SMU

Data Science Machine Learning DS7331.402

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Data Preparation

Definition and Preparation of Class Variables

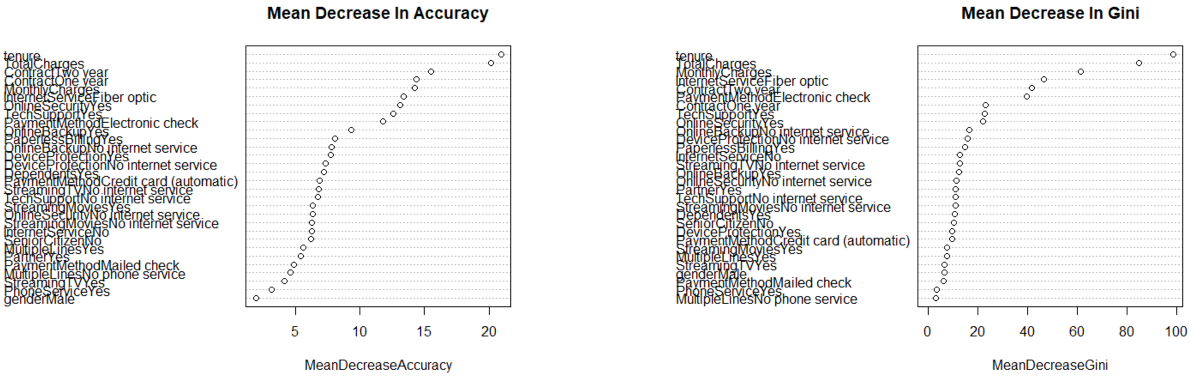
In the cell phone industry, the CRM tools used to describe customers track myriad data. One of the most significant parts of the process in interactively selecting an appropriate prediction model; is to validate the data points that most significantly impact the models ability to predict the outcome. Overt-fitting is always a concern; the goal is to get the smallest amount of data points with the largest impact on prediction.

Using a variable-importance plot can assist in determining how important a variable will be at classifying the data. Focusing on both the mean decrease in accuracy as well as node purity (Gini), tenure emerged as the most important variable to consider. In fact after TotalCharges and tenure, there is a sharp decline before the next group of predictors emerge.

The Gini coefficient measures the inequality among values of a frequency distribution. A Gini coefficient of zero expresses perfect equality, where all values are the same. Using these tools provides that the cost of service varied with the length of time with the current provider appear to contribute to the homogeneity of threnodies and branches of the resulting Random Forest model.

A deduction can be made that a customer's behavior with regard to churn is most similar based on the following attributes and their node purity (note that 2 of the top 5 parameters are moderately correlated: MonthyCharges and TotalCharges):

- tenure
- TotalCharges
- MonthlyCharges
- InternetService
- PaymentMethod
- Contract
- TechSupport



Description of the Final Dataset

In evaluating the data model, Contract emerged to be problematic in classification; therefore it was decided to separate the Contract variable into “bins”. ContractOneYear and ContractTwoYear. The various models supported that most of the churn happens to the clients in the ContractOneYear category. Pairing tenure along with the ContractOneYear was a powerful discovery in tuning the model.

The final dataset for the trees resulted in the following variables:

- tenure
- TotalCharges
- MonthlyCharges
- InternetService
- PaymentMethod
- Contract
- TechSupport

The Sub-vector Machine process had a slightly different take on the variables for prediction and will determine feature importance by coefficient weights. As a general rule, correlation is not causation. The model reflected that bundled services, security services, and data backup features showed positive weights in predicting customers who will remain with the provider more than 12 months and that automatic billing was correlated with longer-term usage.

While Churn is the prediction variable, tenure was added as a classifier to help predict if a customer will continue their tenure at least 12 months. In this context, a new response variable (OneYearYN) is based on the following condition:

- OneYearYN == 1 when the 'tenure' period is equal or larger than 12 regardless of 'Churn'
- OneYearYN == 0 when the 'tenure' period is less than 12 and 'Churn' is 'Yes'
- If the 'tenure' period is less than 12 and 'Churn' is 'No', observations will be removed from the fitting. Such records are not aligned with the business problem since a 12-month period of church cannot be determined.

Modeling and Evaluation

Selection and Evaluation of Performance Metrics

As the model continued to unfold, we were able to iterative and incrementally determine the best metrics to evaluate the success of the model. The 4 evaluation metrics chosen were accuracy, sensitivity, specificity, and area under the curve (AUC).

- **Accuracy** is the proportion of true results among the total number of cases examined. While this metric is chosen as a way to evaluate the model, it will likely be less valuable in our business case given that we could predict that a customer will not churn and likely be accurate.
- **Sensitivity** will measure the model's ability to measure the proportion of actual positivities that are correctly identified. This metric will likely be more valuable to the business case; it is more valuable to predict correctly when an asteroid will hit Earth or correctly predict that a patient will have cancer than to simply say a person has cancer and be wrong. The model success in this instance will be that it can predict when a customer will churn.
- **Specificity** will measure the proportion of actual negatives that are correctly identified which is a valuable metric to determine model performance, but not likely as valuable as Sensitivity for the business outcome of the model (which is to help the business know which customers will churn).
- **Area Under the Curve (AUC)** will measure the performance of the classification problem at various thresholds. This metric will also be significant as the model is tuned based on the business problem of classification and the way that the customers have been placed in bins depending on their length of contract. The closer the model can be tuned toward the number 1, the more likely it has a good measure of separability.

In order to prove which model performs better at prediction, the accuracy metric will take precedence. To determine which model is more accurate, the AUC metric and its corresponding ROC Curve will take precedence in the evaluation. Sensitivity and Specificity are important in determining which model is predicting the outcome variable (churn) more accurately within each category.

Method for Dividing Data (Training and Testing Splits)

Iterating through the options, the best method for predicting the business outcome was to use a combination of techniques as an ensemble to the performance of the model and then aggregate the results across the models. The use of decision trees were employed in combination with 10-fold cross-validation.

10-fold Cross-validation was used to evaluate the predictive qualities of the ensemble by partitioning the original data into a training and testing data set. The training data was split amongst 10 equal proportions. The Random Forest was trained on 9 of the 10 and then would validate the results against the remaining 1 of the 10.

The model would iterate through all 10 possible combinations where 1 of the 10 sections would be omitted in the training iteration. This method protected the model from over-fitting. The Random Forest allowed the use of multiple trees to be constructed (all being split in a variety of ways). The model would randomly include various predictors and based on the "majority rules", the best decision tree will be picked.

3 Different Classification / Regression Models

Naturally in all technology projects, time eventually runs out. Based on iterations through Lab 1 to Mini-Lab, the team has landed on the following Classification and Regression models:

- Logistic Regression
- Decision Tree
- Random Forest
- SVM with Linear Kernel

In addition to the 4 models mentioned above, there were 2 distinct classifiers that stood out for the data set and thus were employed for each of the models. Prediction was summarize using:

- Churn (did the client leave)
- Tenure (predicted length that the client will stay)

The code for all of these models can be found in the following links to each of the models mentioned above. Careful consideration has been taken to make notes and highlight lessons learned as the models were refined as well as the graphics supporting each of the tuning decisions.

R Models (Logistic Regression, Random Forest)

Churn
Tenure

SVM (Linear Kernel)

Churn
Tenure

Decision Tree

Churn
Tenure

Note: Each time the code is re-run, the samples will be randomized. This might result in AUC, Accuracy, RMSE, Sensitivity, etc… deviating from the formal write-up and description by a few %.

Analysis of the Models

Using an iterative process from Lab 1 and the Mini-Lab; the data science team explored tuning the existing models as well as providing additional models listed as "new". After many iterations, the following table outlines the final conclusion of the models that will be used.

Metric	Logistic Regression	Sub-vector-machine	Random Forest	Decision Tree
Accuracy	0.81	0.79	0.80	0.75
Sensitivity	0.56	0.45	0.47	0.75
Specificity	0.90	0.91	0.92	0.76
ROC-AUC	0.86	0.68	0.69	0.75

Advantages of Each Model

After analyzing the myriad results of each model and technique, deductions could be made based on the advantages to the business problem (or lack thereof).

- **Logistic Regression**: Using the split ratio of 80/20 in the testing and training data-sets, a few tests from Lab 1 and the Mini-Lab confirmed the need to perform a new split ratio of 50/50 and 70/30, etc…Thresholds were modified / iterated for the predictions as well as feature selection. The accuracy from these iterations did not improve compared to the original model sampling. Logistic Regression excels at its ability to modify variables and "tweak" the model nearly infinitely. The logistic model can compare the number of times the model predicts a "yes or no" comparison to the actual values, thus accuracy is estimated at 86%.
- **Sub-vector Machine**: Still is likely the more simple technology model in the group as it is drastically more automated. SVM is absent of probabilistic comparisons that allow for adjustment in a higher sensitive and specificity range.
- **Random Forest (new)**: This model performed with less accuracy (the comparison of how many churned clients were correct). However, it did perform with better sensitivity (how accurately did it predict a client would churn and they actually churned). Based on the business outcome at stake (predicting clients who will churn), sensitivity would be the advantage.
- **Decision Tree (new)**: This model has a better interpretability than the others in regards to business outcomes. It is typically much easier to explain classifiers to the layperson and help the marketing group understand the customer characteristics based on the classifiers selected. The feature importance of Decision Tree is similar to what is experienced in SVM or Logistic Regression. Having a month-to-month contract is indicative of classifying churn. This is a rational conclusion given that a client would not have a long-term contract if they decided to leave. The ability however to provide instant feature importance weights was highly valuable and easy to deduce.

In conclusion the Random Forest model (with down-sampling) would be selected since it is well balanced and less biased in regards to its confusion matrix. Naturally the other models might have performed slightly better in some of the metrics used for the decision, the Random Forest model is more balanced for the business outcome.

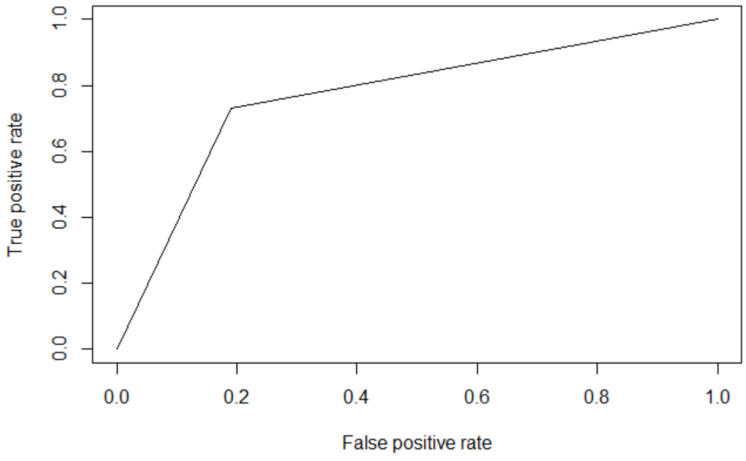
Importance of the Attributes

Many techniques can be employed along the way to fine-tune a models performance. After analyzing the 4 models compared, Random Forest would likely be the final model chosen. One of the challenges represented in this data-set is that it contains highly skewed samples with regard to the number of customers with “Long Term” vs. “Short Term” contract in the Churn model.

Using a technique called down-sampling, the training dataset can help correct the imbalance when selecting the folds for cross-validation. This essentially allows the mode to sample the majority class, making their frequencies closer to the rarest class.

The final Random Forest model provided the following to encourage the decision “for” this model:

RF Model	OOB Error	RMSE	AUC	Accuracy	Sensitivity	Specificity
Default	23.56	49.07	63.42%	75.92%	96.40%	30.43
Manual	22.63	47.30	72.89%	77.63%	85.38%	60.41
Loop-optimized	21.49	46.62	71.66%	78.27%	89.08%	54.53
Down-sampled	25.10	51.61	74.15%	73.37%	72.09%	76.20



Deployment

Measuring the Model's Value

The model selected is useful to the business by using data to predict which clients will churn so retention plans can be deployed to prevent the churn. Focusing the efforts on using Tenure to predict the churn is powerful at preventing the leakage of data.

Marketing research tells the story that it costs 5 times more for the business to onboard and prevision new clients than it does to retain the clients. If the model could accurately predict the clients who are poised to change providers, the business could save a percentage of the costs at risk if that client actually changed providers.

Given that only 1/3 of the clients leave the provider due to lower prices, the retention programs can be aimed at what clients truly desire from their providers:

- quality of service
- advancing technologies and media features
- better cell coverage
- better loyalty programs

Shifting some of the on-boarding expense could potentially raise profitability for the business by ensuring the "at-risk" clients did not change providers and better yet, they are happier customers based on the retention program and its elevation of services tuned to what clients truly desire from their providers.

The business outcome would suggest that if the marketing team could find a counter measure to short-term churn such as "first 3 months free", they could prioritize the lack of churn for those clients. While automatic billing is related to long-term use, marketing team could target these clients with a $10 off coupon when transitioning to auto-billing. Using this data and the model assist in narrowing down the target retention plans.

Instead of using broad-swathing programs, the marketing team could narrow their focus on the clients identified in this analysis to focus their efforts and impact the bottom line of the business earnings by saving costs of acquiring and onboarding new customers.