Customer Relationship Management
A Databased Approach

V. Kumar
Werner J. Reinartz

Instructor’s Presentation Slides
Chapter Six

Customer Value Metrics: Concepts and Practices
Topics Discussed

• Popular Customer-based Value Metrics
• Strategic Customer-based Value Metrics
• Popular Customer Selection Strategies
• Lift charts
• Cases
Customer Based Value Metrics

Popular

- Size Of Wallet
- Share of Category Reqt.
- Share of Wallet
- Transition Matrix

Strategic

- RFM
- Past Customer Value
- LTV Metrics
- Customer Equity
Size-of-Wallet

Size-of-wallet ($\) of customer in a category = $j \sum_{j=1}^{J} S_j$

Where: $S_j = $ sales to the focal customer by the firm $j$

$j = \text{firm}$, $\sum_{j=1}^{J} = \text{summation of value of sales made by all the J firms that sell a category of products to the focal customer}$

Information source:

Primary market research

Evaluation:

Critical measure for customer-centric organizations based on the assumption that a large wallet size indicates more revenues and profits

Example:

A consumer might spend an average of $400 every month on groceries across the supermarkets she shops at. Her size-of-wallet is $400
Share of Category Requirement (SCR)

• \[ \text{SCR} (\%) \text{ of firm or brand in category} = \frac{\sum_{i=1}^{I} V_{ij}}{\sum_{j=1}^{J} \sum_{i=1}^{I} V_{ij}} \]

\( j = \text{firm}, \ V = \text{purchase volume}, \ i = \text{those customers who buy brand} \)

\[ \sum_{i=1}^{I} = \text{summation of volume purchased by all the} \ I \ \text{customers from a firm} \ j, \]

\[ \sum_{j=1}^{J} \sum_{i=1}^{I} = \text{summation of volume purchased by all} \ I \ \text{customers from all} \ J \ \text{firms} \]

Information source:

Numerator: volumetric sales of the focal firm - from internal records

Denominator: total volumetric purchases of the focal firm’s buyer base - through market and distribution panels, or primary market research (surveys) and extrapolated to the entire buyer base

Evaluation:

Accepted measure of customer loyalty for FMCG categories, controls for the total volume of segments/individuals category requirements; however, does not indicate if a high SCR customer will generate substantial revenues or profits
### Computation of SCR Ratio - Example

<table>
<thead>
<tr>
<th></th>
<th>Total requirement of Notebook computers per customer</th>
<th>Total number of Notebook Computers purchased from ABC Computers per customer per period</th>
<th>Share of category requirement for ABC computers per customer per period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customer 1</td>
<td>100</td>
<td>20</td>
<td>.20</td>
</tr>
<tr>
<td>Customer 2</td>
<td>1000</td>
<td>200</td>
<td>.20</td>
</tr>
<tr>
<td>Customer 3</td>
<td>1000</td>
<td>500</td>
<td>.25</td>
</tr>
</tbody>
</table>

Customer 3 has the highest SCR. Therefore, ABC Computers should identify customer 3 and target more of their marketing efforts (mailers, advertisements etc.) towards customer 3. Also, customer 3’s size-of-wallet (column A), is the largest.
Share-of-Wallet (SW)

- Individual Share-of-Wallet

\[
\text{Individual Share-of-Wallet of firm to customer (\%) } = \frac{S_j}{\sum_{j=1}^{J} S_j}
\]

Where: \( S \) = sales to the focal customer, \( j \) = firm, \( \sum_{j=1}^{J} \) summation of value of sales made by all the \( J \) firms that sell a category of products to a buyer

Information source:
- Numerator: From internal records
- Denominator: From primary market research (surveys), administered to individual customers, often collected for a representative sample and then extrapolated to the entire buyer base

Evaluation:
- Important measure of customer loyalty; however, SW is unable to provide a clear indication of future revenues and profits that can be expected from a customer
Share-of-Wallet (contd.)

• Aggregate Share-of-Wallet (ASW) (brand or firm level)

  Aggregate Share-of-Wallet of firm (%)  
  \[ \frac{\sum_{i=1}^{I} \text{Individual Share-of-Wallet}_{ji}}{\sum_{j=1}^{J} \sum_{i=1}^{I} \text{S}_{ij}} \]

  Where: S = sales to the focal customer, j = firm, i = customers who buy brand

Information source:

  Numerator: From internal records
  Denominator: Through market and distribution panels, or primary market research (surveys) and extrapolated to the entire buyer

Evaluation:

  Important measure of customer loyalty
Applications of SCR and SW

- SCR - for categories where the variance of customer expenditures is relatively small
- SW - if the variance of consumer expenditures is relatively high
- Share-of-wallet and Size-of-wallet simultaneously – with same share-of-wallet, different attractiveness as customers:

Example:

<table>
<thead>
<tr>
<th></th>
<th>Share-of-Wallet</th>
<th>Size-of-Wallet</th>
<th>Absolute expenses with firm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buyer 1</td>
<td>50%</td>
<td>$400</td>
<td>$200</td>
</tr>
<tr>
<td>Buyer 2</td>
<td>50%</td>
<td>$50</td>
<td>$25</td>
</tr>
</tbody>
</table>

Absolute attractiveness of Buyer 1 eight times higher than buyer 2
Segmenting Customers Along Share of Wallet and Size of Wallet

The matrix shows that the recommended strategies for different segments differ substantively. The firm makes optimal resource allocation decisions only by segmenting customers along the two dimensions simultaneously.

- **High Share-of-wallet**
  - **Low Size-of-wallet**: Hold on
  - **Large Size-of-wallet**: Maintain and guard

- **Low Share-of-wallet**
  - **Small Size-of-wallet**: Do nothing
  - **Large Size-of-wallet**: Target for additional selling
Share of Wallet and Market Share (MS)

MS of firm = \( \frac{\sum_{i=1}^{I} \text{(Share-of-wallet}_i \times \text{Size of wallet})}{\sum_{j=1}^{J} S_j} \)

Where: \( S \) = sales to the focal customer, \( j = \) firm, \( i = \) customers who buy the brand

- Difference between share-of-wallet and market share:
  - MS is calculated across buyers and non-buyers whereas SW is calculated only among buyers

- MS is measured on a percent basis and can be computed based on unit volume, $ volume or equivalent unit volumes (grams, ounces)

- Example:
  - BINGO has 5,000 customers with an average expense at BINGO of $150 per month (\( = \text{share-of-wallet} \times \text{size of wallet} \))
  - The total grocery sales in BINGO’s trade area are $5,000,000 per month
  - BINGO’s market share is \( \frac{5,000 \times $150}{5,000,000} = 15\% \)
Transition Matrix

<table>
<thead>
<tr>
<th>Brand Currently Purchased</th>
<th>Brand Purchased next time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
</tr>
<tr>
<td>A</td>
<td>70%</td>
</tr>
<tr>
<td>B</td>
<td>10%</td>
</tr>
<tr>
<td>C</td>
<td>25%</td>
</tr>
</tbody>
</table>

Characterizes a customer’s likelihood to buy over time or a brand’s likelihood to be bought.

Example:
- The probability that a consumer of Brand A will transition to Brand B and then come back to Brand A in the next two purchase occasions is 20% * 10% = 2%.
- If, on an average, a customer purchases twice per period, the two purchases could be AA, AB, AC, BA, BB, BC, CA, CB, or CC.
- We can compute the probability of each of these outcomes if we know the brand that the customer bought last.
Strategic Customer Based Value Metrics

- RFM
- Past Customer Value
- LTV Metrics
- Customer Equity
RFM

- Recency, Frequency and Monetary Value - applied on historical data

- Recency - how long it has been since a customer last placed an order with the company

- Frequency - how often a customer orders from the company in a certain defined period

- Monetary value - the amount that a customer spends on an average transaction

- Tracks customer behavior over time in a state-space
Computation of RFM

Two common methods:

• Method 1: Sorting customer data based on RFM, grouping and analyzing results

• Method 2: Computing relative weights for R, F and M using regression techniques
RFM Method 1

Example:

- Customer base: 400,000 customers
- Sample size: 40,000 customers
- Firm’s marketing mailer campaign: $150 discount coupon
- Response rate: 808 customers (2.02%)

Recency coding: Analysis

- Test group of 40,000 customers is sorted in a descending order based on the criterion of ‘most recent purchase date’.
- The earliest purchasers are listed on the top and the oldest are listed at the bottom. The sorted data is divided into five equal groups (20% in each group)
- The top most group is assigned a recency code of 1 and the next group a code of 2 and so on, until the bottom most group is assigned a code of 5
- Analysis of customer response data shows that the mailer campaign got the highest response from customers grouped in recency code 1 followed by code 2 etc
Graph depicts the distribution of percentage of those customers who responded fell within the *recency* code grouping of 1 through 5.

Highest response rate (4.5%) for the campaign was from customers in the test group who fell in the highest recency quintile (recency code =1).
Graph depicts the distribution of what % of those customers who responded fell within the frequency code grouping of 1 through 5.

The highest response rate (2.45%) for the campaign was from customers in the test group who fell in the highest frequency quintile (frequency code = 1).
Response and Monetary Value

Customer data is sorted, grouped and coded with a 1 to 5 value

The highest response rate (2.35%) for the campaign was from those customers in the test group who fell in the highest monetary value quintile (monetary value code =1).
Limitations

- RFM method 1 independently links customer response data with R, F and M values and then groups customers, belonging to specific RFM codes.

- May not produce equal number of customers under each RFM cell since individual metrics R, F, and M are likely to be somewhat correlated.
  - For example, a person spending more (high M) is also likely, on average, to buy more frequently (high F).

- For practical purposes, it is desirable to have exactly the same number of individuals in each RFM cell.
RFM Cell Sorting

Example:

• List of 40,000 test group customers is first sorted for Recency and grouped into 5 equal groups of 8000 each

• The 8000 customers in each group is then sorted based on Frequency and divided into five equal groups of 1600 each- at the end of this stage, there will be RF codes starting from 11 through 55 with each group having 1600 customers

• In the last stage, each of the RF groups is further sorted based on monetary value and divided into five equal groups of 320 customers each
  - RFM codes starting from 111 through 555 each having 320 customers

• Considering each RFM code as a cell, there will be 125 cells (5 recency divisions * 5 frequency divisions * 5 monetary value divisions = 125 RFM Codes)
RFM Cell Sorting (contd.)

Customer Database

Sorted Once

R
1
2
3
4
5

Sorted five times per R quintile

Sorted twenty five times per R quintile

F
11
12
13
14
15
41
42
43
44
45

M
131
132
133
134
135
441
442
443
444
445
Breakeven Value

• Breakeven - net profit from a marketing promotion equals the cost associated with conducting the promotion

• Breakeven Value (BE) = unit cost price/ unit net profit

• BE computes the minimum response rates required in order to offset the promotional costs involved and thereby not incur any losses

• Example: In mailing $150 discount coupons,
  - The cost per mailing piece is $1.00
  - The net profit (after all costs) per used coupon is $45,
    $\text{Breakeven Value (BE)} = \frac{1.00}{45} = 0.0222$ or 2.22%
Breakeven Index

- Breakeven Index (BEI) = ((Actual Response Rate - BE)/BE) * 100

Example: If the actual response rate of a particular RFM cell was 3.5%

BE is 2.22%,

The BEI = ((3.5% - 2.22%)/2.22%)\times100 = 57.66

- Positive BEI value ➞ some profit was made from the group of customers
- 0 BEI value ➞ the transactions just broke even
- Negative BEI value ➞ the transactions resulted in a loss
RFM and BEI (contd.)

- Customers with higher RFM values tend to have higher BEI values
- Customers with a lower recency value but relatively higher F and M values tend to have positive BEI values
- Customer response rate drops more rapidly for the recency metric
- Customer response rate for the frequency metric drops more rapidly than that for the monetary value metric
## RFM & Profitability

<table>
<thead>
<tr>
<th></th>
<th>Test</th>
<th>Full customer base</th>
<th>RFM Selection</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average response rate</td>
<td>2.02%</td>
<td>2.02%</td>
<td>15.25%</td>
</tr>
<tr>
<td># of responses</td>
<td>8080</td>
<td>8080</td>
<td>2732.8</td>
</tr>
<tr>
<td>Average Net profit/Sale</td>
<td>$45</td>
<td>$45</td>
<td>$45</td>
</tr>
<tr>
<td>Net Revenue</td>
<td>$36360</td>
<td>$363600</td>
<td>$122,976</td>
</tr>
<tr>
<td># of Mailers sent</td>
<td>40,000</td>
<td>400,000</td>
<td>17920</td>
</tr>
<tr>
<td>Cost per mailer</td>
<td>$1.00</td>
<td>$1.00</td>
<td>41.00</td>
</tr>
<tr>
<td>Mailing cost</td>
<td>$40,000</td>
<td>$400,000</td>
<td>$17920</td>
</tr>
<tr>
<td>Profits</td>
<td>($3640)</td>
<td>($36400)</td>
<td>$105056</td>
</tr>
</tbody>
</table>
RFM Method 2- Regression Method

• Regression techniques to compute the relative weights of the R, F, and M metrics

• Relative weights are used to compute the cumulative points of each customer

• The pre-computed weights for R, F and M, based on a test sample are used to assign RFM scores to each customer

• The higher the computed score, the more profitable the customer is likely to be in the future

• This method is flexible and can be tailored to each business situation
Recency Score

- 20 if within past 2 months; 10 if within past 4 months; 05 if within past 6 months; 03 if within past 9 months; 01 if within past 12 months;
- Relative weight = 5

<table>
<thead>
<tr>
<th>Customer</th>
<th>Purchases (Number)</th>
<th>Recency (Months)</th>
<th>Assigned Points</th>
<th>Weighted Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>JOHN</td>
<td>1</td>
<td>2</td>
<td>20</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>4</td>
<td>10</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>9</td>
<td>3</td>
<td>15</td>
</tr>
<tr>
<td>SMITH</td>
<td>1</td>
<td>6</td>
<td>5</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>20</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>4</td>
<td>10</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>6</td>
<td>5</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>9</td>
<td>3</td>
<td>15</td>
</tr>
<tr>
<td>MAGS</td>
<td>2</td>
<td>4</td>
<td>10</td>
<td>50</td>
</tr>
</tbody>
</table>
### Frequency Score

- **Points for Frequency:** 3 points for each purchase within 12 months; Maximum = 15 points; Relative weight = 2

<table>
<thead>
<tr>
<th>Customer</th>
<th>Purchases(#)</th>
<th>Frequency</th>
<th>Assigned Points</th>
<th>Weighted Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>JOHN</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>SMITH</td>
<td>1</td>
<td>2</td>
<td>6</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>MAGS</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>2</td>
<td>6</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1</td>
<td>3</td>
<td>6</td>
</tr>
</tbody>
</table>
Monetary Value Score

- Monetary Value: 10 percent of the $ Volume of Purchase with 12 months; Maximum = 25 points; Relative weight = 3

<table>
<thead>
<tr>
<th>Customer</th>
<th>Purchases (Number)</th>
<th>Monetary</th>
<th>Assigned Points</th>
<th>Weighted Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>JOHN</td>
<td>1</td>
<td>$40</td>
<td>4</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>$120</td>
<td>12</td>
<td>36</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>$60</td>
<td>6</td>
<td>18</td>
</tr>
<tr>
<td>SMITH</td>
<td>1</td>
<td>$400</td>
<td>25</td>
<td>75</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>$90</td>
<td>9</td>
<td>27</td>
</tr>
<tr>
<td>MAGS</td>
<td>2</td>
<td>$70</td>
<td>7</td>
<td>21</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>$80</td>
<td>8</td>
<td>24</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>$40</td>
<td>4</td>
<td>12</td>
</tr>
</tbody>
</table>
### RFM Cumulative Score

<table>
<thead>
<tr>
<th>Customer</th>
<th>Purchases (Number)</th>
<th>Total Weighted Points</th>
<th>Cumulative Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>JOHNSON</td>
<td>1</td>
<td>118</td>
<td>118</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>92</td>
<td>210</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>39</td>
<td>249</td>
</tr>
<tr>
<td>SMITH</td>
<td>1</td>
<td>112</td>
<td>112</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>133</td>
<td>133</td>
</tr>
<tr>
<td>MAGS</td>
<td>2</td>
<td>77</td>
<td>210</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>61</td>
<td>271</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>37</td>
<td>308</td>
</tr>
</tbody>
</table>

- Cumulative scores: 249 for John, 112 for Smith and 308 for Mags; indicate a potential preference for Mags
- John seems to be a good prospect, but mailing to Smith might be a misdirected marketing effort
Past Customer Value

• Computation of Customer Profitability

\[
\text{Past Customer Value of a customer} = \sum_{n=1}^{n} GC_{in} \times (1 + r)^n
\]

Where \( I \) = number representing the customer, \( r \) = applicable discount rate
\( n \) = number of time periods prior to current period when purchase was made
\( GC_{in} \) = Gross Contribution of transaction of the \( i^{th} \) customer in the \( n^{th} \) time period

• Since products/services are bought at different points in time during the customer’s lifetime, all transactions have to be adjusted for the time value of money

• Limitations: Does not consider whether a customer is going to be active in the future. Also does not incorporate the expected cost of maintaining the customer in the future
Spending Pattern of a Customer

<table>
<thead>
<tr>
<th></th>
<th>Jan</th>
<th>Feb</th>
<th>March</th>
<th>April</th>
<th>May</th>
</tr>
</thead>
<tbody>
<tr>
<td>$ Amount</td>
<td>800</td>
<td>50</td>
<td>50</td>
<td>30</td>
<td>20</td>
</tr>
<tr>
<td>GC</td>
<td>240</td>
<td>15</td>
<td>15</td>
<td>9</td>
<td>6</td>
</tr>
</tbody>
</table>

Gross Contribution (GC) = Purchase Amount × 0.3

Past Customer Value Scoring =

\[
6(1 + 0.0125) + 9(1 + 0.0125)^2 + 15(1 + 0.0125)^3 + 15(1 + 0.0125)^4 + 240(1 + 0.0125)^5 = 302.01486
\]

The above customer is worth $302.01 in contribution margin, expressed in net present value in May dollars. By comparing this score among a set of customers a prioritization is arrived at for directing future marketing efforts.
Lifetime Value metrics (Net Present Value models)

• Multi-period evaluation of a customer’s value to the firm

- Recurring Revenues
- Recurring costs
- Contribution margin
- Lifetime of a customer
- Discount rate
- Lifetime Profit
- Acquisition cost

LTV
Calculation of Lifetime Value: Simple Definition

\[ LTV = \sum_{t=1}^{T} CM_t \left( \frac{1}{1 + \delta} \right)^t \]

where \( LTV \) = lifetime value of an individual customer in $, \( CM \) = contribution margin,
\( \delta \) = interest rate, \( t \) = time unit, \( \Sigma \) = summation of contribution margins across time periods

• LTV is a measure of a single customer’s worth to the firm
• Used for pedagogical and conceptual purposes

Information source:
CM and T from managerial judgment or from actual purchase data.
The interest rate, a function of a firm’s cost of capital, can be obtained from financial accounting

Evaluation:
Typically based on past customer behavior and may have limited diagnostic value for future decision-making
LTV: Definition Accounting for Varying Levels of Contribution Margin

\[
LTV = \sum_{t=1}^{T} (S_{it} - DC_{it}) - MC_{it} \left( \frac{1}{1+\delta} \right)^t
\]

Where, LTV = lifetime value of an individual customer \( i \) in $, \( S = \) Sales to customer \( i \),
\( DC = \) direct cost of products purchased by customer \( i \),
\( MC = \) marketing cost of customer \( i \)

Information source:

Information on sales, direct cost, and marketing cost comes from internal company records

Many firms installing Activity-Based-Costing (ABC) schemes to arrive at appropriate allocations of customer and process-specific costs
LTV: Definition Accounting for Acquisition Cost and Retention Probabilities

\[ LTV = \left( \sum_{t=1}^{T} \left( \prod_{t=1}^{T} Rr \right) CM_{it} \left( \frac{1}{1+\delta} \right)^{t} \right) - AC \]

Where, LTV = lifetime value of an individual customer in $

Rr = retention rate

Π = Product of retention rates for each time period from 1 to T,

AC = acquisition cost

T = total time horizon under consideration

Assuming that \( T \to \infty \) and that the contribution margin \( CM \) does not vary over time,

\[ LTV_i = \frac{CM}{1 - Rr + \delta} - AC \]
Customer Equity

- Sum of the lifetime value of all the customers of a firm

\[ CE = \sum_{i=1}^{I} \sum_{t=1}^{T} CM_{it} \left( \frac{1}{1+\delta} \right)^{t} \]

- Indicator of how much the firm is worth at a particular point in time as a result of the firm’s customer management efforts

- Can be seen as a link to the shareholder value of a firm

Customer Equity Share, \( CES_j = CE_j / \sum_k CE_k \),

where, \( CE = \) customer equity, \( j = \) focal brand, \( k = \) all brands
## Customer Equity Calculation: Example

<table>
<thead>
<tr>
<th>Year from Acquisition</th>
<th>2 Sales per Customer</th>
<th>3 Manufacturer Margin</th>
<th>4 Manufacturer Gross Margin</th>
<th>5 Mktg and Servicing Costs</th>
<th>6 Actual Retention Rate</th>
<th>7 Survival Rate</th>
<th>8 Expected Number of Active Customer</th>
<th>9 Profit per Customer per period per Manufacturer</th>
<th>10 Discounted Profit per Customer per Period to Manufacturer</th>
<th>11 Total Disctd. Profits per Period to the Manufacturer</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Popular Customer Selection Strategies

• Decision Trees
  – Used for finding the best predictors of a 0/1 or binary dependent variable
  – Useful when there is a large set of potential predictors for a model
  – Decision tree algorithms can be used to iteratively search through the data to find out which predictor best separates the two categories of a binary target variable
  – Typically, this search is performed on two-thirds of the available data with one-third of the data reserved for later use for testing the model that develops
  – Problem with the approach: prone to over-fitting; the model developed may not perform nearly as well on a new or separate dataset
Decision Trees - Example

Customer data for purchases of hockey equipment from a sporting goods catalog

Step 1

<table>
<thead>
<tr>
<th>Gender</th>
<th>Buyer</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>1000</td>
<td>5000</td>
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<tr>
<td>No</td>
<td>4000</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>280</td>
<td>3000</td>
</tr>
<tr>
<td>No</td>
<td>2720</td>
<td></td>
</tr>
</tbody>
</table>
Step 2

Decision Trees - Example (contd.)

<table>
<thead>
<tr>
<th>Gender</th>
<th>Yes</th>
<th>No</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>280</td>
<td>2720</td>
<td>3000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
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<th>Total</th>
</tr>
</thead>
<tbody>
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<td>1400</td>
<td>1600</td>
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<tr>
<td>No</td>
<td>80</td>
<td>1320</td>
<td>1400</td>
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</table>
Step 2 (contd.) The process can be repeated for each sub-segment

<table>
<thead>
<tr>
<th></th>
<th>Yes</th>
<th>No</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
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<td></td>
</tr>
<tr>
<td>Buyer</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>1000</td>
<td></td>
<td>5000</td>
</tr>
<tr>
<td>No</td>
<td>4000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- Bought Scuba Equipment

<table>
<thead>
<tr>
<th></th>
<th>Yes</th>
<th>No</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
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<tr>
<td>No</td>
<td>1140</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- Male

<table>
<thead>
<tr>
<th></th>
<th>Yes</th>
<th>No</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>2860</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Total 3800
Popular Customer Selection Strategies (contd.)

• Logistic Regression
  – Method of choice when the dependent variable is binary and assumes only two discrete values
  – By inputting values for the predictor variables for each new customer – the logistic model will yield a predicted probability
  – Customers with high ‘predicted probabilities’ may be chosen to receive an offer since they seem more likely to respond positively
Logistic Regression - Examples

• Example 1: Home ownership
  – Home ownership as a function of income can be modeled whereby ownership is delineated by a 1 and non-ownership a 0
  – The predicted value based on the model is interpreted as the probability that the individual is a homeowner
  – With a positive correlation between increasing income and increasing probability of ownership, can expect results as
    • predicted probability of ownership is .22 for a person with an income of $35,000
    • predicted probability of .95 for a person with a $250,000 income
Example 2: Credit Card Offering

- Dependent Variable-- whether the customer signed up for a ‘gold’ card offer or not

- Predictor Variables-- other bank services the customer used plus financial and demographic customer information

- By inputting values for the predictor variables for each new customer, the logistic model will yield a predicted probability

- Customers with high ‘predicted probabilities’ may be chosen to receive the offer since they seem more likely to respond positively
Linear and Logistic Regressions

- In linear regression, the effect of one unit change in the independent variable on the dependent variable is assumed to be a constant represented by the slope of a straight line.
- For logistic regression, the effect of a one-unit increase in the predictor variable varies along an s-shaped curve. This means that at the extremes, a one-unit change has very little effect, but in the middle a one unit change has a fairly large effect.
Logistic Regression Transformation Steps

**Step 1:** If $p$ represents the probability of an event occurring, take the ratio $\frac{p}{1-p}$.

Since $p$ is a positive quantity less than 1, the range of this expression is 0 to infinity.

**Step 2:** Take the logarithm of this ratio: $\log\left(\frac{p}{1-p}\right)$.

This transformation allows the range of values for this expression to lie between negative infinity and positive infinity.
Logistic Regression Transformation Steps (contd.)

- **Step 3:** The value \( \log\left(\frac{p}{1-p}\right) \) can be considered as the dependent variable and a linear relationship of this value with predictor variables in the form \( z = \alpha + \beta x + e \)

  The \( \alpha \) and \( \beta_s \) can be estimated

- **Step 4.** In order to obtain the predicted probability \( p \), a back transformation is to be done

  Since \( \log\left(\frac{p}{1-p}\right) = z = \alpha + \beta x + e \), \( \frac{p}{1-p} = e^z \)

  Then calculate the probability \( p \) of an event occurring, the variable of interest, as

  \[
p = \left(\frac{1}{1+e^{-z}}\right)
\]
Techniques to Evaluate Alternative Customer Selection Strategies

• Lift Charts

  – Lifts indicate how much better a model performs than the ‘no model’ or average performance

  – Can be used to track a model’s performance over time, or to compare a model’s performance on different samples

  – The lift will then equal (response rate for each decile) ÷ (overall response rate) × 100

  – The cumulative lift = (cumulative response rate) ÷ (overall response rate) × 100

  – The cumulative response rate = cumulative # buyers ÷ cumulative # customers
## Lift Performance Illustration

<table>
<thead>
<tr>
<th>Decile</th>
<th># of Customers</th>
<th># of Buyers</th>
<th>Response Rate</th>
<th>Lift</th>
<th>Cumulative Lift</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5000</td>
<td>1759</td>
<td>35.18%</td>
<td>3.09</td>
<td>3.09</td>
</tr>
<tr>
<td>2</td>
<td>5000</td>
<td>1126</td>
<td>22.52%</td>
<td>1.98</td>
<td>5.07</td>
</tr>
<tr>
<td>3</td>
<td>5000</td>
<td>998</td>
<td>19.96%</td>
<td>1.75</td>
<td>6.82</td>
</tr>
<tr>
<td>4</td>
<td>5000</td>
<td>554</td>
<td>11.08%</td>
<td>0.97</td>
<td>7.80</td>
</tr>
<tr>
<td>5</td>
<td>5000</td>
<td>449</td>
<td>8.98%</td>
<td>0.79</td>
<td>8.59</td>
</tr>
<tr>
<td>6</td>
<td>5000</td>
<td>337</td>
<td>6.74%</td>
<td>0.59</td>
<td>9.18</td>
</tr>
<tr>
<td>7</td>
<td>5000</td>
<td>221</td>
<td>4.42%</td>
<td>0.39</td>
<td>9.57</td>
</tr>
<tr>
<td>8</td>
<td>5000</td>
<td>113</td>
<td>2.26%</td>
<td>0.20</td>
<td>9.76</td>
</tr>
<tr>
<td>9</td>
<td>5000</td>
<td>89</td>
<td>1.78%</td>
<td>0.16</td>
<td>9.92</td>
</tr>
<tr>
<td>10</td>
<td>5000</td>
<td>45</td>
<td>0.90%</td>
<td>0.08</td>
<td>10.00</td>
</tr>
</tbody>
</table>
The Decile analysis distributes customers into ten equal size groups.
For a model that performs well, customers in the first decile exhibit the highest response rate.
Lifts that exceed 1 indicate better than average performance
Less than 1 indicate a poorer than average performance

For the top decile the lift is 3.09; indicates that by targeting only these customers one can expect to yield 3.09 times the number of buyers found by randomly mailing the same number of customers.
The cumulative lifts for the model reveal what proportion of responders we can expect to gain from targeting a specific percent of customers using the model.

Choosing the top 30% of the customers from the top three deciles will obtain 68% of the total responders.
Lift Performance Comparison

Logistic models tend to provide the best lift performance.
The Past Customer Value approach provides the next best performance.
The traditional RFM approach exhibits the poorest performance.
Minicase: Catalina - Changing Supermarket Shopper Measurement

- Catalina Inc. a Florida-based company that specializes in supermarket shopper tracking and coupon issuing
- Built its business model on issuing coupons to grocery shoppers online when they checkout at the cashier
- System consists of a printer connected to the cashier’s scanner as well as a database
- The information on each shopping basket that checks out via the scanner is then stored in the database
Minicase: Catalina (contd.)

- Using the person’s credit card number or check number, the database links individual shopping baskets over time.

- The system then allows both manufacturers and retailers to run individualized campaigns based on the information in the database.

- For customers who use Catalina as a secondary store, the decision to allocate a gift of say $10, for shopping for 4 weeks in a row spending at least $40, per week in the store.

- Goal is to selectively target those shoppers where the store only captures a low share-of-wallet and to entice them to change their behavior.
Minicase: Akzo Nobel, NV- Differentiating Customer Service According to Customer Value

• One of the world's largest chemical manufacturers and paint makers

• The polymer division, which serves exclusively the B-to-B market, established a “tiered customer service policy” in the early 2000’s

• Company developed a thorough list of all possible service activities that is currently offered

• To formalize customer service activities, the company implemented a customer scorecard mechanism to measure and document contribution margins per individual customer

• Service allocation, differentiated as:
  – services to be free for all types of customers
  – services subject to negotiation for lower level customer groups
  – services subject to fees for lower level customers
  – services not available for the least valuable set of customers
Summary

• Firms use different surrogate measures of customer value to prioritize their customers and to differentially invest in them

• Firms can use information about size of wallet and share of wallet together for optimal allocation of resources

• Transition matrix provides the probability that a customer will purchase a particular brand if what brand has been purchased the last time is known

• The higher the computed RFM score, the more profitable the customer is expected to be, in the future

• Firms employ different customer selection strategies to target the right customers

• Lift analysis, decile analysis and cumulative lift analysis are various techniques firms use to evaluate alternative selection strategies

• Logistic Regression is superior to Past Customer Value and RFM techniques