Consumer Data Research Centre

An ESRC Data Investment

SHOP DIRECT

An investigation of what triggers customer activation of credit facilities

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Project Background

Shop Direct wants to understand the behaviours that prompt its cash customers to start using credit facilities in order to provide the best possible user journeys and outstanding service for individual customers. The research, based on this business case study, is an investigation of the characteristics of those cash customers that are most likely to apply for credit facilities to purchase products in future.

Data and Methods

The investigation scope starts from June 2014 to July 2015. The total sample set was 374,320 customer records, including all customers who successfully converted their account and sampled cash customers who purchased products during the period. The target was set as binary indicator; 1 – represent credit conversion customers and 0- represents non-credit conversion customers. The data relevant to customers' characteristics and purchasing behaviors one year before conversion date were collected into one sample set. However, those who received email contact about cash to credit promotion were excluded due to the absence of any cash to credit marketing campaigns during the study period. The overall methodology consisted of data mining procedures. A decision tree was selected as a main technique for attempting to answer the research question, while logistic regression plays a notable role as a competing model. Both data modelling processes were performed in SAS Enterprise Miner. Prior to building the models, data cleaning and missing value replacement procedures were run. This was especially important for the logistic regression model which is quite sensitive to missing values.

Key Findings

The result between the two algorithms were similar; however the logistic regression contributed a broader range of answers. With the high number of new membership who converted their accounts, it became difficult to further investigate due to the lack of their historical purchasing data and profiles. Therefore, new memberships were removed from this analysis scope. The analysis revealed that customers who had previously been refused credit and frequently visited the website were most likely to convert their accounts. These two aspects were also found in the results of logistic regression. However, this algorithm contributed additional possible factors such as gender, customer segment group, age, tenure, products viewed, purchasing channels, and month conversion (Table 1). The gain chart is used to measure model performances in terms of response rate (Figure 1). It is found that more predictive answers do not always generate the greater result. It is suggested that a combination of the two algorithms provide the optimal insight.

Model type	Effect variables	Evaluation output
Logistic Regression	Gender	Female > males
	Customer segment group	Most are in Financially stratched group, following by customers in Confortable Communities group
	Age	Younger age group
	Tenure	More than 2 years
	Visited site	1. More frequently viewed products , especially in electronic department and furniture 2. Viewed credit information before conversion
	Purchasing behaviour	1. Credit request refusal experience: Yes > no 2. Month conversion: Purchased in May 3. Order channel: Offline > online 4. Payment pattern: switch to purchase with credit card before conversion 5. Incentive uses: use discount code (pound off) 6. Low or no any purchasing amount in Home products
Decision Tree	Effect variables	Evaluation output
	Visited site	Frequently viewed product ; more than 8.5 times
	Purchasing behaviour	experienced credit request refusal before

Table 1 Output interpretation

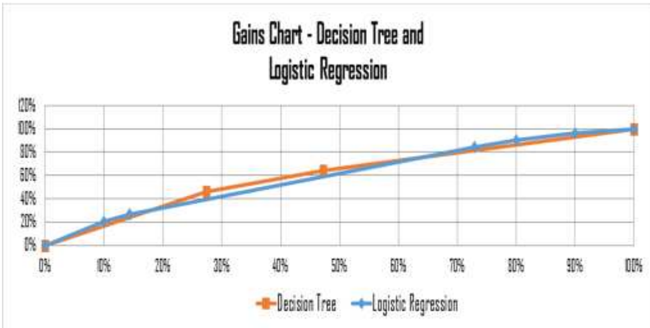

Figure 1. Gain Chart

Value of the Research

This output could be further analysed to deliver a recommendation plan in order to create the optimal user journeys for pure cash customers and those who are likely to want to become credit customers in future. With this information, the customer teams can create retail and financial service strategies that serve the right information to the right people.