DataFactZ Case Study

Using Data Analytics to find Customer Lifetime Value

Introduction

A fundamental goal of a business marketing function is to maximize the lifetime value of the company's customers. Lifetime value (LTV) is usually defined as the expected present value of net cash flows from a firm's relationship with customers over the lifetime of the relationship. LTV is a key metric used by companies not only to measure customer equity (the sum of the lifetime values of all the company's customers), but to also set an upper limit on spending to acquire customers.
DataFactZ has implemented one such CLV model for an Analytics team at a direct marketing company. This model helped the team's direct mail business line. The modeling objective was to predict the lifetime value of individual/segmented customers as accurately as possible, with the ultimate goal of assessing the quality of the customer listings purchased from vendors.

Current Landscape and Challenges

The client in focus had no automated model that predicted customer lifetime value, and were exploring this data science capability for the first time. The challenges they had been facing with implementing such a model were a lack of foundational knowledge, and in-house talent. As a partner with a rich experience in Data Sciences, DataFactZ was asked to assess the current landscape, and deploy a CLV model if assessment results permitted.

Assessment

DataFactZ had a team of Data Science Engineers and Data Scientists assess the client's current landscape. The team found that the organization had abundant data, but located in dissimmiar systems, with business-specific purposes that didn't have clear definitions or documentation. Much of the data was found to be redundant and inconsistent.

'Greater insights into Customer Lifetime will prepare for the Future'

Implementation Strategy

The modeling strategy explored a range of standard multivariate regression models as well as various machine learning methods, for the purposes of characterizing the quality of the customer listings. These were acquired initially, and on an ongoing basis, as the organization accumulated customer activity history in response to the efforts.The high-level implementation strategies used were:

Data Analysis, Preparation and Processing

- Reconfiguring datasets for use in models developed
- Verification and testing of datasets for conformance to the model requirements
- Clarification for the data fields and relations

Model Development and Optimization

- Engineering and optimizing customer features

- Customer and key level LTV calculations and roll-ups
- Developing models for 3, 6, 12 month observation periods
- Model development for individual months as well as aggregate data
- Experimenting with multiple predictive models including neural networks, parametric models, and regression models
- Optimizing accuracy and generalizability of the predictive models through parameter configuration, model scoring, cross validations

Testing and Validation

- Statistical accuracy results, heat maps, confusion matrices, error histograms, regression plots, absolute errors
- Testing with holdout sample and single month mailing

Results Preparation and Presentation

- Documenting, organizing and presenting results of model testing and validation through presentations and excel spreadsheets
- Creating Key level results through rollup.

Deployment in SAS

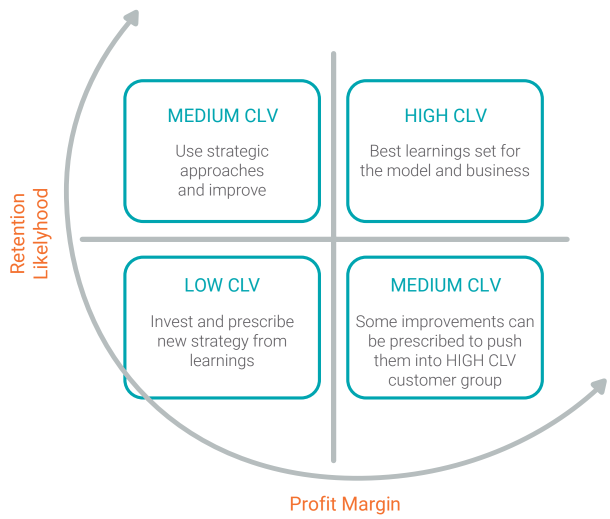
Above tasks were completed in a rapid prototyping environment with a full range of predictive modeling capability exploration while ensuring and verifying portability into SAS Enterprise Miner. In return for the time-savings and quality improvements, the following tasks were required to port the models into SAS:

- Porting preprocessing steps: These steps extract the features from the customer Order Data (in response to initial effort within the observation period) and Effort Data (efforts made for each customer within the observation period)
- Models porting
- Developing customer and key level LTV prediction reports

Conclusion

DataFactZ's assessment module and implementation module was not only unique to the client's organization, but also defined a structure for them. As a result, their data and source tables are now well documented. New relationships that made business sense were added, and a forecasting model was deployed to help the analytics team calculate its customer lifetime value.

'A prediction model with greater insights into Customer Lifetime Value equipped the team to better plan for what's in store.'



The Next Step

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