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Managing Customer Dynamics

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Learning Objectives

- **Understand why an effective marketing strategy must manage customer dynamics**

- **Critically explain the main approaches for managing customer dynamics**
  – Dynamic customer segmentation approach
  – Customer lifetime value approach

- **Use the analytical tools:**
  – Choice model
  – Customer lifetime value

Customer Dynamics

- **Change in the customer’s preferences over time**

- **Customer’s desires/needs for most products and services change over time or due to specific events**
  - Individual consumer needs change (age, experience, and due to trigger events)
  - Customers are embedded in industries/markets, which change overtime (PCs 20 years ago and now)

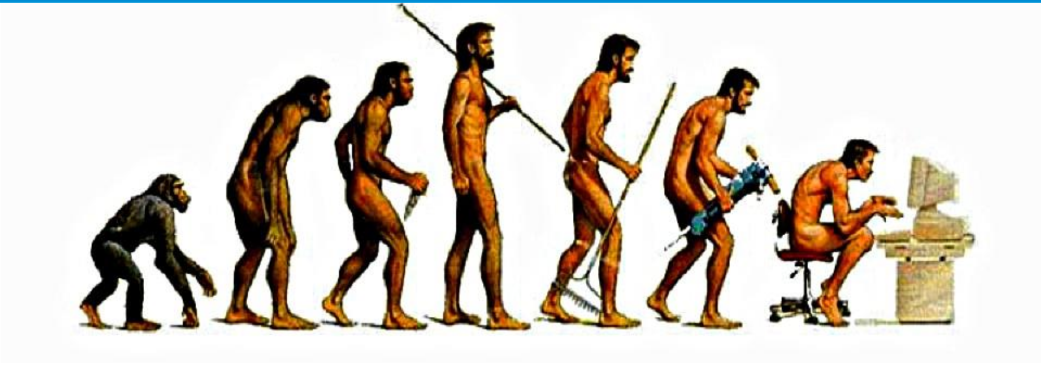
- **Customer's needs vary not only due to inherent differences in people (heterogeneity) but also as people and markets change (dynamics)**

- **Thus, we need to adapt our “static” segmentation of all customers based on “generic” needs by focusing on our existing customers and accounting for their time dependent needs.**

Customer Dynamics

- **Thus, customer dynamics is a fundamental "problem" that all firms must address when developing an effective marketing strategy**
- **Customers change; failure to understand and address these dynamics will lead to poor business performance**

Marketing principle #2: all customers change and an effective marketing strategy must manage customer dynamics



Approaches for Managing Customer Dynamics

Slow	**Speed of Response**	Fast
All Customers	**Size of Segment Managed**	Niche Segment

Lifecycle Approach

Uses generic customer stages of growth and their position in the lifecycle to determine customer preferences and associated strategies.

- Customer lifecycle
- Product lifecycle
- Industry lifecycle

Pros	Cons
Simplicity	Assumes all customers follow one curve
Ease of use	Averages all customers
	Ignores causes of customer dynamics

Dynamic Customer Segmentation

Segments a firm's existing customers on the basis of their similar acquisition, expansion and retention stages.

- A **choice model** can perform analysis across all AER stages, because it predicts the likelihood of observed customers choices

Pros	Cons
Combines lifecycle and segmentation methods	Segments are not perfectly homogeneous
Matches strategic marketing thinking	Puts continuous change into discrete stages
Identifies temporally homogeneous groups	

Customer Lifetime Value

Captures the contribution of customers according to their expected migration path over the entire lifetime with the firm.

- **CLV analysis** uses discounted cash flows, and provides all information to make optimal AER decisions.

Pros	Cons
Provides insights for AER decisions	Requires insight into future migration
Supports a customer-centric culture	Requires detailed financial data
Captures dynamics and heterogeneity	

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Managing Customer Dynamics I
Choice Model

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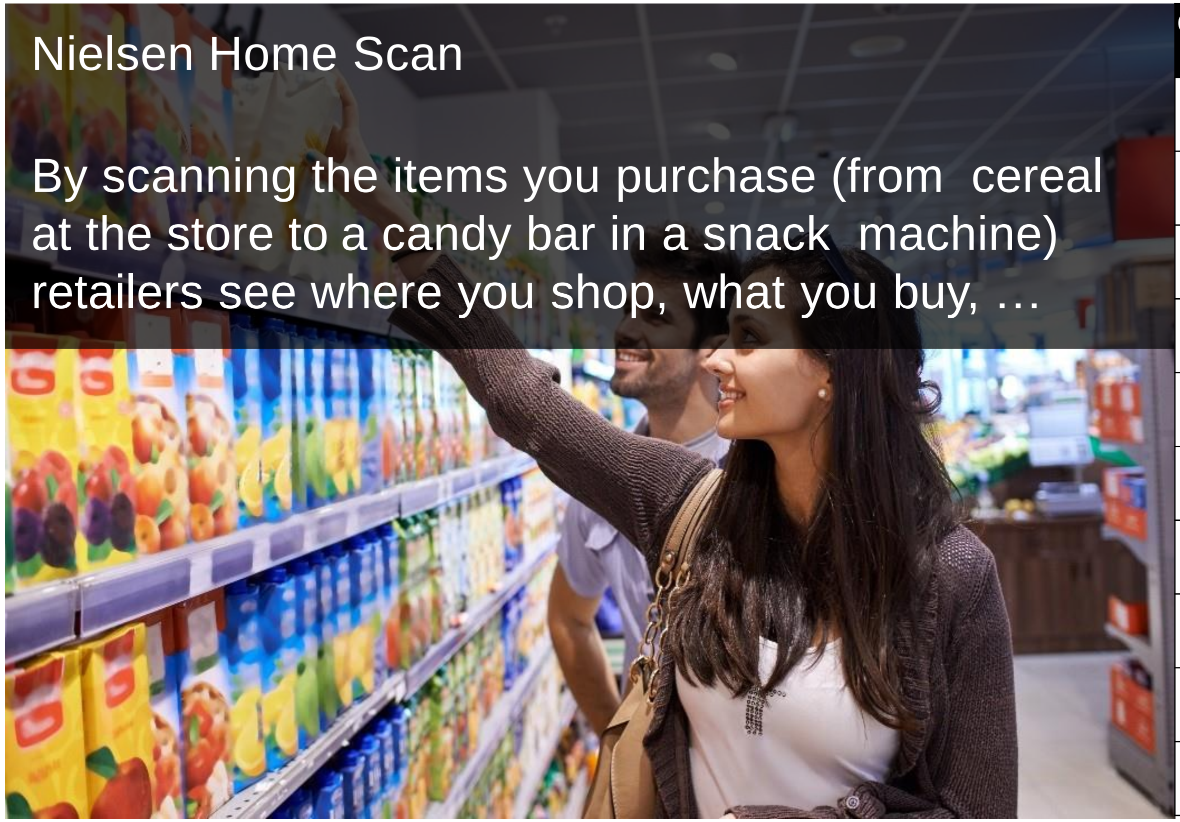
Example

Brand	Hilton
Location	10 minutes ride to destination
Restaurant	Restaurant within walking distance
Gym	No gym
Wireless	Wireless Internet connection throughout the hotel
Rewards	Earn Standard Rewards Points
Room Rate	$200
Choice	**Yes or No**

Example

Nielsen Home Scan

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, …



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

Choice Model

- **A choice model attempts to determine the impact of different factors (price, promotion) on consumer's individual choices (joining, cross buying, leaving). It is the most popular individual-level response model.**
- **Input:**
  - Use database of past marketing actions and demographics linked to actual customer responses (choices) in a stage.
  - Uses past behavioral data; no need to survey or get customer input (infers weights from past customer's behaviors)
- **Output**
  - Coefficient estimates for every input variable on outcome (e.g., how does age, kids, credit, and direct mail impact choice)
  - Probabilities of customer's choice (probability of upselling, retaining, and can run on lists for acquisition targeting)

Choice Model

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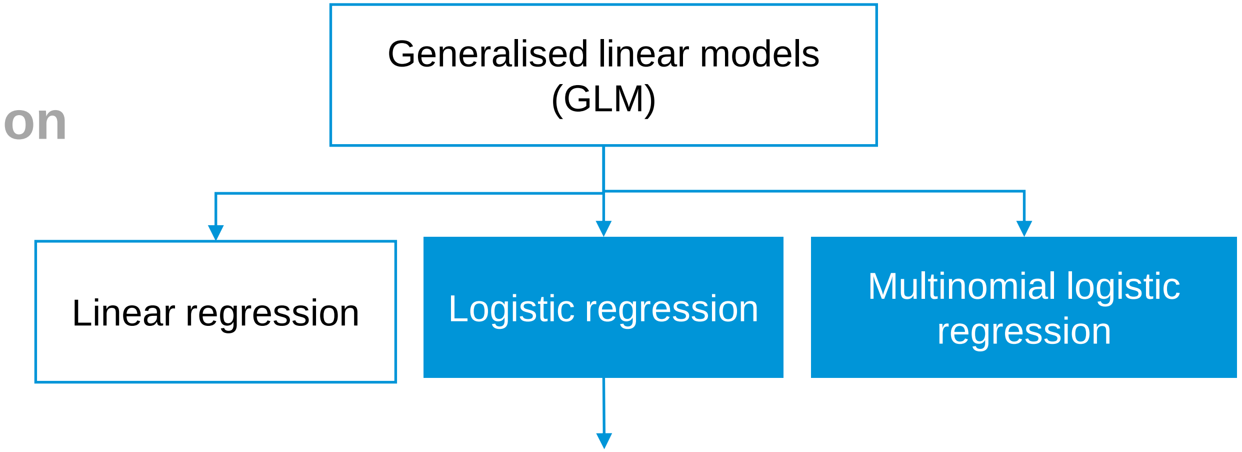
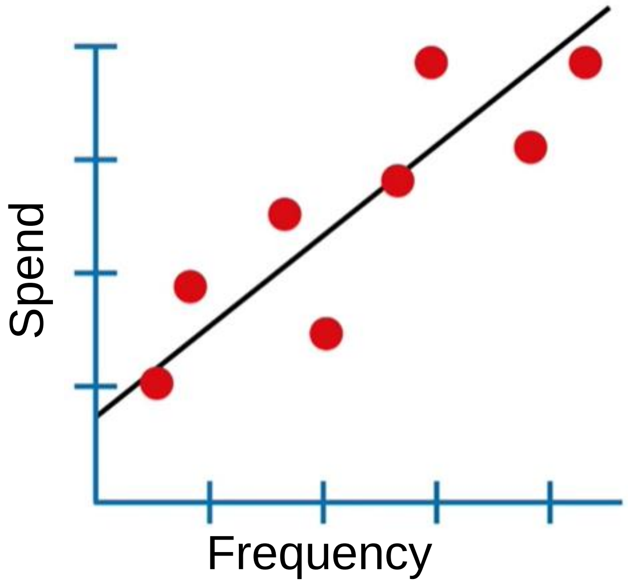
- **Binary choice: logistic regression**
- Multiple choice: multinomial logistic regression



- Response to marketing efforts
  - Did the customer buy after being sent a coupon or an email ad?
- Online/Catalogue purchase (Buy/No-Buy)
  - Recency, Frequency, Monetary value (RFM) measures as predictors of purchase.

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

A Quick Look at Linear Regression



Spend = β_1Frequency + β_0

The line slope: the effect of frequency on money spend.
The intercept: the money spend when frequency is 0.

Linear regression uses the data to estimate β_1 and β_0
Spend = 0.5 Frequency + 0.6

Then using this regression model, we can predict the money spend given a frequency.

Logistic Regression

If one customer has an 80% probability of purchase, then what are the customer's odds of purchase?

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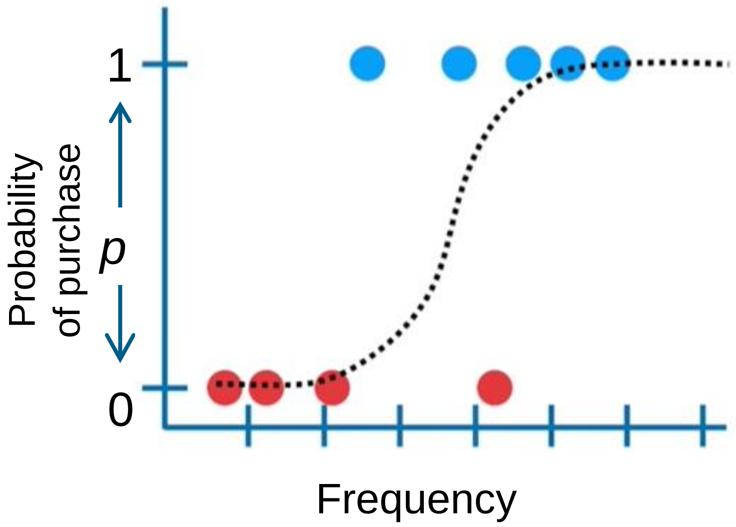
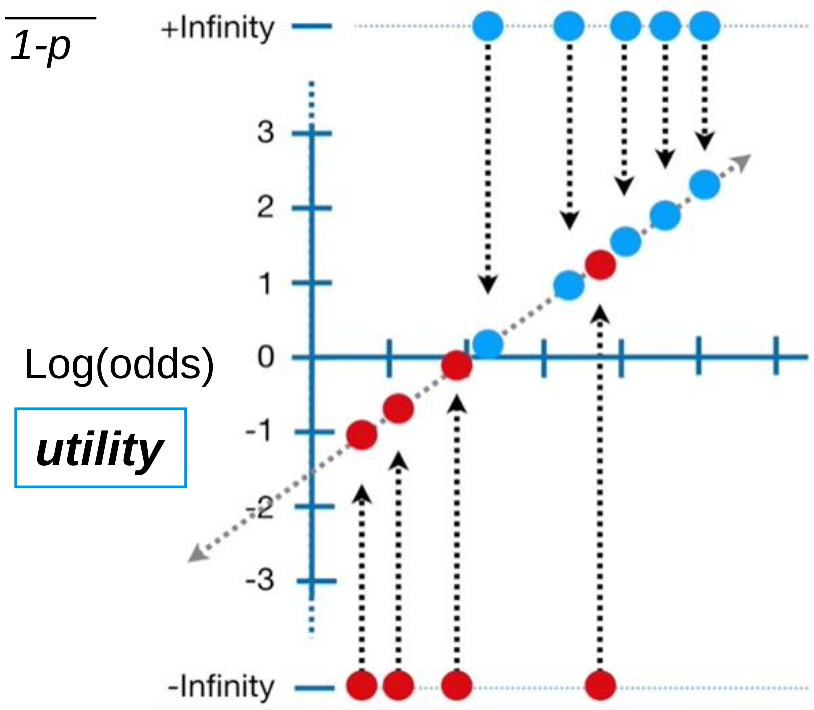
$$\text{odds} = \frac{\text{Probability of purchase}}{\text{Probability of no-purchase}} = \frac{p}{1-p}$$



$$\log\left(\frac{p}{1-p}\right) = \log(\text{odds})$$

$$p = \frac{e^{\log(odds)}}{1 + e^{\log(odds)}}$$

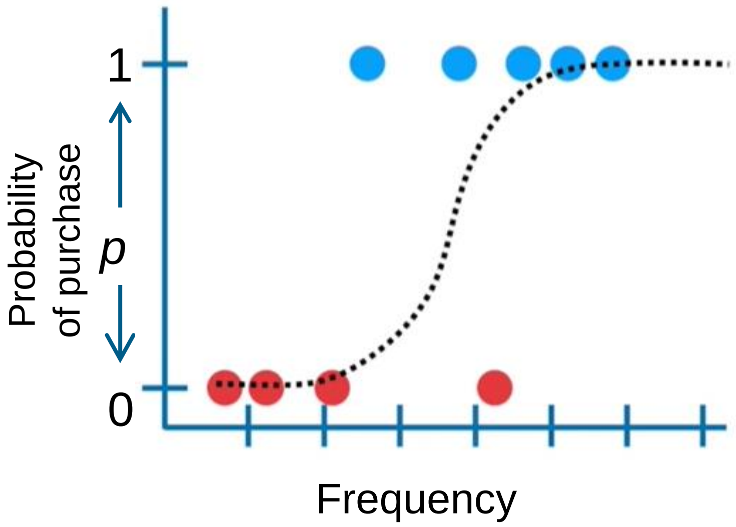


$$p = \beta_1 \text{ frequency} + \beta_0$$

$$\textbf{Log(odds)} = \beta_1 \text{ frequency} + \beta_0$$

The slope is the effect of frequency on log(odds), i.e. utility

Logistic Regression

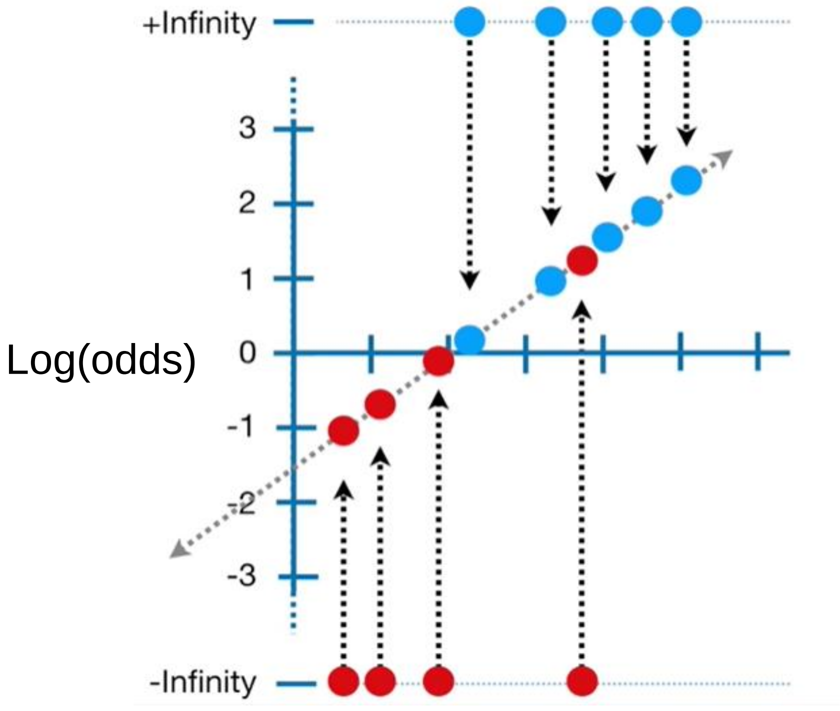


Logit: qlogis()

$$\log\left(\frac{p}{1-p}\right) = \log(\text{odds})$$

$$p = \frac{e^{\log(odds)}}{1 + e^{\log(odds)}}$$

Logistic: plogis( )



$p = \beta_1 \, frequency + \beta_0$

$\textbf{Log(odds)} = \beta_1 \, frequency + \beta_0$

Odds and Choice Probability

- Utility:

$$\mathbf{V_b = log(} \frac{p}{1-p} \mathbf{)}$$

Logit: qlogis()

- Odds

$$\mathbf{odds = exp(V_b) =} \frac{p}{1-p}$$

- Probability

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

Logistic: plogis( )

- Given the utility from buying $V_b = 2$, what are the followings values (note: e = 2.718):
  - Utility from not buying: $V_n = 0$
  - Odds of buying: $\exp(2) = e^2 = 7.39$
  - Odds of not buying: $\exp(0) = 1$
  - Probability of buying:

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

Utility

- **The model states that a consumer has a utility 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 $V_b > V_n=0$

- **For RFM data, the utility of buying varies across customers as a Function of RFM variables**
  - $V_b = \beta_0 + \beta_1 \text{Recency} + \beta_2 \text{Frequency} + \beta_3 \text{Monetary}$

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

Example: Catalogue Data

- **Dependent Variable**
  - Purchase (Yes/No)
- **Explanatory Variables**
  - Recency – how many days since last purchase
  - Frequency – how many times the consumer buys
  - Monetary Value – Total $ amount spent

	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

Logistic Regression Output

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Likelihood ratio test

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

P-value
Significance-level

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 (e.g., Frequency) on utility.**

Should be less than 0.05

Logistic Regression Output:
Interpretation of Exp(beta)

odds

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

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

Predicting Purchase Probabilities

- **Estimated utility function in RFM data:**

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

- **Predicting purchase probability:** $p = \dfrac{\exp(V)}{\exp(V)+1}$

	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

Lift Calculation

- **Impact of Increasing Monetary Value by $1 on Purchase Probability**

- **Compute new utility of purchase**

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

- **Compute new probability of purchase** $$p_{new} = \frac{\exp(V_{new})}{\exp(V_{new}) + 1}$$

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

Lift Calculation

	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

Avg. base probability=0.45 Avg. new probability=0.45789

- Lift=(0.45789-0.45)/0.45=1.75%

Classification

- **All people with probability less ½ → No purchase**
- **All people with probability above ½ → Purchase**

	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
         0 51  2
         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
```

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

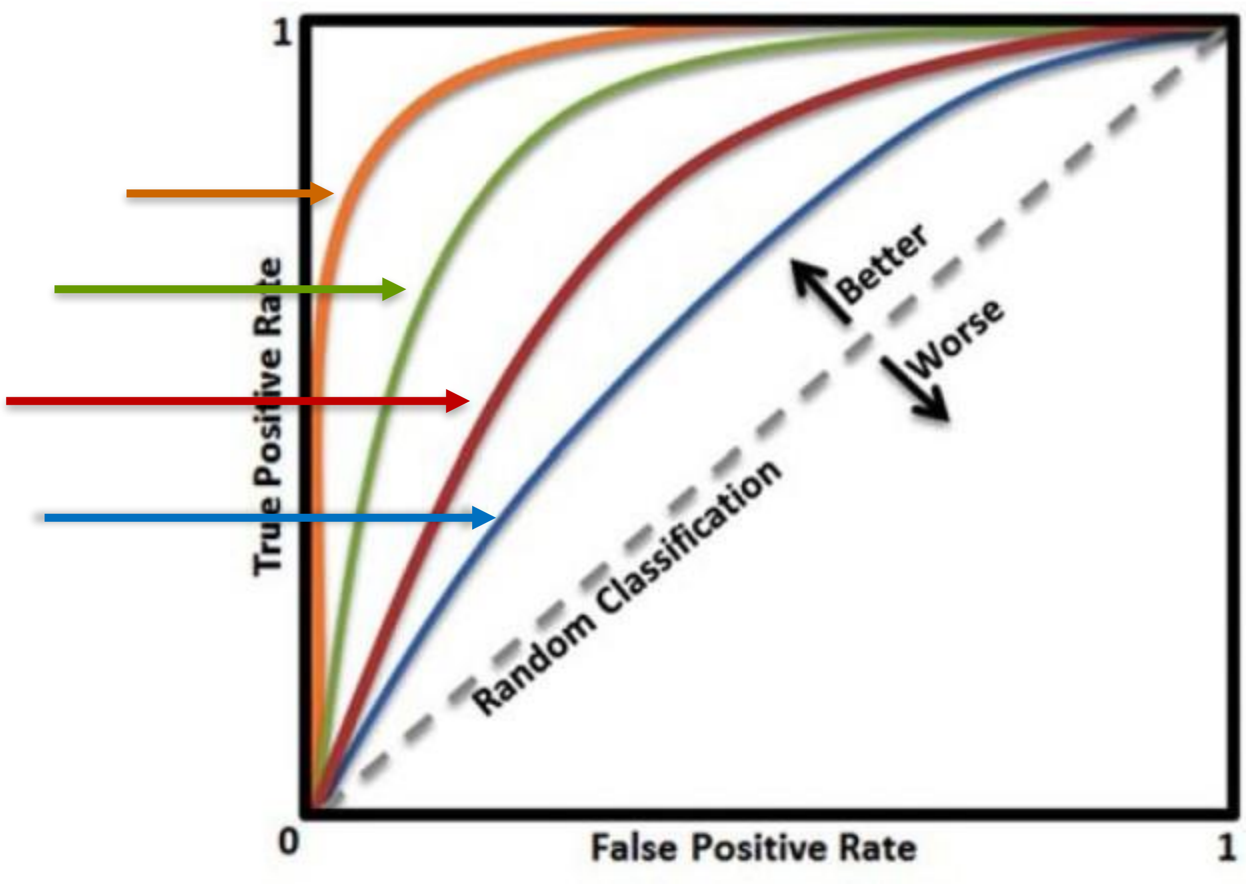
Sensitivity: True positive rate=43/(43+2)=96%

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

False positive rate =1-93%=7%

ROC (Receiver Operating Characteristic) Curve

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



Dynamic Segmentation

- **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)

Takeaway

- **A choice model is a mathematical model that predicts how the likelihood of an observed customer choice, is influenced by a firm's marketing.**
- **Choice modelling is quite pervasive in marketing research**
  - Used to understand all kind of consumer decisions
- **Two popular methods for choice analysis**
  - Logistic regression for binary choice
  - Multinomial logistic model for more than two alternatives in the choice set

Workshop

- **RFM Analysis**