters for l1_ratio and alpha is 0.1 and 0.000012 respectively. The parameters were used to build a Elastic Net Regressor. After penalizing unimportant variables, the model reduced MSE to 0.001, with R-Squared of 0.59.

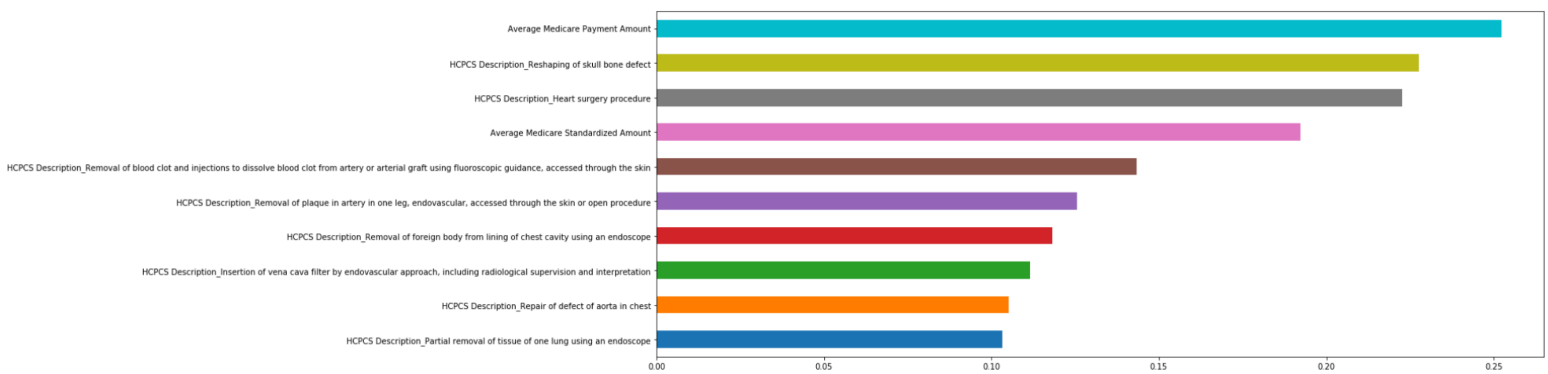

Figure 2. Feature Importance of Elastic Net Regressor

The Elastic Net far better fit to the data compared to linear regression model.

The Elastic Net showed that Average Medicare Payment Amount is the most important feature, followed by Average Medicare Standardized Amount and Heart Surgery in providers of Thoracic Surgery [Figure 2].

Random Forest Regressor

Random Forest is a collection of decision trees on different random sub-datasets to prevent overfitting and averages out the performance from every tree to improve the predictive accuracy overall. Here, there are 200 trees in this collection, with minimum samples of 2 per leaf, and The minimum number of samples required to split per internal node of 15. The result showed that MSE was reduced to 0.0009, and R-Squared was increased to 0.64.

The Random Forest Regressor showed that Average Medicare Payment Amount and Average Medicare Standardized Amount are the most two important features [Figure 3].

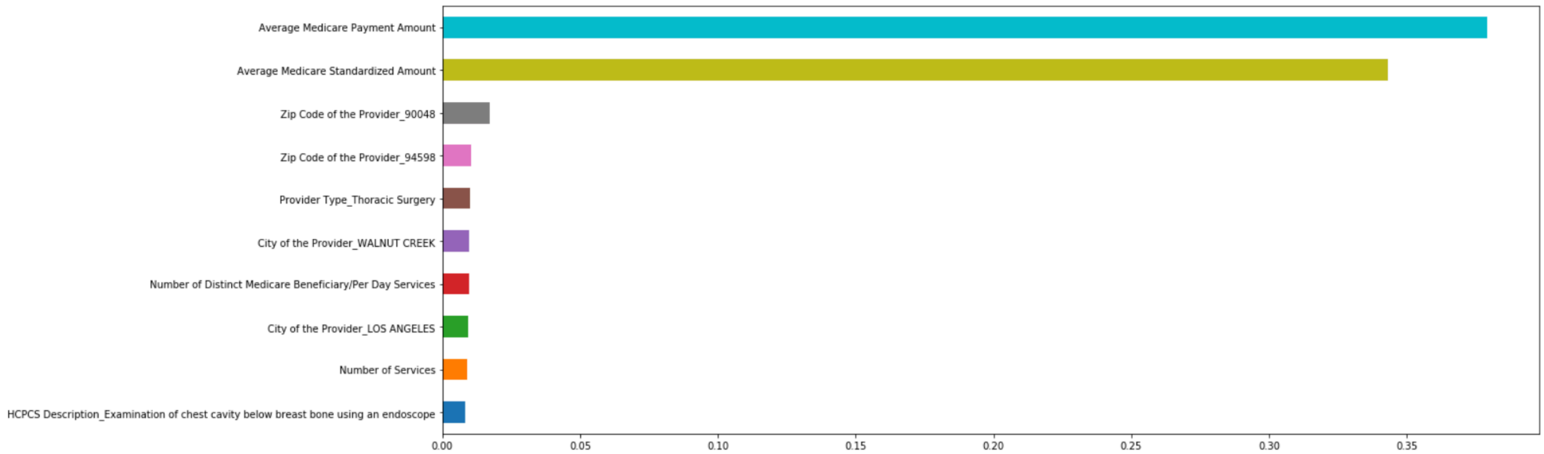

Figure 3. Feature Importance of Random Forest Regressor

eXtreme Gradient Boosting

A eXtreme Gradient Boosting (xgboosting) regressor was built with 200 estimators. The result showed that MSE was 0.00086, and R-Squared was 0.62 [Figure 4].

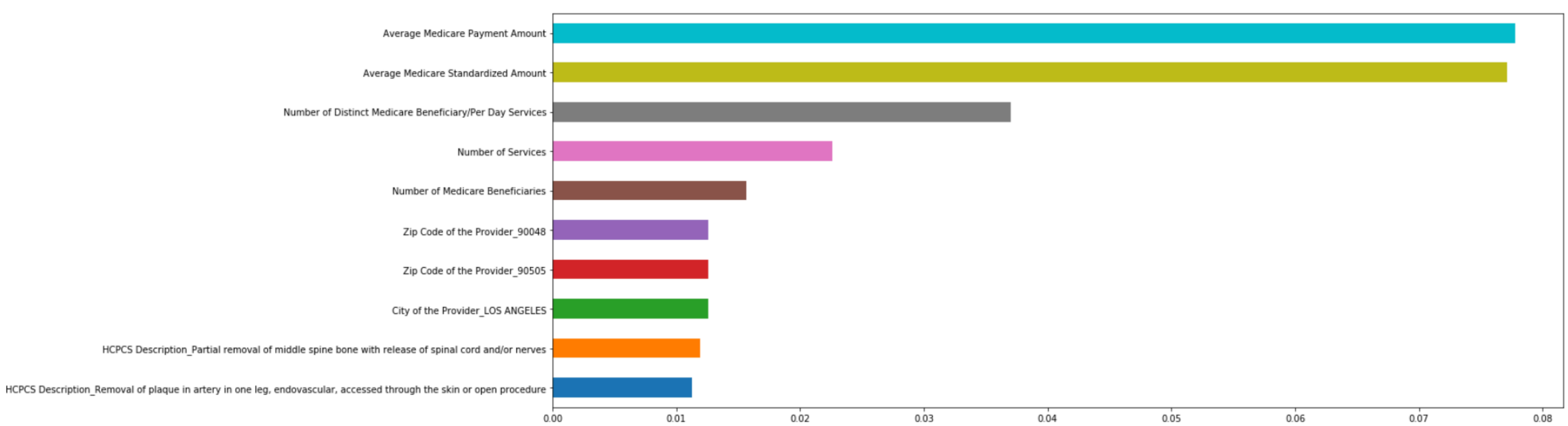

Figure 4. Feature Importance of eXtreme Gradient Boosting

Neural Network

A MLP regressor was built with 3 hidden layers, each layer consists of 30 nodes. The result showed that with implementing neural network, MSE was 0.00068, and R-Squared was 0.70.

Stacking

A stacking model was combined by Random Forest Regressor, eXtreme Gradient Boosting Regressor, and MLP regressor. The optimal ratio of each type of regressor is determined by linear optimization, which is 1:1:1. the result showed that with implementing Stacking, MSE was 0.00073, and R-Squared was 0.68.

Comparison between Models

The result showed that xgboosting regressor has the highest MSE, while the MLP regressor has the lowest MSE. As the R-Squared value, xgboosting has the lowest R-Squared, while MLP regressor has the highest R-Squared value, indicating its accuracy in AMD prediction.

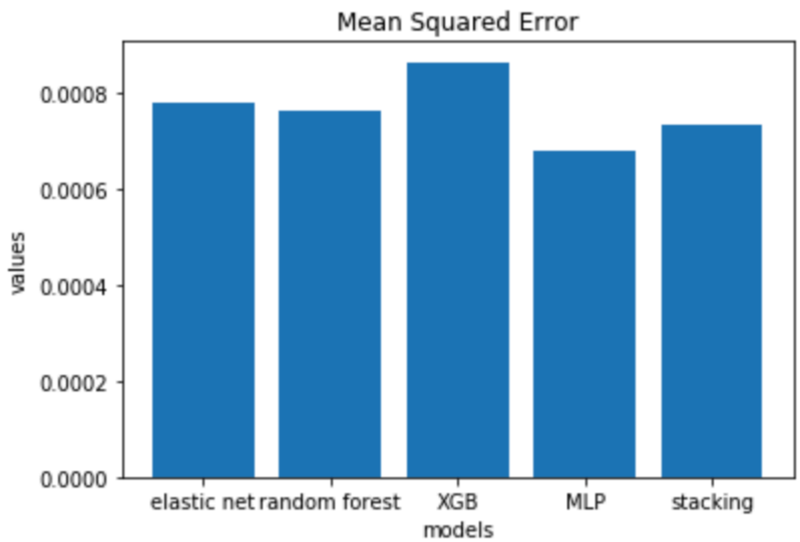

Figure 5. Mean Squared Error for Models

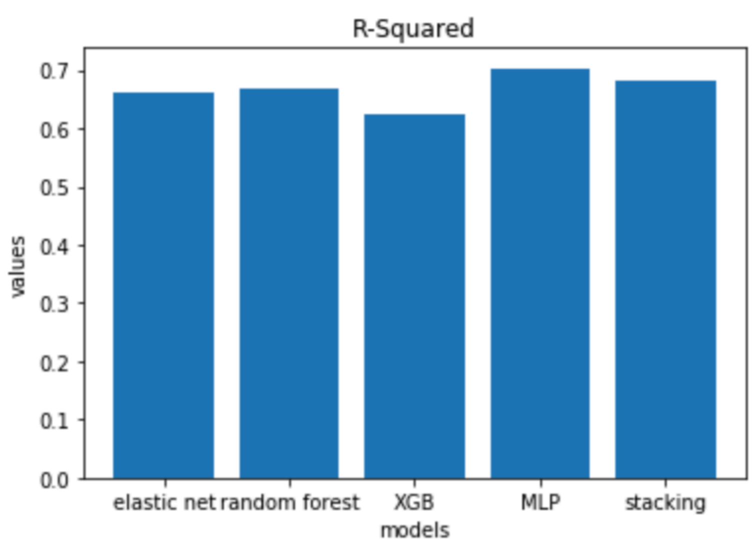

Figure 5. R-Squared for Models

Linear Regression on Most Important Features

Another linear regression model was built based on the selected features from previous models: Average Medicare Payment Amount, Average Medicare Standardized Amount, heart surgery procedure, and reshaping of skull bone defect. The result showed that R-Squared was 0.57, which has been significantly improved compared to baseline linear regression model in prediction [Table 4].

Table 4. OLS Regression Result

Dep. Variable:	Average Medicare Difference	**R-squared:**	0.568
Model:	OLS	**Adj. R-squared:**	0.568
Method:	Least Squares	**F-statistic:**	3767.
Date:	Wed, 22 Aug 2018	**Prob (F-statistic):**	0.00
Time:	12:50:35	**Log-Likelihood:**	22796.
No. Observations:	11475	**AIC:**	-4.558e+04
Df Residuals:	11471	**BIC:**	-4.556e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Average Medicare Payment Amount	-0.4151	0.067	-6.225	0.000	-0.546	-0.284
Average Medicare Standardized Amount	0.9695	0.058	16.750	0.000	0.856	1.083
HCPCS Description_Heart surgery procedure	0.2653	0.023	11.301	0.000	0.219	0.311
HCPCS Description_Reshaping of skull bone defect	0.1095	0.019	5.711	0.000	0.072	0.147

Omnibus:	11496.400	**Durbin-Watson:**	1.931
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3173593.505
Skew:	4.343	**Prob(JB):**	0.00
Kurtosis:	84.007	**Cond. No.**	23.3

Discussions and Conclusions

Procedures v.s. AMD
Based on the analysis on top procedures in each provider type, it can be inferred procedures that with cardiac- and vessel- related surgery are prone to have higher AMD. Providers with such type may required to derive strategies that maximize profit from private insurance companies and cost from medicare. Therefore coming up a proper negotiation and contract between private insurance companies and these providers becomes crucial to avoid unnecessary cost.

Models
The result showed that in addition to baseline model linear regression, the rest five models significantly reduced mean squared error, at the same time, R-Squared significantly were increased among the rest five models. Among the five models, MLP model showed the lowest mean squared error and highest R-Squared. It is interested to note that MLP perform the same or even slightly better than the stacking model.

Noted that stacking model was built based on the mean value from cross validation and the training set and testing set were resampled, it is unlikely that stacking model did not perform the best because of overfitting issue. Instead, it may be explained by the fact that the model may be suboptimal. It can be inferred that neural network performed the best because random forest regressor and xgboosting regressor did not fit to the optimal parameters [3], grid search can be implemented to get the optimal value and increase performance in stacking model.

Also, noted that random forest regressor also outperformed xgboosting regressor, it is very likely that xgboosting regressor did not for to the optimal values. It is also possible that neural network may better predict numerical value compared to xgboosting and random forest in this case [4]. For the future work, optimal parameters should be achieved. In addition to MSE and R-Squared, other analysis can be also conducted to accurately define what is the "best model”.

Average Medicare Payment Amount and Average Medicare Standardized Amount
Based on the result from the models, average Medicare payment amount and average Medicare standardized amount are two significant features that influence AMD.

Statistical Interpretation
From the linear regression statistics, it showed that with 0.42 unit decrease in Average Medicare Payment Amount, 0.97 unit increase in Average Medicare Standardized Amount, 0.27 increase in HCPCS Description_Heart surgery procedure, and 0.11 increase in HCPCS Description_Reshaping of skull bone defect would result in 1 unit increase in AMD. Noted that reamining other factors the same, one unit increase in procedure of heart surgery procedure

would result in more than three unit increase in AMD. Similarly, one unit increase in procedure of Reshaping of skull bone defect would result in approximately 10 unit increase in AMD. Therefore, participating providers that conduct large amount cases of these procedures should develop a strategy and make a proper contract with private insurance.

Other Factors to Derive a Optimal Model for Prediction

In addition to optimizing parameters for models, it is also important to collect more information that related to the dataset to have better insight to the data. Domain knowledge is crucial to understand the background of the study. Having background knowledge helps us to dissect the questions more accurately and thus we can better distinguish between noise and meaningful values and features. Such as datasets that include inpatient and outpatient information. Dataset containing information between providers and private insurance would be also helpful. Therefore, to improve the model, gaining more information from other datasets is suggested and it helps us to rule out unnecessary noise.

References

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