Targeting Current Customer (Resource Allocation)

Manish Gangwar

ABB Electric Case

- Incorporated in 1970.
- Design and manufacture line of medium power transformers, breakers, switch gear, relays, etc.
- Customers mostly electrical utilities.
  - Investor-own electrical utilities (largest), Rural electrification cooperation Municipalities Industrial firms
- Competition: ABB share was 6% and concentrated on first group
  - GE, Westinghouse, McGraw-Edison.
- 1974 (and years following) = downturn in demand.
- Total industry sales of electrical equipment dropped 50% in 1973
- Losing money every year.

ABB Example

- Suppose you are the regional sales manager for ABB Electric, and you have been given a budget for a supplementary direct marketing campaign aimed at **20 percent** of the companies in your region.
- At present you have demographic information (see the Descriptor Data tab of the ABB Electric Data.xls spreadsheet) about the location of customers (districts 1, 2 and 3) and the sales potential of each account or prospect. Based on this information alone,
  - To what companies would you direct the new direct marketing program? Specify the accounts and customer or prospect types.

Whom Should ABB Target (20%)

	Customer	Ann. Purchase Volume ($ K)	District	Firm Chosen
1	**35**	$14,798	2	D
2	**43**	$12,514	2	C
3	**44**	$10,997	2	A
4	**66**	$9,793	3	B
5	**32**	$6,270	1	C
6	**11**	$1,722	3	A
7	**84**	$1,404	3	B
8	**17**	$1,364	3	B
9	**74**	$1,219	1	B
10	**20**	$1,009	2	B
11	**53**	$989	2	C
12	**47**	$956	2	B
13	**12**	$928	1	D
14	**26**	$899	2	D
15	**16**	$894	3	B
16	**33**	$890	3	D
17	**23**	$871	2	D
18	**27**	$871	1	D

Segmentation

- **ABB Electric Loyal Segment (Loyal):** Customers in this segment have a probability of purchasing from ABB Electric that is significantly higher than the probability that they would buy from the next closest competitor.
- **Competitive Segment (Competitive):** Customers in this segment have a slightly higher probability of purchasing from ABB Electric than from the next most preferred supplier. Thus the probability of purchasing from ABB Electric is highest, but not significantly above the probabilities of purchasing from one or more competitors.
- **Switchable Segment (Switchable):** Customers in this segment have a slightly lower probability of purchasing from ABB Electric than their most preferred supplier. Thus the probability of purchasing from a competitor is highest, but not significantly higher than the probability of purchasing from ABB Electric.
- **Competitor Loyal Segment (Lost):** Customers in this segment have a significantly lower probability of purchasing from ABB Electric than from their most preferred supplier. Thus these customers are highly likely to buy only from a competitor and can be classified as lost customers.

ABB Case : 21 product service attribute analyzed
Factor Analysis gave 8 items for survey

Supplier Performance Rating

List the suppliers you are considering or would consider when purchasing your next substation:

_____ _____

_____ _____

_____ _____

For each supplier on your list, indicate your perception of this supplier on the following attributes:

Invoice Price	Poor	Good
Supplier A	|----------	----------|
Supplier B	|----------	----------|
Supplier C	|----------	----------|
Supplier D	|----------	----------|

Exhibit 1: Sample Survey Question

ABB Case Data and Analysis

- Choice modeling approach based on the responses provided by 88 firms from your region. The data consists of the evaluation of ABB Electric and the three main competitors on eight variables:
  - (1) Price, (2) Energy losses, (3) Maintenance requirements, (4) Warranty,
  - (5) Availability of spare parts, (6) Ease of installation, (
  - 7) Salesperson problem solving support and (8) Perceived product quality.
- Perform a purchase propensity based segmentation for your customers and prospects.
  - Which variables are the key drivers of choice in this market?
  - Based on your analyses, on which firms would you focus your efforts? Why?

Applying Choice Models for Customer Segmentation and Targeting at ABB

Decision Problem:

How to allocate limited marketing budget across customers? Whom to target for direct marketing?

Research Objective:

Segment customers on the basis of probability of choice.

Analytics Tool:

Choice modeling

Segmenting Customers

	Respondents / Choice probabilities	ABB probability	GE probability	Westinghouse probability	Edison probability	Volume	Type
1	Customer 35	0.00	0.00	0.00	1.00	$14,798	4-Lost
2	Customer 43	0.01	0.00	0.99	0.00	$12,514	4-Lost
3	Customer 44	0.93	0.00	0.07	0.00	$10,997	3-Loyal
4	Customer 66	0.16	0.69	0.14	0.01	$9,793	2-Winnable
5	Customer 32	0.00	0.00	1.00	0.00	$6,270	4-Lost
6	Customer 11	0.22	0.05	0.73	0.00	$1,722	2-Winnable
7	Customer 84	0.52	0.48	0.00	0.00	$1,404	1-Losable
8	Customer 17	0.21	0.13	0.08	0.58	$1,364	2-Winnable
9	Customer 74	0.01	0.99	0.00	0.00	$1,219	4-Lost
10	Customer 20	0.00	1.00	0.00	0.00	$1,009	4-Lost
11	Customer 53	0.18	0.00	0.82	0.00	$989	2-Winnable
12	Customer 47	0.00	0.96	0.00	0.03	$956	4-Lost
13	Customer 12	0.00	0.00	0.01	0.99	$928	4-Lost
14	Customer 26	0.35	0.00	0.07	0.58	$899	2-Winnable
15	Customer 16	0.56	0.17	0.20	0.07	$894	1-Losable
16	Customer 33	0.00	0.01	0.00	0.99	$890	4-Lost
17	Customer 27	0.00	0.00	0.00	1.00	$871	4-Lost
18	Customer 23	0.01	0.00	0.00	0.99	$871	4-Lost

ABB Case

- Assume that marketing efforts targeted at companies in the Loyal and Lost categories result in no incremental gain. On the other hand, suppose that you could retain or win **half the companies in the Switchable and Competitive segments** with this program. How much improvement in sales productivity can you realize by applying this choice model to the allocation of your efforts?
- What other recommendations would you offer to ABB Electric to improve its segmentation marketing program?

Modeling Approach
Choice Models

The objective of the model in our context is to predict the probabilities that the individual will choose each of several choice alternatives The model has the following properties:

- The probabilities lie between 0 and 1, and sum to 1.
- The model is consistent with the proposition that customers pick the choice alternative that offers them the highest utility on a purchase occasion, but the utility has a random component that varies from across purchases.
- Technical Note: The simple logit model has the proportional draw property -- each choice alternative draws from other choice alternatives in proportion to their utility.

Contexts in Which Choice Models are Appropriate

- Binary Choice
  - Buy or Not Buy
  - Yes or No
  - Own or Don't own
  - Won or Lost

- Multinomial Choice
  - Tide, Cheer, Yes, or Wisk
  - Bus, Train, or Plane
  - Yes, No, Don't Know

Choices are mutually exclusive. The customer chooses only one of the options at a given choice occasion.

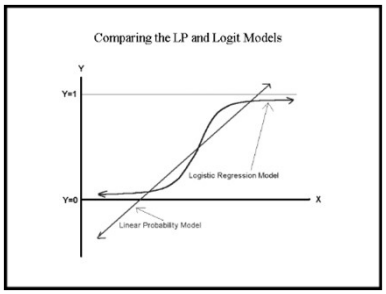
Multinomial Logit Model

- Regression requires that outcome variable (Y) to be continuous
- What if observed outcome is categorical
  - Which firm won the bid
  - Which brand was chosen
    - Latent choice probability

$$F(x) = \exp\left(-\exp\left(\frac{x-\mu}{\gamma}\right)\right)$$

$$P(ch=i) = \frac{\exp(U_i)}{\sum_{j \in I} \exp(U_j)}$$

$$U_i = x_i \beta$$



Technical Specification of the Multinomial Logit Model

On each purchase occasion, the (unobserved) utility that **customer n** gets from **alternative j** is given by:

$$U_{nj} = V_{nj} + \varepsilon_{nj}$$

Notice that utility is the sum of an observable term (V_{nj}) and an unobservable term (ε_{nj}).

Understanding MNL

$$U_{nj} = V_{nj} + \varepsilon_{nj},$$

$$P_{ni} = \text{Prob}(U_{ni} > U_{nj}\ \forall j \neq i)$$

$$P_{ni} = \text{Prob}(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}\ \forall j \neq i)$$

$$P_{ni} = \int_{\varepsilon} I(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}\ \forall j \neq i) f(\varepsilon_n)\, d\varepsilon_n$$

Understanding MNL

Gumbel $\quad f(\varepsilon_{nj}) = e^{-\varepsilon_{nj}} e^{-e^{-\varepsilon_{nj}}} \qquad F(\varepsilon_{nj}) = e^{-e^{-\varepsilon_{nj}}}$

Independent $\quad \varepsilon^*_{nji} = \varepsilon_{nj} - \varepsilon_{ni} \qquad F\left(\varepsilon^*_{nji}\right) = \dfrac{e^{\varepsilon^*_{nji}}}{1 + e^{\varepsilon^*_{nji}}}$

$$\text{Prob}(\varepsilon_{nj} < \varepsilon_{ni} + V_{ni} - V_{nj}\ \forall j \neq i)$$

$$P_{ni} \mid \varepsilon_{ni} = \prod_{j \neq i} e^{-e^{-(\varepsilon_{ni} + V_{ni} - V_{nj})}}$$

$$P_{ni} = \int \left(\prod_{j \neq i} e^{-e^{-(\varepsilon_{ni} + V_{ni} - V_{nj})}} \right) e^{-\varepsilon_{ni}} e^{-e^{-\varepsilon_{ni}}}\, d\varepsilon_{n}$$

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}}$$

Appendix - Logit: IIA property

- Independence from Irrelevant Alternatives

$$\frac{P_{ni}}{P_{nk}} = \frac{e^{V_{ni}} / \sum_j e^{V_{nj}}}{e^{V_{nk}} / \sum_j e^{V_{nj}}}$$

- When would IIA hold in real world?

Appendix - Nested Logit

$$U_{nj} = W_{nk} + Y_{nj} + \varepsilon_{nj}$$

$$P_{ni} = P_{ni \mid B_k} P_{nB_k}$$

$$P_{ni \mid B_k} = \frac{e^{Y_{ni}/\lambda_k}}{\sum_{j \in B_k} e^{Y_{nj}/\lambda_k}} \quad P_{nB_k} = \frac{e^{W_{nk} + \lambda_k I_{nk}}}{\sum_{\ell=1}^{K} e^{W_{n\ell} + \lambda_\ell I_{n\ell}}}$$

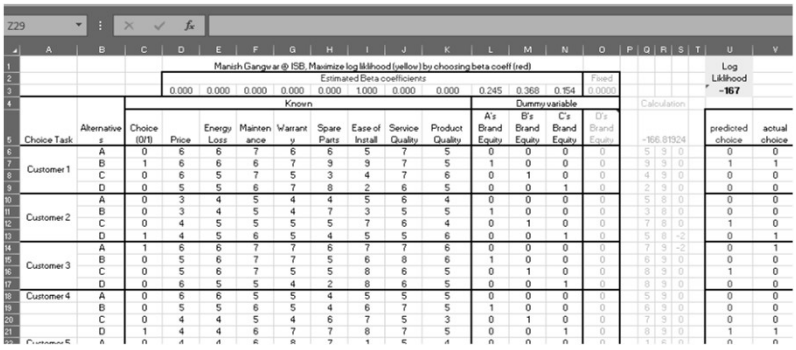
$$I_{nk} = \ln \sum_{j \in B_k} e^{Y_{nj}/\lambda_k}$$

Appendix - Latent Class

$$P_{ni} = \sum_{m=1}^{M} s_m \left(\frac{e^{b'_m x_{ni}}}{\sum_j e^{b'_m x_{nj}}} \right)$$

$$L(H_k) = \sum_i \left[\exp(\lambda_i) L(H_k|i) \Big/ \sum_{i'} \exp(\lambda_{i'}) \right]$$

Logit Estimation



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1				Manish Gangwar @ ISB, Maximize log likihood (yellow) by choosing beta coeff (red)																	Log Likihood	
2				Estimated Beta coefficients											Fixed						-167	
3				0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.245	0.368	0.154	0.0000							
4			Known									Dummy variable					Calculation					
5	Choice Task	Alternatives	Choice (0/1)	Price	Energy Loss	Maintenance	Warranty	Spare Parts	Ease of Install	Service Quality	Product Quality	A's Brand Equity	B's Brand Equity	C's Brand Equity	D's Brand Equity		-166.81924				predicted choice	actual choice
6	Customer 1	A	0	6	6	7	6	6	5	7	5	0	0	0	0		5	9	0		0	0
7		B	1	6	6	6	7	9	9	7	5	1	0	0	0		9	9	0		1	1
8		C	0	6	5	7	5	3	4	7	6	0	1	0	0		4	9	0		0	0
9		D	0	5	5	6	7	8	2	6	5	0	0	1	0		2	9	0		0	0
10	Customer 2	A	0	3	4	5	4	4	5	6	4	0	0	0	0		5	8	0		0	0
11		B	0	3	4	5	4	7	3	5	5	1	0	0	0		3	8	0		0	0
12		C	0	4	5	5	5	5	7	6	4	0	1	0	0		7	8	0		1	0
13		D	1	4	5	6	5	4	5	5	6	0	0	1	0		5	8	-2		0	1
14	Customer 3	A	1	6	6	7	7	6	7	7	6	0	0	0	0		7	9	-2		0	1
15		B	0	5	6	7	7	5	6	8	6	1	0	0	0		6	9	0		0	0
16		C	0	5	6	7	5	5	8	6	5	0	1	0	0		8	9	0		1	0
17		D	0	6	5	5	4	2	8	6	5	0	0	1	0		8	9	0		0	0
18	Customer 4	A	0	6	6	5	5	4	5	5	5	0	0	0	0		5	9	0		0	0
19		B	0	5	5	6	5	4	6	7	5	1	0	0	0		6	9	0		0	0
20		C	0	4	4	5	4	6	7	5	3	0	1	0	0		7	9	0		0	0
21		D	1	4	4	6	7	7	8	7	5	0	0	1	0		8	9	0		1	1

mlogit in R code ….

other machine learning models (e.g. decision tree and random forest)