

REPLACE WITH COVER PAGE



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Data Preparation

Definition and Preparation of Class Variables

Use proper variable representations (int, float, one-hot, etc.). Use pre-processing methods (as needed) for dimensionality reduction, scaling, etc. Remove variables that are not needed/ useful for the analysis.

Description of the Final Dataset

Used for classification/regression (include a description of any newly formed variables you created).

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.

Metric	Logistic Regression	Sub-vector-machine	Random Forest
Accuracy	0.82	0.79	0.80
Sensitivity	0.56	0.45	0.47
Specificity	0.90	0.91	0.92
ROC-AUC	0.81	0.68	0.69

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

(e.g., random forest, KNN, and SVM). Two modeling techniques must be new (but the third could be SVM or logistic regression). Adjust parameters as appropriate to increase generalization performance using your chosen metric.

Analysis of the Models

Use visualizations of the results to bolster the analysis. Explain any visuals and analyze why they are interesting to someone that might use this model.

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).

- **Random Forest**: This model performed with less accuracy (the comparison of how many churned clients did we get 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 thus the Random Forest model would be selected.
- **Logistic Regression**: Lorum ipsum dolar
- **Sub-vector Machine**: Lorum ipsum dolar

Importance of the Attributes

Use proper methods discussed in class to evaluate the importance of different attributes. Discuss the results and hypothesize about why certain attributes are more important than others for a given classification task.

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. Marketing research tells the story that it costs 5 times more for the business to onboard and provision 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.