Choice Modeling

Marketing Analytics

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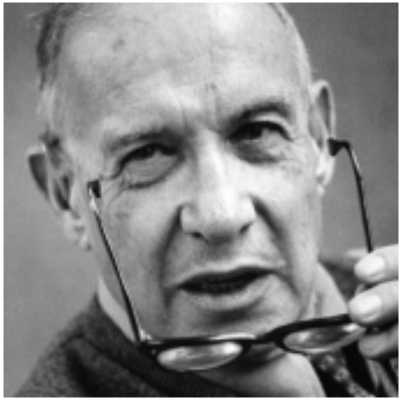
The aim of marketing is to *know and understand* the customer so well the product or service fits him and sells itself.



Peter Drucker

Founder of Modern Management

Consumer Choice Behavior

- Consumers decide on:
  - Whether to buy (purchase incidence)
  - What to buy (brand consideration and choice)
  - Where to buy (channel choice)
  - Whether to buy again (loyalty/churn)

- Marketers learn about consumers through:
  - What they do (revealed choice)
  - What they say (stated choice)

Uses of Choice Modeling in Marketing

- Segmentation and targeting
- Product positioning
- Marketing mix decisions
  - Product design
  - Pricing
  - Advertising and promotions
  - Customer churn management

Example: Product Design
Choice-Based-Conjoint (CBC)

<table>
<tr><td>Brand</td><td>Hilton</td><td>WESTIN</td><td>NEW HOTEL</td><td rowspan="7">None - I would not choose any of these.</td></tr>
<tr><td>Location</td><td>10 minute ride to destination</td><td>30 minute ride to destination</td><td>Walking distance to destination</td></tr>
<tr><td>Restaurant</td><td>Restaurant within walking distance</td><td>Restaurant within 5 minute car ride</td><td>Restaurant in hotel</td></tr>
<tr><td>Gym</td><td>No gym</td><td>On-site gym</td><td>Partner gym within 5 minutes</td></tr>
<tr><td>Wireless</td><td>Wireless Internet connection throughout the hotel</td><td>Wireless “hot spots” in the hotel, but not in the room</td><td>No wireless access</td></tr>
<tr><td>Rewards</td><td>Earn Standard Rewards Points</td><td>Earn Double Rewards Points</td><td>Earn Triple Rewards Points</td></tr>
<tr><td>Room Rate</td><td>$200</td><td>$225</td><td>$150</td></tr>
<tr><td>Choose one</td><td>A</td><td>B</td><td>C</td><td></td></tr>
</table>

Example: Scanner-Panel Data
Nielsen HomeScan

By scanning the items you purchase (from cereal at the store to a candy bar in a snack machine) retailers see where you shop, what you buy, …

Sample Scanner-Panel Data

Customer ID	Date	Store ID	Brand	Quantity	Regular Price	Discount	Display	Feature
1001	3/1/2016	2345	Tide	50oz	$3.55	$0.43	No	No
1001	3/29/2016	5678	Tide	64oz	$3.99	$0.54	Yes	Yes
1001	4/25/2016	2345	Tide	50oz	$3.55	$0.45	No	No
1001	5/28/2016	5678	All	50oz	$2.99	$0.50	Yes	No
1001	6/27/2016	2345	Tide	50oz	$3.60	$0.45	No	No
1001	7/22/2016	5678	Tide	50oz	$3.60	$0.20	No	No
1001	8/29/2016	2345	All	64oz	$3.15	$0.60	Yes	Yes
1001	9/24/2016	5678	Tide	50oz	$3.65	$0.42	No	No
1001	10/28/2016	2345	All	50oz	$4.99	$1.00	Yes	Yes
1001	11/25/2016	5678	Tide	50oz	$3.99	$0.50	No	No

Example: Monthly Churn Rate for Wireless Carriers in U.S.

- Monthly churn rates in 2017 (Q2)
  - Verizon 1.19%
  - AT&T 1.28%
  - U.S. Cellular 1.52%
  - Sprint 2.24%
  - T-Mobile 2.28%
  - Shentel 2.88%

  - **Average 1.90%**

Source: https://www.statista.com/statistics/283511/average-monthly-churn-rate-top-wireless-carriers-us/

Outline

- Logistic regression (binary choice)
- Multinomial logit (multiple choice)

Logistic Regression Motivation

- Online/Catalog purchase (Buy/No-Buy)
  - Recency, Frequency, Monetary value (RFM) measures as predictors of purchase
- Response to marketing efforts
  - Did the customer buy after being sent a coupon or an email ad?
- Churn
  - Can we predict customer churn before it happens?

What is Common to these Examples?

- The outcome variable is binary
  - Coded: Y = 1 (if “Yes”) and Y = 0 (if “No”)
- There is a set of variables (x’s) that we can use to explain and predict the binary outcome variable

Example - Catalog Data

- Explanatory Variables
  - Recency – how many days since last purchase
  - Frequency – how many times the consumer buys
  - Monetary Value – Total $ amount spent

- Dependent Variable
  - Purchase (Yes/No)

Excerpt from the RFM Data

```
RFMdata <- read.csv(file = "RFMData.csv",row.names=1)
kable(head(RFMdata,5),row.names = TRUE)
```

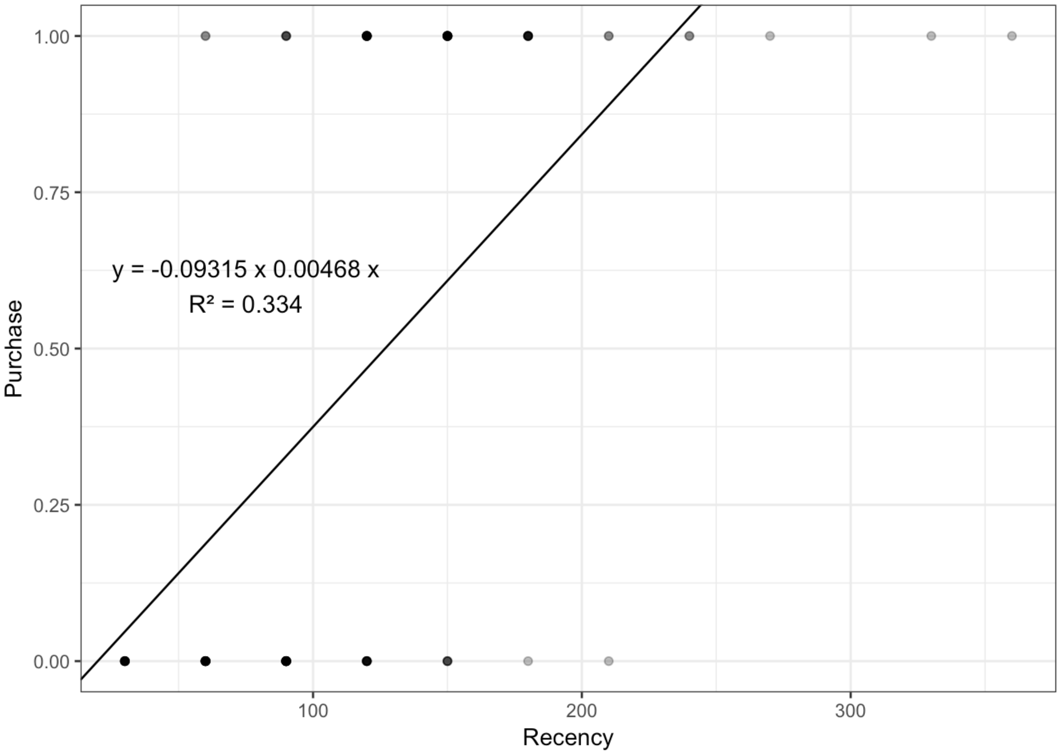
	Recency	Frequency	Monetary	Purchase
1	120	7	41.66	0
2	90	9	46.71	0
3	120	6	103.99	1
4	270	17	37.13	1
5	60	5	88.92	0

Purchase rate in RFM data=45/100=45%

Why Can’t We Just Use Regression?

- Predictions could be outside the range of [0,1] interval
- Statistical tests from regression would be wrong

Recency vs. Purchase



Logistic Regression Model

- The model states that a consumer has a utility (a desire) from buying and a utility from not buying (keep the money)
- Utility from buying: V_b
- Utility from not buying: $V_n=0$
- Consumer buys if $V_b > V_n=0$

The Choice Probability

The probability of buying is proportional to its utility (i.e., attractiveness):

$$p = \frac{\exp(V_b)}{\exp(V_b) + \exp(V_n)} = \frac{\exp(V_b)}{\exp(V_b) + 1}$$

Example

- Utility from buying: $V_b = 2$
- Utility from not buying: $V_n = 0$
- Probability of buying:
- Odds of buying

$$p = \frac{\exp(2)}{\exp(2)+1} = \frac{7.39}{7.39+1} = 0.88$$

$$\frac{p}{1-p} = \frac{0.88}{1-0.88} = 7.39 = \exp(2)$$

Utility Varies across Customers as a Function of RFM variables

- For RFM data, the utility of buying:

$$V_b = \beta_0 + \beta_1 \text{Recency} + \beta_2 \text{Frequency} + \beta_3 \text{Monetary}$$

- Logistic regression software uses the data to estimate the model parameters (the betas)

R-Code for Logistic Regression

Outcome Variable

Independent Variables

Binary Outcome

```
model <- glm(Purchase~Recency+Frequency+Monetary, data=RFMdata, family = "binomial")
output <- cbind(coef(summary(model))[, 1:4],exp(coef(model)))
colnames(output) <- c("beta","SE","z val.","Pr(>|z|)",'exp(beta)')
kable(output,caption = "Logistic regression estimates")
```

See Logistic Regression R Notebook for programming details.

Logistic Regression Output

```r
# Likelihood ratio test
reduced.model <- glm(Purchase ~ 1, data=RFMdata, family = "binomial")
kable(xtable(anova(reduced.model, model, test = "Chisq")),caption = "Likelihood ratio test")
```

Likelihood ratio test

Resid. Df	Resid. Dev	Df	Deviance	Pr(>Chi)
99	137.62776	NA	NA	NA
96	30.48715	3	107.1406	0

Observed χ^2

P-value

Significance-level

Likelihood ratio test:
Assess overall significance

Logistic Regression Output

Logistic regression estimates

	beta	SE	z val.	Pr(>|z|)	exp(beta)
(Intercept)	-30.2976692	8.5522913	-3.542638	0.0003961	0.000000
Recency	0.1114175	0.0309797	3.596464	0.0003226	1.117862
Frequency	0.5941268	0.2429393	2.445577	0.0144620	1.811448
Monetary	0.1677054	0.0465645	3.601572	0.0003163	1.182588

Regression coefficients measure impact of x on utility

t-test for significance

How Do You Interpret Exp(beta)?

Logistic regression estimates

	beta	SE	z val.	Pr(>|z|)	exp(beta)
(Intercept)	-30.2976692	8.5522913	-3.542638	0.0003961	0.000000
Recency	0.1114175	0.0309797	3.596464	0.0003226	1.117862
Frequency	0.5941268	0.2429393	2.445577	0.0144620	1.811448
Monetary	0.1677054	0.0465645	3.601572	0.0003163	1.182588

Interpretation of Exp(beta)

- Consider two consumers (1 & 2) with identical values on recency and frequency, but consumer 1 spends $1 more than consumer 2.
  - Then the odds of buying for consumer 1 are 1.183 the odds of consumer 2.
  - More generally, the odds of buying are 18.3% higher for each increase of Monetary Value by $1.

Predicting Purchase Probabilities

- Estimated utility function in RFM data:

V= -30.29 + .111Recency + .594Frequency + .168Monetary

- Logistic regression predictions

$$p = \frac{\exp(V)}{\exp(V) + 1}$$

Predicting Purchase Probabilities in R

```
# calculate logit probabilities
RFMdata$Base.Probability <- predict(model, RFMdata, type="response")
kable(head(RFMdata,5),row.names = TRUE)
```

	Recency	Frequency	Monetary	Purchase	Probability
1	120	7	41.66	0	0.0030728
2	90	9	46.71	0	0.0008332
3	120	6	103.99	1	0.9833225
4	270	17	37.13	1	0.9999999
5	60	5	88.92	0	0.0032378

Classification

All people with probability less ½ ➔ No purchase
All people with probability above ½ ➔ Purchase

```
# purchase vs. no purchase <-> p>0.5 or p<0.5
RFMdata$Predicted.Purchase <- 1*(RFMdata$Base.Probability>=0.5)
kable(head(RFMdata,5),row.names = TRUE)
```

	Recency	Frequency	Monetary	Purchase	Base.Probability	Predicted.Purchase
1	120	7	41.66	0	0.0030728	0
2	90	9	46.71	0	0.0008332	0
3	120	6	103.99	1	0.9833225	1
4	270	17	37.13	1	0.9999999	1
5	60	5	88.92	0	0.0032378	0

Classification (Hit Rate)

```
Confusion Matrix and Statistics

          Reference
Prediction  0  1
No Buy    0 51  2
Buy       1  4 43

               Accuracy : 0.94
                 95% CI : (0.874, 0.9777)
    No Information Rate : 0.55
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.8793
 Mcnemar's Test P-Value : 0.6831

            Sensitivity : 0.9556
            Specificity : 0.9273
         Pos Pred Value : 0.9149
         Neg Pred Value : 0.9623
             Prevalence : 0.4500
         Detection Rate : 0.4300
   Detection Prevalence : 0.4700
      Balanced Accuracy : 0.9414

       'Positive' Class : 1
```

```
confusionMatrix(RFMdata$Predicted.Purchase,RFMdata$Purchase,positive = "1")
```

Hit Rate=(51+43)/100=94%

True positive rate (Recall)=43/(43+2)=96%

True negative rate=51/(51+4)=93%

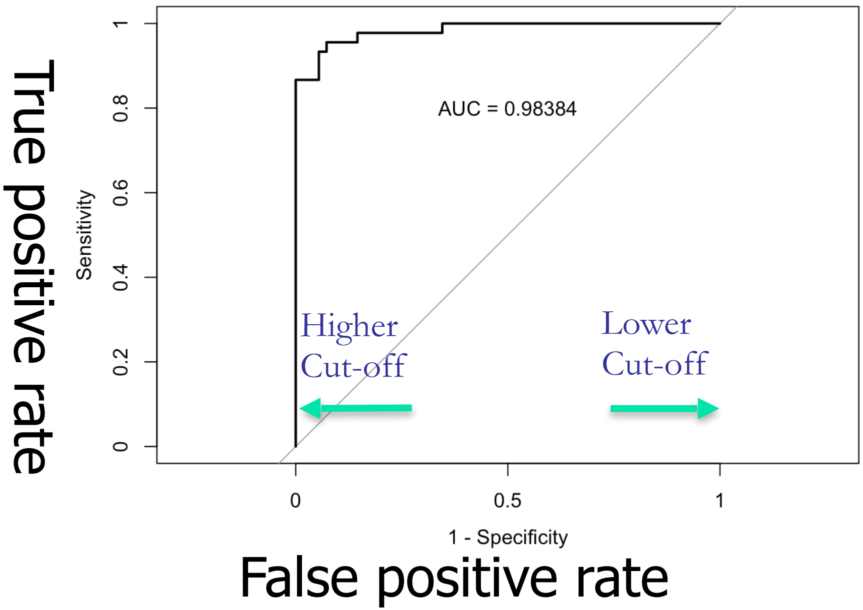
False positive rate =1-93%=7%

ROC (Receiver Operating Characteristic) Curve

```
library(pROC)
rocobj <- roc(RFMdata$Purchase, RFMdata$Base.Probability)
{plot(rocobj,legacy.axes=TRUE)
text(0.5, 0.8, labels = sprintf("AUC = %.5f",rocobj$auc))}
```

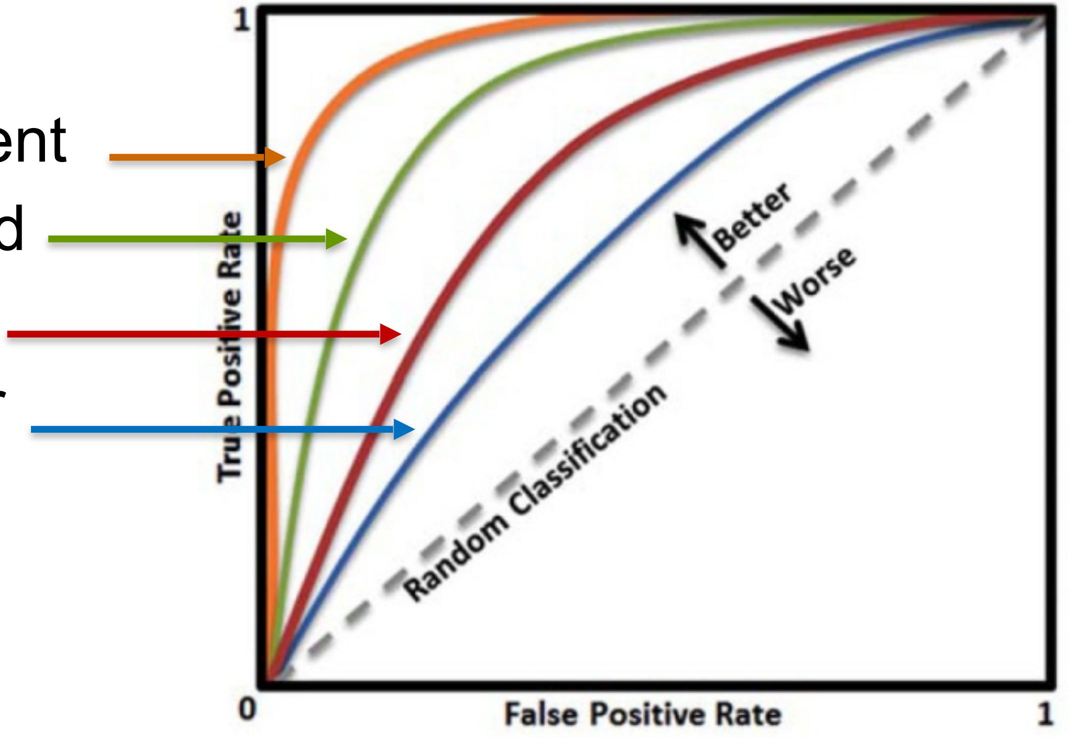
Area under the curve: 0.984

It means that in 98.4% of the time, a buyer will have a higher purchase probability than non-buyer.



ROC Values

- ROC Values
  - >0.9: excellent
  - 0.8-0.9 Good
  - 0.7-0.8 Fair
  - 0.6-0.7 Poor



Impact of Increasing Monetary Value by $1 on Purchase Probability

- Compute new utility of purchase

$$V_{new} = -30.29 + .111\text{Recency} + .594\text{Frequency} + .168(\text{Monetary}+1)$$

- Compute new probability of purchase

$$p_{new} = \frac{\exp(V_{new})}{\exp(V_{new}) + 1}$$

- Lift

$$\text{Lift} = \frac{p_{new} - p_{base}}{p_{base}}$$

Impact of Increasing Monetary Value by $1 on Purchase Probability

```r
# calculate new logit probabilities (Monetary+1)
RFMdata_new <- RFMdata
RFMdata_new$Monetary <- RFMdata_new$Monetary + 1
RFMdata$New.Probability <- predict(model, RFMdata_new, type="response")
```

	Recency	Frequency	Monetary	Purchase	Base.Probability	New.Probability
1	120	7	41.66	0	0.0030728	0.0036319
2	90	9	46.71	0	0.0008332	0.0009852
3	120	6	103.99	1	0.9833225	0.9858611
4	270	17	37.13	1	0.9999999	0.9999999
5	60	5	88.92	0	0.0032378	0.0038267

Impact of Increasing the Monetary Value by $1 on Purchase Probability

- Avg. base purchase probability=0.45
- Avg. new purchase probability=0.45789
- Lift=(0.45789-0.45)/0.45=1.75%

Uses of Logistic Regression

- Rank customers from highest to lowest on a probability scale. Target those clients who:
  - Are at the top X% (“Customer Management/Allocation of Resources)
  - Who have probability above some cutoff (“Good Prospects”)
  - Who have slipped below some cutoff (About to “die” customers, Marketing Dashboard)
- Measure customers’ responsiveness to marketing actions
- Regression is not ok as you get estimates outside the range of [0,1] and wrong statistical tests

Multinomial Logit (MNL) Choice Model

Development of theory and methods for analyzing discrete choice in 2000

Daniel McFadden

James Heckman

A Choice-Based Conjoint Study on Tablets

- When choosing a tablet:
  - How do consumers trade-off between the tablet attributes/features?
  - How much are consumers willing to pay for:
    - One brand relative to another?
    - A product feature (7hrs vs. 9hrs battery)?
- Can we predict the market share for a new tablet?

$5 \times 4 \times 4 \times 3 \times 3 \times 5$

Tablet Conjoint Study Design

$= 3600$

Attribute	Levels	
Brand	iPad, Galaxy, Kindle, Surface, Nexus	5
Screen size in inch	7, 8, 9, 10	4
Hard drive in GB	16, 32, 64, 128	4
RAM size in GB	1, 2, 4	3
Battery life in hours	7, 8, 9	3
Price in US $	169, 199, 299, 399, 499	5

A tablet can be described by picking one level from each attribute

Example of a Conjoint Choice Task

Which tablet would you choose?

Brand	iPad	Microsoft Surface	nexus
Screen size	9 inch	10 inch	9 inch
Hard drive	64 gb	128 gb	32 gb
RAM size	4 gb	4 gb	2 gb
Battery life	8 h	7 h	9 h
Price	$399	$399	$199
Alternative	1	2	3

Each consumer was presented 15 choice tasks

Excerpt from the Conjoint Data

```
# loading data
data <- read.csv(file = "conjoint_tablet_data.csv")
```

There are 137 consumers in dataset

ConsumerId	ChoiceSetId	AlternativeIdInSet	Choice	Brand	Size	Storage	Ram	Battery	Price
1	1	1	1	iPad	sz7inch	st32gb	r4gb	b7h	499
1	1	2	0	Surface	sz10inch	st64gb	r2gb	b9h	399
1	1	3	0	Kindle	sz9inch	st16gb	r2gb	b8h	499
1	2	1	1	iPad	sz8inch	st32gb	r1gb	b8h	399
1	2	2	0	Surface	sz10inch	st128gb	r4gb	b7h	299
1	2	3	0	Nexus	sz7inch	st64gb	r1gb	b9h	199

Data Source: Courtesy SawtoothSoftware.com

The MNL Model Assumes the Consumer has a Utility for each Tablet

- Utility is a function of product attributes
  - It is a measure of tablet attractiveness

- Faced with a choice set, the consumer selects the tablet that has the maximum utility

Every Attribute Level has a Sub-Utility (Part-Worth)

- For example, each brand is worth
  - Galaxy: β_{Gal}
  - iPad: β_{iPad}
  - Kindle: β_{Kind}
  - Surface: β_{Surf}
  - Nexus: 0 (reference value)
- The betas (β) are parameters to be estimated from the data

Consumer Utility for a Tablet

$V_j = \beta_{iPad} iPad_j + \beta_{Gal} Gal_j + \beta_{Kind} Kind_j + \beta_{Surf} Surf_j$ ← Brand value

$+ \beta_{10"} 10inch_j + \beta_{9"} 9inch_j + \beta_{8"} 8inch_j$ ← Screen size value

$+ \beta_{128gb} hd128_j + \beta_{64gb} hd64_j + \beta_{32gb} hd32_j$ ← Hard drive value

$+ \beta_{ram4} ram4gb_j + \beta_{ram2g} ram2gb_j$ ← RAM value

$+ \beta_{batt9} batt9hrs_j + \beta_{batt8} batt8hrs_j$ ← Battery life value

$+ \beta_{price} Price_j$ ← Price value

Except Price, all the variables are binary (0/1) variables to indicate the attribute levels of tablet j

Utility of Tablet 1 in Choice Task Example

Brand	iPad	β_{iPad}
Screen size	**9 inch**	$\beta_{9"}$
Hard drive	**64 gb**	β_{64gb}
RAM size	**4 gb**	β_{ram4}
Battery life	**8 h**	β_{batt8}
Price	**$399**	$\beta_{price}\$399$

$$V_1 = \beta_{iPad} + \beta_{9''} + \beta_{64gb} + \beta_{ram4} + \beta_{batt8} + \beta_{price}\$399$$

Utility of Tablet 2 in Choice Task Example

Brand	Microsoft Surface	β_{iSurf}
Screen size	**10 inch**	$\beta_{10''}$
Hard drive	**128 gb**	β_{128gb}
RAM size	**4 gb**	β_{ram4}
Battery life	**7 h**	β_{batt7}
Price	**$399**	$\beta_{price}\$399$

$$V_2=\beta_{iSurf}+\beta_{10''}+\beta_{128gb}+\beta_{ram4}+\beta_{batt7}+\beta_{price}\$399$$

Utility of Tablet 3 in Choice Task Example

Brand	nexus	0
Screen size	**9 inch**	$\beta_{9''}$
Hard drive	**32 gb**	β_{32gb}
RAM size	**2 gb**	β_{ram2}
Battery life	**9 h**	β_{batt9}
Price	**$199**	$\beta_{price}\$199$

$$V_3 = \beta_{9''} + \beta_{32gb} + \beta_{ram2} + \beta_{batt9} + \beta_{price}\$199$$

Choice Probabilities

$$p_1 = \frac{\exp(V_1)}{\exp(V_1) + \exp(V_2) + \exp(V_3)}$$

$$p_2 = \frac{\exp(V_2)}{\exp(V_1) + \exp(V_2) + \exp(V_3)}$$

$$p_3 = \frac{\exp(V_3)}{\exp(V_1) + \exp(V_2) + \exp(V_3)}$$

$$0 \le p_j \le 1, \forall j$$

$$p_1 + p_2 + p_3 = 1$$

```
model <- mlogit(Choice~0+Brand+Size+Storage+Ram+Battery+Price,data=mdata)
```

```
summary(model)$CoefTable
```

< 0.05

Estimation Results

	Estimate	Std. Error	t-value	Pr(>|t|)
BrandGalaxy	0.3378857	0.0925056	3.652596	0.0002596
BrandiPad	0.9780287	0.0937336	10.434136	0.0000000
BrandKindle	0.2630105	0.0996254	2.639995	0.0082907
BrandSurface	0.1450365	0.0938521	1.545373	0.1222560
Sizesz10inch	0.3240632	0.0841953	3.848949	0.0001186
Sizesz8inch	0.1890775	0.0829232	2.280151	0.0225987
Sizesz9inch	0.4355415	0.0808408	5.387644	0.0000001
Storagest128gb	0.5897703	0.0870533	6.774822	0.0000000
Storagest32gb	0.2168719	0.0829213	2.615395	0.0089124
Storagest64gb	0.5782183	0.0808259	7.153877	0.0000000
Ramr2gb	0.3189348	0.0672579	4.741970	0.0000021
Ramr4gb	0.6357438	0.0645225	9.853053	0.0000000
Batteryb8h	0.1299599	0.0651501	1.994777	0.0460672
Batteryb9h	0.1253824	0.0650588	1.927216	0.0539528
Price	-0.0050888	0.0002752	-18.488626	0.0000000

continuous

Tablet Conjoint (sub) Utilities

(β Parameters Estimates)

Attributes	Levels	Utilities
Brand	Galaxy	0.33788568
	iPad	0.97802873
	Kindle	0.26301055
	Surface	0.1450365
	Nexus	0
Screen Size	10 inch	0.32406323
	9 inch	0.43554151
	8 inch	0.18907747
	7 inch	0
Hard Drive	128 gb	0.58977033
	64 gb	0.57821825
	32 gb	0.21687192
	16 gb	0
RAM	4 gb	0.63574383
	2 gb	0.31893478
	1 gb	0
Battery	9h	0.12538242
	8h	0.12995991
	7h	0
Price		-0.0050888

0.98

.43

.59

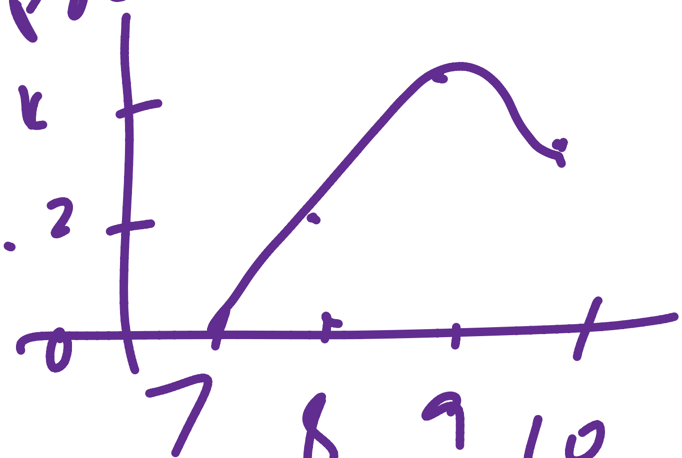
.64

.13

Range = max - min

- Reference levels are marked in grey

part worth



-0.005x169 Max =

-0.005×495 min

Model Fit

```
model.constrained <- mlogit(Choice~0+Brand,data=mdata)
lrtest(model,model.constrained)
```

```
## Likelihood ratio test
##
## Model 1: Choice ~ 0 + Brand + Size + Storage + Ram + Battery + Price
## Model 2: Choice ~ 0 + Brand
##   #Df  LogLik  Df  Chisq Pr(>Chisq)
## 1  15 -1938.9
## 2   4 -2218.0 -11 558.29  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

p-value

Predicted Market Share

Suppose these are the three tablets in the market:

ConsumerId	ChoiceSetId	AlternativeIdInSet	Choice	Brand	Size	Storage	Ram	Battery	Price
1	1	1	1	iPad	sz7inch	st32gb	r4gb	b7h	499
1	1	2	0	Surface	sz10inch	st64gb	r2gb	b9h	399
1	1	3	0	Kindle	sz9inch	st16gb	r2gb	b8h	499

```
kable(head(predict(model,data),1))
```

	alternative 1	alternative 2	alternative 3
Predicted share	0.3717263	0.4405521	0.1877216

Hit Rate: Choice Prediction Accuracy

Confusion Matrix and Statistics

	Reference		
Prediction	1	2	3
1	362	158	130
2	164	449	149
3	136	160	347
Tot	662	767	626

Total number of observations is 2055 (=15 tasks*137 consumers)

Hit Rate=(362+449+347)/2055
=56.4% > 33.3%

vs. 33.3% random prediction

Conjoint Simulator

What is the impact of a 2GB RAM upgrade on Galaxy market share?

Hypothetical market scenario

Brand	Size	Storage	Ram	Battery	Price	Predicted.Share
iPad	sz7inch	st64gb	r2gb	b8h	399	0.3423928
Galaxy	sz10inch	st32gb	r2gb	b7h	299	0.2540301
Surface	sz10inch	st64gb	r1gb	b7h	399	0.1313854
Kindle	sz7inch	st32gb	r1gb	b9h	169	0.2721917

Suppose Galaxy improves its RAM by 2 GB

Brand	Size	Storage	Ram	Battery	Price	Updated Predicted.Share
iPad	sz7inch	st64gb	r2gb	b8h	399	0.3127768
Galaxy	sz10inch	st32gb	r4gb	b7h	299	0.3185544
Surface	sz10inch	st64gb	r1gb	b7h	399	0.1200209
Kindle	sz7inch	st32gb	r1gb	b9h	169	0.2486479

Utility Exchange Rate

1/.005088

- A $1 increase in price leads to a utility decrease by 0.005088 “utiles”

- Thus each “utile” is worth $196.54 (= $1/0.005088)

What is the Brand Value of iPad Relative to Galaxy?

$$\beta_{iPad} - \beta_{Galaxy} \approx 0.6401$$

iPad Value=0.6401*$196.54
= $125.80

$

An average consumer would be indifferent between getting a Galaxy tablet vs. paying $125.80 more and getting an iPad.

Similar techniques are often used in litigation, e.g., Samsung vs. Apple: http://www.greenbookblog.org/2014/05/01/how-apple-samsung-and-conjoint-came-together/

```
# brand equity - dollar value of an upgrade from Galaxy to iPad
-(coef(model)['BrandiPad']-coef(model)['BrandGalaxy']) / coef(model)['Price']
```

```
## BrandiPad
##  125.7944
```

Willingness to Pay for an Attribute Upgrade

$$\beta_{4gbRAM} \approx 0.6357$$
$$\beta_{1gbRAM} = 0$$

4GB Ram

iPad Value=0.6357*$196.54
= $124.94

An average consumer would be willing to pay up to $124.94 to upgrade from 1gb to 4gb RAM, holding all other attributes fixed

```
# dollar value of an upgrade from 1gb to 4gb ram
-coef(model)['Ramr4gb'] / coef(model)['Price']
```

```
##  Ramr4gb
## 124.9299
```

Conclusion

- Choice modeling is quite pervasive in marketing research
  - Used to understand all kind of consumer decisions
- Quite useful for
  - Segmentation, targeting and positioning
  - Marketing mix decisions
    - Pricing, product design, communication, churn management