Marketing Analytical Framework

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Agenda

- Marketing Analytical Framework
- Direct Marketing Application
- Customer Base Analysis
Marketing Analytical Framework
Management Challenge: Marketing Mix

Marketing Mix
- Seminars
- Conferences
- Trade Shows
- Influencers
- Field Sales Calls
- Teleprospecting
- Mail
- E-Mail
- Web

Sales Channels
- Field Sales
- Distributor
- Telesales
- Web

Revenues

Wall St. Commitments

Products

Customers

Geo
- A
- B
- C
Mix & Sequence Varies Through The Pipeline
Marketing Optimization: Growing The Pipeline

Sales & Marketing Pipeline

- Awareness
- Interest
- Consideration
- Coverage
- Propose
- Sale
- Revenue $$
- Support

mass Media

Direct Mail

E-Channels

Tele-Channels

Field Sales

% Awareness
Here?, or here?
Branding/Media Investment
% Consideration
Here?, or here?
Direct Marketing
Revenue per Rep
Here?, or here?
Sales Resources
Interactive Effect Drive Optimization

1. Portfolio & Media Mix
   Brand Effect
   - Segment Lifecycle
   - Brand vs. DR

2. Offering Position
   Attribute Effect
   - Bundling
   - Messaging
   - Pricing

3. Sequence
   Cumulative Effect
   - Routes
   - Touches
   - Sequence

Market Management
Offering Management
Campaign Execution
Marketing “Portfolio Management” Framework

Customer/User Response Model

**Portfolio Attributes**
- Geography
- Market – Lifecycle, Competitive Economics

**Proposition Attributes**
- Messaging
- Pricing, Bundling
- Features/Service

**Media Attributes**
- Brand/Channel
- Sequencing (Time)

**Segment Attributes**
- Demographics
- Psychographics
- Purchase Relationship

**Loyalty Attributes**
- Usage
- Customer Satisfaction
- Importance

What Are We Trying To Optimize?
- Awareness
- Consideration
- Purchase (Revenue)
- Profit
- Life-time value (retention)
Analytical Framework

**Pipeline Lever**
- Awareness (Brand-Building)
- Demand Generation (Target Marketing)
- Sales Enablement

**Stimulus Tactic**
- Advertising
- Sponsorships
- PR
- Internet
- Events
- Direct Mail
- Interactive
- Telemarketing
- Sales Force Training
- New Offering
- Sales Tools
- Intranal
- Customer Research
- Database Mining
- Market Analyses
- Strategic Planning
- Offering Development

**Goals Response Metric**
- Increase Propensity to Buy
- Provide Qualified Leads
- Enable the Sales Force

**Yield**
- Increase Revenue
- Increase Profit
- Increase Customer Base

- Awareness
- Consideration
- Preference
- $ Leads
- Win Revenue
- % New Leads
- Revenue per Rep
- Sales Cycle
- Sales Productivity
Direct Marketing Application
The “Segmentation” Approach

1. Divide the customer list into a set of (homogeneous) segments.

2. Test customer response by mailing to a random sample of each segment.

3. Rollout to segments with a response rate (RR) above some cut-off point,

   e.g., \( RR > \frac{\text{cost of each mailing}}{\text{unit margin}} \)
• A consumer durable product (unit margin = $161.50, mailing cost per 10,000 = $3343)

• 126 segments formed from customer database on the basis of past purchase history information

• Test mailing to 3.24% of database
Standard approach:
  
  - Rollout to all segments with

    \[
    \text{Test RR} > \frac{3343/10,000}{161.50} = 0.00207
    \]

  - 51 segments pass this hurdle
Test vs. Actual Response Rate
Modeling Objective

Develop a model that leverages the whole data set to make better informed decisions.
Model Development

Notation:

\[ N_s = \text{size of segment } s \ (s = 1, \ldots, S) \]
\[ m_s = \# \text{ members of segment } s \text{ tested} \]
\[ X_s = \# \text{ responses to test in segment } s \]

Assume: All members of segment \( s \) have the same (unknown) response probability \( p_s \Rightarrow X_s \) is a binomial random variable

\[
P(X_s = x_s | m_s, p_s) = \binom{m_s}{x_s} p_s^{x_s} (1 - p_s)^{m_s-x_s}
\]
Distribution of Response Probabilities

- Heterogeneity in $p_s$ is captured using a beta distribution:

$$g(p_s) = \frac{1}{B(\alpha, \beta)} p_s^{\alpha-1} (1 - p_s)^{\beta-1}$$

- The beta function, $B(\alpha, \beta)$, can be expressed as

$$B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha + \beta)}$$

- The mean of the beta distribution is given by

$$E(p_s) = \frac{\alpha}{\alpha + \beta}$$
The Beta Binomial Model

The aggregate distribution of responses to a mailing of size \( m_s \) is given by

\[
P(X_s - x_s | m_s) = \int_0^1 P(X_s - x_s | m_s, p_s) g(p_s) \, dp_s
\]

\[
= \binom{m_s}{x_s} \frac{B(\alpha + x_s, \beta + m_s - x_s)}{B(\alpha, \beta)}
\]
Estimating Model Parameters

The log-likelihood function is defined as:

\[
LL(\alpha, \beta | \text{data}) = \sum_{s=1}^{126} \ln[P(X_s = x_s | m_s)] = \sum_{s=1}^{126} \ln \left[ \frac{m_s!}{(m_s - x_s)!x_s!} \frac{\Gamma(\alpha + x_s)\Gamma(\beta + m_s - x_s)}{\Gamma(\alpha + \beta + m_s)} \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \right] \frac{1}{B(\alpha + x_s, \beta + m_s - x_s)}
\]

The maximum value of the log-likelihood function is \( LL = -200.5 \), which occurs at \( \hat{\alpha} = 0.439 \) and \( \hat{\beta} = 95.411 \).
Estimated Distribution of $p$

$\hat{\alpha} = 0.439, \hat{\beta} = 95.411, \hat{p} = 0.0046$
Applying the Model

What is our best guess of $p_s$ given a response of $x_s$ to a test mailing of size $m_s$?

Intuitively, we would expect

$$E(p_s|x_s, m_s) \approx \omega \frac{\alpha}{\alpha + \beta} + (1 - \omega) \frac{x_s}{m_s}$$
Bayes Theorem

- The *prior distribution* $g(p)$ captures the possible values $p$ can take on, prior to collecting any information about the specific individual.

- The *posterior distribution* $g(p|x)$ is the conditional distribution of $p$, given the observed data $x$. It represents our updated opinion about the possible values $p$ can take on, now that we have some information $x$ about the specific individual.

- According to Bayes theorem:

$$g(p|x) = \frac{f(x|p)g(p)}{\int f(x|p)g(p) \, dp}$$
Bayes Theorem

For the beta-binomial model, we have:

\[
g(p_s | X_s = x_s, m_s) = \frac{\binom{\text{binomial}}{P(X_s = x_s | m_s, p_s) g(p_s)}}{\text{beta} \int_0^1 P(X_s = x_s | m_s, p_s) g(p_s) \, dp_s}
\]

\[
= \frac{1}{B(\alpha + x_s, \beta + m_s - x_s)} p_s^{\alpha + x_s - 1} (1 - p_s)^{\beta + m_s - x_s - 1}
\]

which is a beta distribution with parameters \( \alpha + x_s \) and \( \beta + m_s - x_s \).
Distribution of $\rho$

- prior ($\hat{\alpha} = 0.439, \hat{\beta} = 95.411$)
- posterior with $x_s = 80, m_s = 1235$
- posterior with $x_s = 0, m_s = 171$

$p$

$g(p)$

$\rho = 0.0046$
$\rho = 0.0016$
$\rho = 0.0604$
Applying the Model

Recall that the mean of the beta distribution is $\alpha/ (\alpha + \beta)$. Therefore

$$E(p_s | X_s = x_s, m_s) = \frac{\alpha + x_s}{\alpha + \beta + m_s}$$

which can be written as

$$\left( \frac{\alpha + \beta}{\alpha + \beta + m_s} \right) \frac{\alpha}{\alpha + \beta} + \left( \frac{m_s}{\alpha + \beta + m_s} \right) \frac{x_s}{m_s}$$

- a weighted average of the test RR ($x_s/m_s$) and the population mean ($\alpha/(\alpha + \beta)$).
- “Regressing the test RR to the mean”
Model-Based Decision Rule

- Rollout to segments with:

\[ E(p_s | X_s = x_s, m_s) > \frac{3343/10,000}{161.5} = 0.00207 \]

- 66 segments pass this hurdle

- To test this model, we compare model predictions with managers’ actions. (We also examine the performance of the “standard” approach.)
Customer Base Analysis
The simple models for three behavioral processes

- Timing → “when”
- Counting → “how many”
- “Choice” → “whether/which”

1. Each of these simple models has multiple applications
2. More complex behavioral phenomena can be captured by combining models from each of these processes
Further Applications: Timing Models

• Repeat purchasing of new products
• Response times:
  - Coupon redemptions
  - Survey response
  - Direct mail (response, returns, repeat sales)
• Customer retention/attrition
• Other durations:
  - Salesforce job tenure
  - Length of web site browsing session
Further Applications: Count Models

- Repeat purchasing
- Customer concentration ("80/20" rules)
- Salesforce productivity/allocation
- Number of page views during a web site browsing session
Further Applications: “Choice” Models

• Brand choice

\[
\begin{align*}
\text{HH } & \#1 \quad \text{A} \quad \text{B} \quad \text{A} \quad \text{A} \\
\text{HH } & \#2 \quad \text{B} \quad \quad \quad \quad \quad \text{B} \\
\text{HH } & \#3 \quad \text{B} \quad \text{A} \\
\vdots \\
\text{HH } & \#h \quad \text{A} \quad \text{B} \quad \text{B} \quad \text{B}
\end{align*}
\]

• Media exposure
• Multibrand choice
• Taste tests (discrimination tests)
• “Click-through” behavior
Thanks and Any question?