Class 14: Hyper-Personalization – Next-Product-to-Buy Models

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MKTG 482: Customer Analytics
Kellogg School of Management

Customer Analytics Course Structure

Customer Centric Marketing
- Customer Analytics and AI Overview (Class 1)
  AI and Analytics,
  Why Customer Analytics and AI Needs Customer Centricity

Getting Ready for Analytics
- Using R for Customer Analytics and AI (Class 2)
- Statistics Review (Class 3)

Targeting Customers for Acquisition and Development
- Predicting Response with RFM analysis (Class 4)
- Case Analysis: “Tuango: RFM Analysis for Mobile App Push Messaging” (Class 5)
  Lift and Gains
- Predicting Response with Logistic Regression (Class 6)
- Predicting Response with Neural Networks (Class 7)
- Using Neural Networks for Customer Analytics and AI (Class 8)
  Training Machine Learning Models
- Case Analysis: Intuit QuickBooks Upgrade: Moving to the Cloud (Class 9)
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- Hyper-Personalization: Next-Product-to-Buy Models (Class 14)

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- Predicting Attrition (Class 15)
- Linking Analytics with a Business Outcomes Model (Class 16)
- Case Analysis: “S-Mobile: Churn Management” (Class 17)
  From Prediction to Action

Selecting the Right Offers
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- Case Analysis: “Capital One: Information-Based Credit Card Design” (Class 19)

Scaling Analytics
- Scaling Analytics in Practice (Class 20)
  Course Wrap-up

So far we have been interested in the response to a given product offering

COMPARISON OF QUESTIONS

- Given a certain product we want to offer, which customer is the most likely to positively respond to the offer?
  - Prospecting
  - "Simple" add-on/cross-selling
  - Up-selling
- Given that we would like to target a certain customer, which product is the most likely to lead to a positive response (or maximize profits)?
  - Add-on/cross-selling

"Next Product To Buy" Model (NPTB)

NPTB models rely on a different economic trade-off than response models

COST-REWARD TRADE-OFF COMPARISON

Response model	NPTB Model
- Contribution from sale of product	- Profit from offer of product 1
- Cost of marketing	- Opportunity cost of offering products 1, i.e. the profit from selling prod 2,3, etc. instead

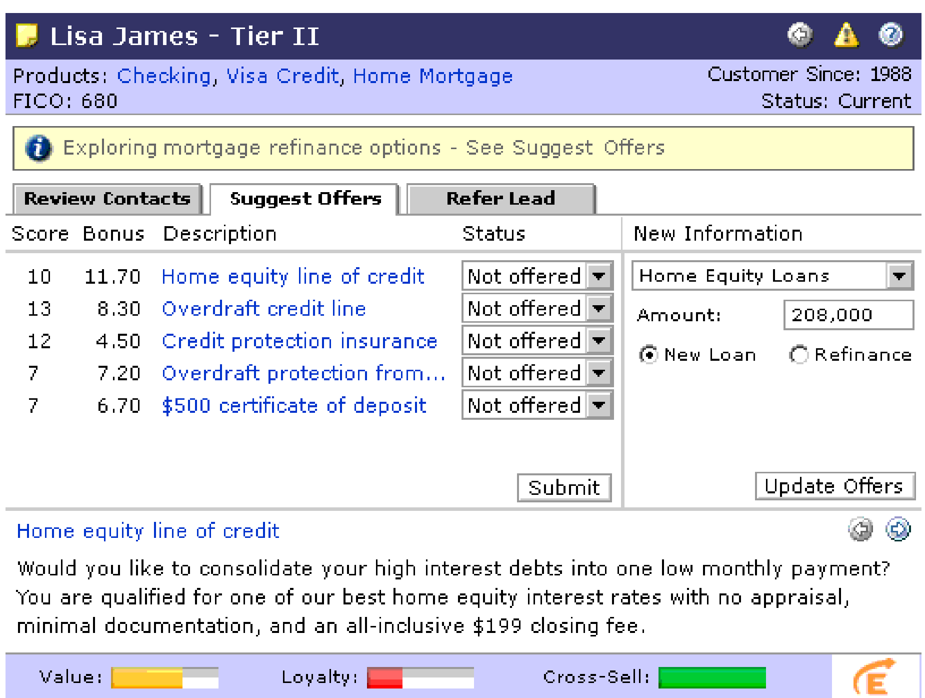
Model of choice when marketing costs are not the "limiting resource"

NPTB models have many applications

APPLICATIONS

- Banks:
  - Which financial product to offer next?
- Call centers:
  - Which additional product to offer during an inbound call?
- eRetailers:
  - Which product to promote in a weekly e-mail
  - Which product recommendation to offer on the home page
  - Hyper-personalization
- B2B:
  - Which product to push in the next sales call
- ...

BANKING CROSS-SELL EXAMPLE (EPIPHANY):



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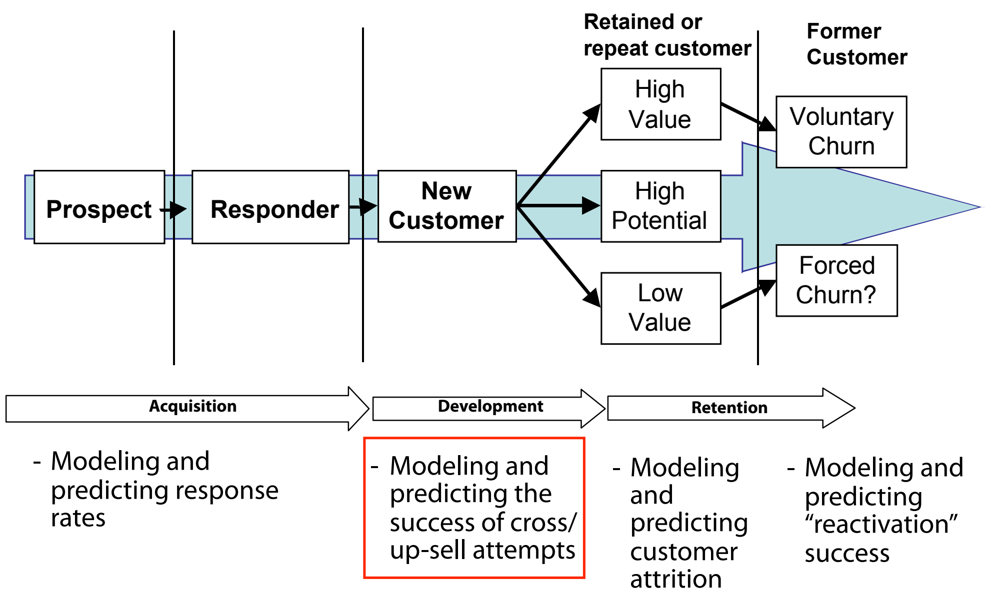
APPLICATIONS OF PREDICTIVE TECHNIQUES



To decide on a NPTB model we need to first determine our setting

APPLICATIONS OF NPTB MODELS

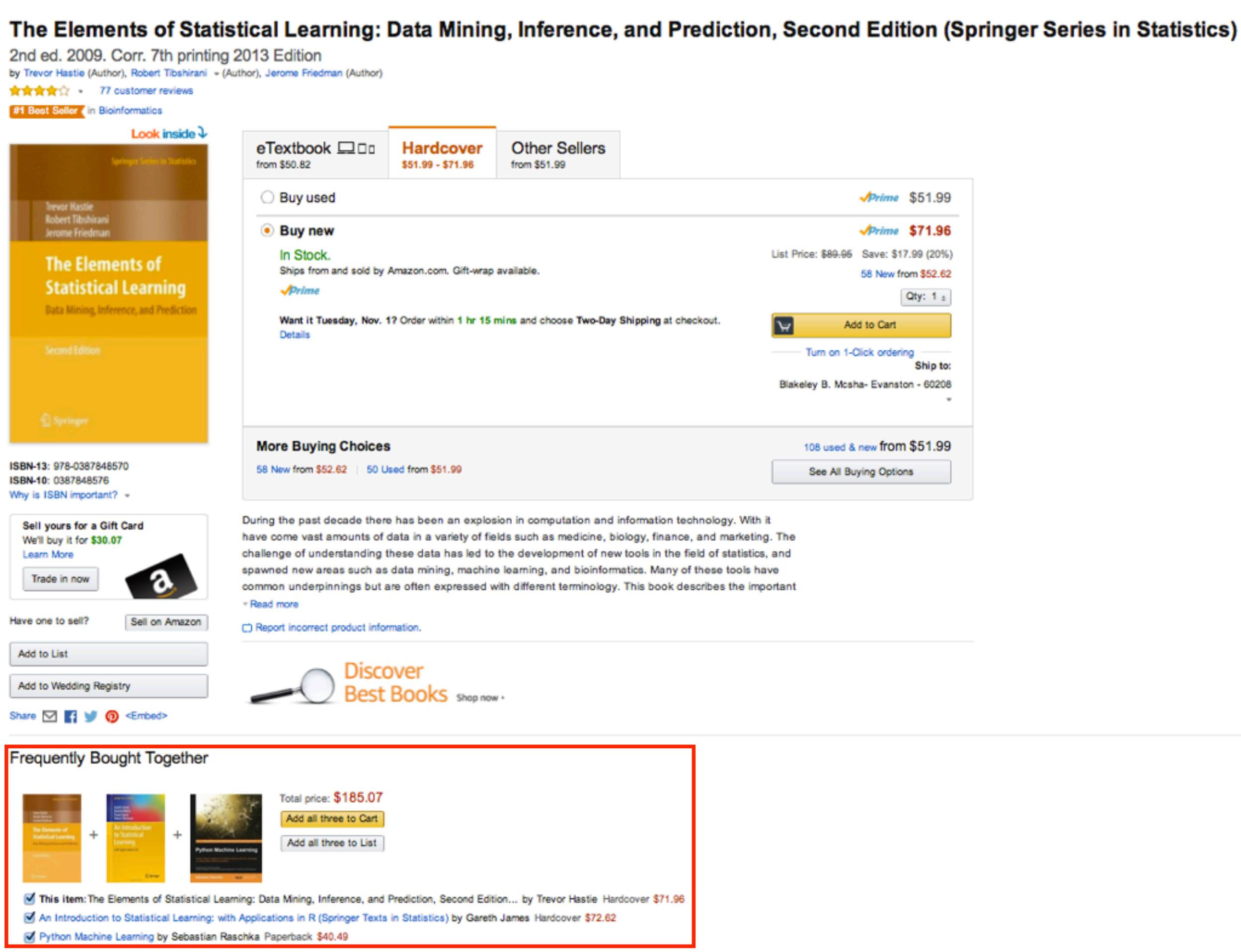
What is the scope of the prediction?

Situational:

"If a consumer is <u>currently</u> considering product X, what product Y should we offer?"

General:

"Considering a consumers <u>entire purchase history</u>, what is the next product we should offer than consumer?"



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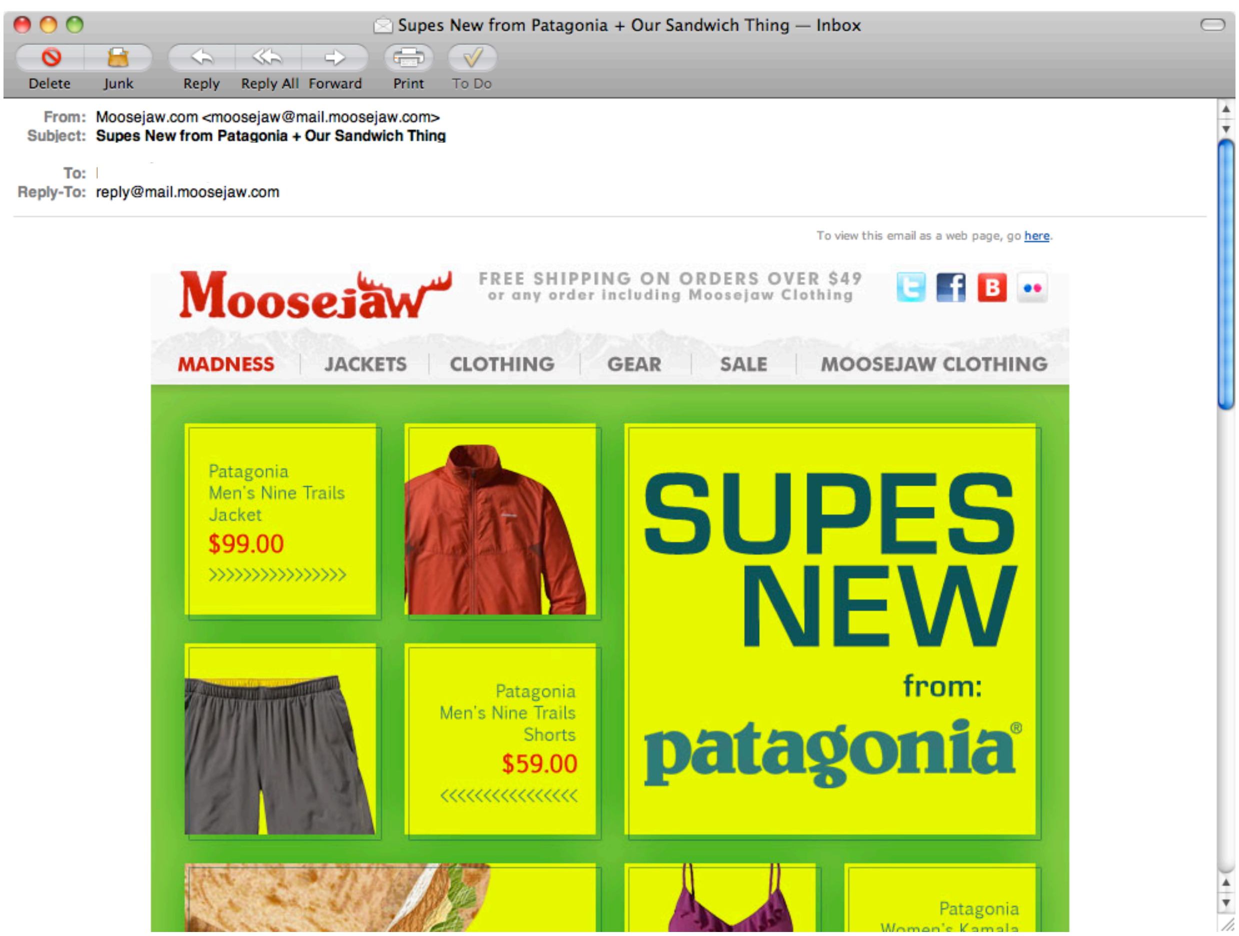

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amazon.com

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"Considering a consumers <u>entire purchase history</u>, what is the next product we should offer than consumer?"

TARGET

Moosejaw

The most common method for generating situational NPTB recommendations is a "Market Basket Analysis" (MBA)

MARKET BASKET ANALYSIS

Basket ID	Purchases
1	pizza, soda
2	milk, cleaner
3	soda, pizza, detergent
4	pizza, detergent
5	cleaner, soda
6	pizza, cleaner, soda
7	pizza, soda
8	cleaner, detergent
9	soda, pizza

basket	cleaner	deter-gent	milk	pizza	soda
1	0	0	0	1	1
2	1	0	1	0	0
3	0	1	0	1	1
4	0	1	0	1	0
5	1	0	0	0	1
6	1	0	0	1	1
7	0	0	0	1	1
8	1	1	0	0	0
9	0	0	0	1	1

Goal: Implement a rule "If buy/consider product A then offer product B"

For each pair of products we calculate four key measures

MARKET BASKET ANALYSIS

1. How statistically strong is the correlation between buying product A and product B?

   p-value from cross-tab of A vs. B

2. How practically strong is this correlation: how much more likely are consumers to buy product B when purchasing product A than they are likely to buy product B overall?

$$\text{Lift/Improvement} = \frac{Prob(B|A)}{Prob(B)} = \frac{(\frac{\text{\# of baskets with A and B}}{\text{\# of baskets with A}})}{(\frac{\text{\# of baskets with B}}{\text{\# of baskets}})}$$

3. How likely is product B purchased once consumers purchase product A?

$$\text{Confidence} = Prob(B|A) = \frac{\text{\# of baskets with A and B}}{\text{\# of baskets with A}}$$

4. How likely is this rule to apply?

$$\text{Support} = Prob(A) = \frac{\text{\# of baskets with A}}{\text{\# of baskets}}$$

The four measures suggest whether to use a rule and if so, what rule to use

IMPLEMENTING RULES IN MBA

Goal: Implement a rule "If buy/consider product A then offer product B "

- A sufficiently small p-value (and if relevant, sufficiently high "Support") are typically used to pre-screen rules
- If "Improvement" and "Confidence" are "high enough," then implement rule.
- If multiple rules pass the hurdle (if A then B, if A then C),
  - Recommend multiple products to buy next (e.g., Amazon recommends 2)
  - Recommend product B rather than product C if

$$Prob(B|A) * \text{Profit B} > Prob(C|A) * \text{Profit C}$$

There are various other considerations when using MBA

CONSIDERATION IN MARKET BASKED ANALYSIS (1)

At which level do we describe products?

- At **high-level** (few products), rules are not actionable.
  - "If buy a CD, recommend a book"
  - with exceptions ... "If buy a bike, recommend a helmet"

- At **low-level** (many products), computational cost is very high and rules have very low confidence (and significance levels).
  - Product B is rarely bought with product A
  - Example: 5/16 inch impact drill bits are rarely purchased with 1/2x40 inch galvanized water pipes

$$\text{Confidence} = Prob(B|A) = \frac{\#\text{ of baskets with A and B}}{\#\text{ of baskets with A}}$$

There are various other considerations when using MBA

CONSIDERATION IN MARKET BASKED ANALYSIS (2)

- Market Basket Analysis can be easily extended to more complicated condition clauses
  - If A1 and A2 then B –> form a super-product that is A1 and A2 = A1*A2
  - If A not bought then B –> form an anti-product "anti-A"=1-A
  - If A bought, then not B –> form an anti-product "anti-B"=1-B

basket	cleaner	detergent	milk	pizza	soda	cl_det	anti_det	anti_soda
1	0	0	0	1	1	0	1	0
2	1	0	1	0	0	0	1	1
3	0	1	0	1	1	0	0	0
4	0	1	0	1	0	0	0	1
5	1	0	0	0	1	0	1	0
6	1	0	0	1	1	0	1	0
7	0	0	0	1	1	0	1	0
8	1	1	0	0	0	1	0	1
9	0	0	0	1	1	0	1	0

There are various other considerations when using MBA

CONSIDERATION IN MARKET BASKED ANALYSIS (3)

The data generating process differs from the prediction setting

- RFM/Logistic:
  - Offer first sent to a randomly selected sample
  - Based on observed responses, we use RFM/Logistic to predict response rate of the other customers outside of the sample
  - The same offer is than sent to those people with high response rates
- Market Basket Analysis
  - There is no data collected under the environment with recommendations
  - We use available market data to predict what would happen if we started to recommend
  - The assumption is that the behavioral reason for consuming A and B together does not change due to the recommendation

  --> **Needs testing and adjusting**

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amazon.com

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TARGET.
Moosejaw

How about using a Market Basket Analysis?

USING MBA WITH FULL PURCHASE HISTORIES

- Market Basket Analysis makes recommendations looking at only one purchase (or look) at a time
  - **“If customer has purchased/looked at product A then offer customer product B”**
- How do we make recommendations based on a collection of purchases?
- Need:
  - **“If customer has purchased products A1, A2, A3, then offer customer product B”**
- Need to have observed enough people who purchased products A1, A2, A3, and B

One key approach is to do Market Basket Analysis on each product separately and combine recommendations

AMAZON’S APPROACH (PATENT 6,266,649)

- Key idea: Reduce a multi-product problem into a sequence of pairwise problems
- Define **similarity** between two product as:

$$s_{A,B} = \frac{n_{A,B}}{\sqrt{n_A * n_B}}$$

$$n_{A,B} = 10, n_A = 100, n_B = 100 \Rightarrow s_{A,B} = 0.1$$
$$n_{A,B} = 20, n_A = 25, n_B = 25 \Rightarrow s_{A,B} = 0.8$$
$$n_{A,B} = 20, n_A = 20, n_B = 20 \Rightarrow s_{A,B} = 1$$

  - $n_{A,B}$ is number of times products A and B are purchased together
  - n_A is total number of times product A is purchased; similar for n_B
- Suppose Bob has purchased product A, B, C, and D previously.
- Place product E on a “short-list” if the similarity between E and any of product A, B, C, and D is sufficiently high. Repeat for products F, G, H, etc.
- Sort products on the short list by the highest similarity score an item has with any of the items in the purchase history
- Combine and sort short lists

Consider an example that uses this approach

EXAMPLE OF MBA WITH FULL PURCHASE HISTORIES

- Customer has purchased photo products in the past
- Digital photography department wants to make e-mail/website offer for camera accessory

Purchase history	Potential accessories
• Canon S95 digital camera • 4 GB SD card • Nikon D80 digital SLR camera	• Eye-Fi Wifi SD card • Lens cleaning kit • Camera case (universal) • Battery (S95) • External flash • Lens cap • Book: "Understanding Close-ups"

Consider an example that uses this approach

SIMILARITY RATINGS $s_{A,B}$ AND SHORT LISTS

Canon S95 digital camera		4 GB SD card		Nikon D80 digital SLR camera	
Eye-Fi Wifi SD card	**0.03**	Eye-Fi Wifi SD card	0.00	**Eye-Fi Wifi SD card**	**0.06**
Lens cleaning kit	0.001	Lens cleaning kit	0.00	**Lens cleaning kit**	**0.21**
Camera case (universal)	**0.12**	**Camera case (universal)**	**0.05**	Camera case (universal)	0.004
Battery (S95)	**0.08**	**Battery (S95)**	**0.03**	Battery (S95)	0.00
External flash	0.00	External flash	0.00	**External flash**	**0.14**
Lens cap	0.00	Lens cap	0.02	Lens cap	0.00
"Understanding Close-ups"	0.02	"Understanding Close-ups"	0.01	"Understanding Close-ups"	0.02

COMBINED SHORT LISTS

Eye-Fi Wifi SD card	0.03, **0.06**
Lens cleaning kit	**0.21**
Camera case (universal)	**0.12**, 0.05
Battery (S95)	**0.08**, 0.03
External flash	**0.14**

SORTED FINAL LIST

Lens cleaning kit	**0.21**
External flash	**0.14**
Camera case (universal)	**0.12**
Battery (S95)	**0.08**
Eye-Fi Wifi SD card	**0.06**

This version of Market Basket Analysis uses only data on basket IDs, products, and (in this version) customer IDs

DATA USED FOR MBA

Basket ID	Product ID	Customer ID
1	Nikon D80	10045
1	Eye-Fi SD	10045
1	Lens Cap	10045
2	Canon A80	38930
2	Battery (A80)	38930
3	External Flash	10045
4	Canon S95	98543
4	4GB SD	98543
4	Cam. Case	98543
5	Lens Cleaning Kit	38930

There is often much more purchase-related information available

TYPICALLY AVAILABLE PURCHASE-RELATED DATA

			Transaction Details			Buyer Details		
Basket ID	Product ID	Customer ID	Time	Price	Other...	Age	Income	Other...
1	Nikon D80	10045	3/23/2007	$784	Searched	34	50-60K	10+ reviews
1	Eye-Fi SD	10045	3/23/2007	$49	Promotion	34	50-60K	10+ reviews
1	Lens Cap	10045	3/23/2007	$18	Front page	34	50-60K	10+ reviews
2	Canon A80	38930	10/4/2008	$199	...	23	10-20K	4 returns
2	Battery (A80)	38930	10/4/2008	$46	...	23	10-20K	4 returns
3	External Flash	10045	12/1/2010	$110	...	52	40-50K	...
4	Canon S95	98543	1/13/2011	$399	...	65	90-100K	...
4	4GB SD	98543	1/13/2011	$24	...	65	90-100K	...
4	Cam. Case	98543	1/13/2011	$35	...	65	90-100K	...
5	Lens Cleaning Kit	38930	2/2/2011	$5	...	23	10-20K	...

We can better exploit purchase data by building a model that relates current choices to rich descriptions of past behavior

DATA REQUIREMENTS FOR RICHER NPTB MODEL

		t-4	t-3	t-2	t-1	t
Customer 10045:	Buyer descriptors	A		A	B	A
Customer 38930:	Buyer descriptors					
Customer 10045:	Buyer descriptors	A	D			B
Customer 98543:	Buyer descriptors	C		C	D	D
Customer ... :	...	B	B			
Customer ... :	...					
Customer ... :	...					
Customer ... :	...	A		D		C

Time

(Summary variables are fine!)

Independent Variables **Dep. Variables**

Can we use logistic regression?

CHARACTERISTICS OF LOGISTIC REGRESSION

- Great flexibility on independent variables
- Expresses probabilities of choice
- Easy to interpret

but

- Binary dependent variable

=> How can we adapt logistic regression to model NPTB?

We can use a variety of approaches to estimate a richer NPTB model

MODEL ALTERNATIVES FOR NPTB MODEL

- Binary Logistic Regression with different product offers
  - Different consumers are offered different products
  - Predict for each consumer the probability of choosing each product
  - Used in Pentathlon Part III e-mail customization case
- Multinomial Logistic Regression (and Nested Logistic Regression)
  - Like logistic regression but dependent variable is the chosen product (J values)
- Machine Learning
  - Like binary NN and RF but dependent variable is the chosen product (J values)

Let's look at an example of a cross/upselling model using a binary logistic regression

BBB NEXT-PRODUCT-TO-BUY EXAMPLE

- Stan Lawton (marketing director) prepares for **hyper-personalization** and the NPTB problem!
- Sends out one of three offers to 10,000 consumers each:
  - Offering in the art category: "The Art History of Florence."
  - Offering in the do-it-yourself category: "Painting Like a Pro."
  - Offering in the cooking category: "Vegetarian Cooking for Everyone."
- Profit varies between books:
  - "The Art History of Florence" --> $6
  - "Painting Like a Pro" --> $4
  - "Vegetarian Cooking for Everyone" --> $7
- Cost of making the offer is irrelevant (e-mail marketing)
- Assume: Consumers can't buy unless they get an offer
- **Key problem: Which book offer is the best match for each customer?**

R Demo

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