Session Detail Information

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Cluster : Contributed Session

Session Information : Friday Jun 13, 15:30 - 17:00

Title: Predictive Modeling-Methods

Chair: Makoto Abe,Professor, The University of Tokyo, Graduate School of Economics, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-0033, Japan, abe@e.u-tokyo.ac.jp

Abstract Details

Title: Semi-supervised Learning for Response Modeling

Presenting Author: Sungzoon Cho,Professor, Department of Industrial Engineering, Seoul National University, San 56-1, Shillim-dong, Kwanak-gu, Seoul, Korea, Republic of, zoon@snu.ac.kr

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Hyunjung Shin,Professor, Department of Industrial and Systems Engineering, Ajou University, San 5, Wonchon-dong, Youngtong-gu, Suwon, Korea, Republic of, shin@ajou.ac.kr

Abstract: Response modeling is concerned with targeting customers who are likely to purchase a promoted product or service based on customers' data. A well developed response model can increase profitability while reducing marketing costs. Modeling is usually carried out in a supervised learning framework where only those customer data labeled from the past campaign are used. A response model would predict labels of other customers who are not labeled. One disadvantage of this approach is that only a small percentage of customer data is labeled, thus available for modeling. A semi-supervised learning framework has recently been proposed to improve classification performance by exploiting unlabeled as well as labeled data in modeling based on an intuitive assumption: similar attributes lead to similar labels. In order to address this issue, we propose to use semi-supervised learning approaches for response modeling where a large number of unlabeled data are available. In particular, the multiple graph algorithm fits well to response modeling where customer data come from qualitatively different sources. Through experiments on the CoIL Challenge 2000 dataset, it is shown that the algorithm results in a better model than conventional supervised algorithms in terms of a variety of performance measures. Semi-supervised learning is a viable option and merits further investigation.

Title: Contextual Determinants of the Predictive Accuracy of Binary Prediction Models

Presenting Author: **Bas Donkers**,School of Economics, Erasmus University Rotterdam, PO Box 1738, Rotterdam -, Netherlands, donkers@few.eur.nl

Co-Author: **Aur?ie Lemmens**,Assistant Professor, School of Economics, Erasmus University Rotterdam, P.O. Box 1738, Rotterdam ZH, Netherlands, lemmens@few.eur.nl
Peter C. Verhoef,Professor of Marketing, University of Groningen, P.O. Box 800, Groningen GR NL-9700 AV, Netherlands, P.C.Verhoef@rug.nl

Abstract: Previous research has investigated what models perform well in specific prediction tasks, including customer churn, CLV, etc. Recently, Lemmens et al. (2006) proposed bagging and in particular boosting as attractive alternatives to the frequently used logit model to predict customer defection in the US telecommunication industry. They advocate the advantages of these aggregation methods in presence of large datasets that contain a high number of predictors. However, further research is needed to investigate whether the high predictive power of these approaches can generalize to other settings. This paper therefore asks the question: What conditions affect the predictive performance of the various approaches to model binary choices? and What model should managers prefer under specific conditions? We compare four approaches, bagging, boosting, logit and latent class logit models. To investigate the determinants of predictive accuracy, we generate many datasets with varying characteristics, such as, among others, sample size, asymmetry of the distribution of 0/1, inclusion of irrelevant variables, nonlinearity of the relationship. The predictive performance is then investigated through a validation sample, using as performance criteria the hit-rate, the gini coefficient and the top-decile lift. We find that bagging does not live up to expectations, but that the other three approaches all have their merits. The non-parametric nature of bagging and boosting, relative to the logit models, proves beneficial for nonlinear relationships, while it hurts performance the more variables are included. We illustrate the findings from the simulation study using a number of real-life marketing datasets that differ in the dimensions identified as influential in the simulation study.

Title: Optimizing the Value of Incentives for New Customers

Presenting Author: **Jeanette Heiligenthal**,University of Frankfurt, Mertonstra? 17, Frankfurt 60054, Germany, heiligen@wiwi.uni-frankfurt.de

Co-Author: **Bernd Skiera**,Professor Dr., University of Frankfurt, Faculty of Business and Economics, Mertonst. 17-25, Frankfurt HE, Germany, skiera@wiwi.uni-frankfurt.de

Abstract: Firms often use very appealing incentives to attract new customers. Newspapers, for example, use reduced prices for the first year of subscription, sometimes even in combination with additional gifts. Thereby, firms need to determine the amount of incentives which they would like to provide. Very small incentives lead only to a limited number of (most likely) loyal customers, whereas high incentives lead to a high number of customers. Yet, those customers are likely to suffer from "adverse selection" because they tend to be rather non-loyal as they are primarily attracted by the incentive and not by the product itself. Hence, the value of the incentive has two effects: it determines the number of customers as well as the average customer lifetime value, which means that an optimal value for the incentive exists. Despite the importance of this problem, research on that problem is rare. Only Cao/Gruca (2005) deal with adverse selection in the credit approval process and present an approach for selecting customers for a cross-selling campaign based on response and approval likelihoods. Yet, they do not focus on the optimal value of possible incentives. Therefore, we address in our paper the problem of how to determine the optimal value of the incentive for new customers. We develop a model and use an empirical data-set from a major European Bank to illustrate the application of the model and to calculate a possible increase in long-term profitability. Based on those results we derive managerial implications for customer acquisition activities under adverse selection.

Title: Counting your Customers?One by One: A Hierarchical Bayes Extension to the Pareto/NBD Model

Presenting Author: **Makoto Abe**,Professor, The University of Tokyo, Graduate School of Economics, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-0033, Japan, abe@e.u-tokyo.ac.jp

Abstract: This research extends a Pareto/NBD model of customer-base analysis using a hierarchical Bayesian (HB) framework to suit today갽s customized marketing. The proposed HB model presumes three tried and tested assumptions of Pareto/NBD models: (1) a Poisson purchase process, (2) a memoryless dropout process (i.e., constant hazard rate), and (3) heterogeneity across customers, while relaxing the independence assumption of the purchase and dropout rates and incorporating customer characteristics as covariates. The model also provides useful output for CRM, such as a customer-specific lifetime and survival rate, as by-products of the MCMC estimation. Using three different types of databases --- music CD for e-commerce, FSP data for a department store and a music CD chain, the HB model is compared against the benchmark Pareto/NBD model. The study demonstrates that recency-frequency data, in conjunction with customer behavior and characteristics, can provide important insights into direct marketing issues, such as the demographic profile of best customers and whether long-life customers spend more.

Semi-Supervised Learning for Response Modeling

Hyoung-joo Lee	University of Oxford
Hyunjung Shin	Ajou University
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Sungzoon Cho*	Seoul National University
Douglas MacLachlan	University of Washington

INFORMS Marketing Science Conference

13 June 2008

Response Modeling

Objective

Identifying a subset of likely responders to an offer

In the subset, an accurate response model include

- Many responders (Profit opportunities)
- Few non-responders (Marketing cost)

Empirical approaches

Statistical models

- Logistic regression, Discriminant analysis, etc.

Machine learning

- CBR, DT, K-NN, MLP, SVM, etc.

Supervised Learning

Supervised Learning for Response Modeling

Labels obtained from a preliminary campaign

Training a model based on the labeled customer data

Predicting the labels of the unlabeled (test) customer

Problems of Supervised Learning

Labeled data come only from actual campaigns

Only a small part of data are labeled

Unable to utilize the unlabeled data

Semi-supervised Learning

Motivation

To make use of unlabeled data

“Cluster” or “Smoothness” assumption

- Data with similar attributes lead to similar labels

Useful when …

- Labeled data are difficult to collect
- Unlabeled data are readily available or relatively easy to collect

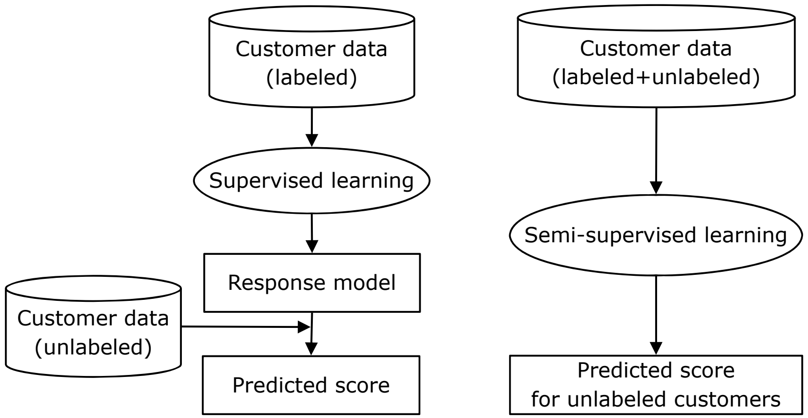
Semi-supervised Learning for Response Modeling

Predicting the labels of the unlabeled (test) customer

By considering the relationship between customers

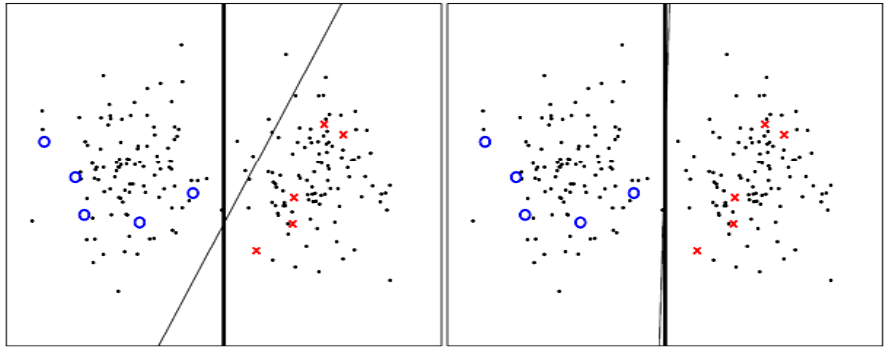
Semi-supervised Learning

Supervised learning / **Semi-supervised learning**



Semi-supervised Learning

Supervised learning / **Semi-supervised learning**



In This Presentation

Semi-supervised Learning for Response Modeling

To exploit the information of unlabeled customer data

Graph-based semi-supervised learning

- Single graph algorithm
- Multiple graph algorithm

Case Study: CoIL2000 Challenge Data Set

Supervised learning algorithms

- Logistic regression
- K-nearest neighbors (K-NN)
- Support vector machine (SVM)

Semi-supervised learning algorithms

- Single graph algorithm
- Multiple graph algorithm

Graph-based Learning

Graph Representation

Each customer: Each vertex

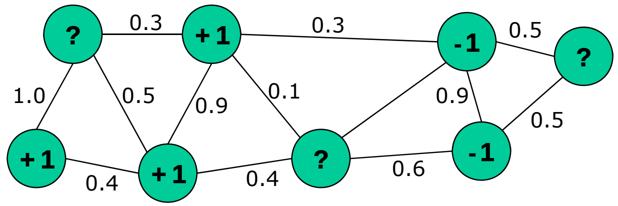
A similarity between customers: A weight of an edge

Labels: +1 / -1 / ? (unlabeled)

Vector → Graph Representation

RBF kernel for K-NN customers $w_{ij} = \exp(-\frac{\|\mathbf{x}_i-\mathbf{x}_j\|^2}{2\sigma^2})$

Similarity matrix "W"



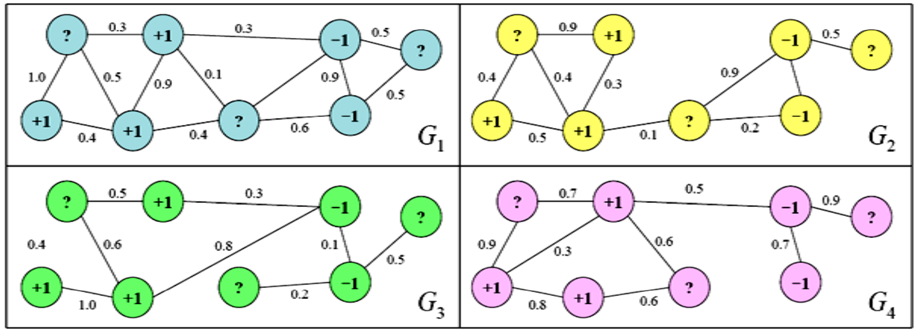
Graph-based Learning

Multiple Graph Learning

Multiple sources of data → Multiple graphs

Ex) Demographic, RFM, customer care, billing, etc.

Learning by integrating multiple graphs



Graph-based Learning

Outline of Graph-based Learning

Graph representation

- Transforming vector data into the graph representation
- Labeling vertices (+1 / -1 / ?)

Predicting the labels of unlabeled vertices

- By exploiting the graph structure of both labeled and unlabeled nodes
- Convex optimization

Single and multiple graph algorithm

- Single graph algorithm
- Multiple graph algorithm (multiple graphs available)

Single Graph Algorithm

Trade-off coefficient

$$\min \underbrace{\boxed{\sum_{i}^{n_L} (\hat{y}_i - y_i)^2}}_{\text{Loss function}} + C \underbrace{\boxed{\sum_{i,j=1}^{n} w_{ij} (\hat{y}_i - \hat{y}_j)^2}}_{\text{Smoothness}}$$

$$\Rightarrow \min_{\hat{\mathbf{y}}} (\hat{\mathbf{y}} - \mathbf{y})^\top (\hat{\mathbf{y}} - \mathbf{y}) + C \hat{\mathbf{y}}^\top \mathbf{L} \hat{\mathbf{y}}$$

L: graph Laplacian matrix

$$\Rightarrow \hat{\mathbf{y}} = (\mathbf{I} + C\mathbf{L})^{-1} \mathbf{y}$$

Multiple Graph Algorithm

Primal

$$\min_{\hat{\mathbf{y}}, \gamma} (\hat{\mathbf{y}} - \mathbf{y})^\top (\hat{\mathbf{y}} - \mathbf{y}) + C\gamma,$$

$$\text{subject to } \hat{\mathbf{y}}^\top \mathbf{L}_m \hat{\mathbf{y}} \leq \gamma, \quad m = 1, \ldots, M$$

Dual

$$\min_{\boldsymbol{\alpha}} d(\boldsymbol{\alpha}) \equiv \mathbf{y}^\top (\mathbf{I} + \sum_{m=1}^{M} \alpha_m \mathbf{L}_m)^{-1} \mathbf{y}$$

$$\text{subject to } \sum_{m=1}^{M} \alpha_m = C$$

Solution $\hat{\mathbf{y}} = (\mathbf{I} + \sum_{m=1}^{M} \alpha_m \mathbf{L}_m)^{-1} \mathbf{y}$

Dual solution:
a weight of an individual graph

Case Study: CoIL2000 Challenge

Data Set

An insurance company case

Response modeling for caravan insurance policies

Training / Test: 5,822 / 4,000

86 variables: demographic, frequency, monetary

Preprocessing

Binary encoding for categorical variables

Graph representation

- Single graph based on all variables
- 3 graphs based on each source: demographic, frequency, monetary

30 random splits of training/test sets

Case Study: CoIL2000 Challenge

Response Models

Supervised learning (parameters)

- Logistic regression (none)
- K-NN (the number of neighbors, K)
- SVM (the kernel width, σ & the trade-off coefficient, C)

Semi-supervised learning (parameters)

- Single graph algorithm (K, σ, C)
- Multiple graph algorithm (K, σ, C)

Parameter selection

- The number of actual respondents among top 800 prospects

Case Study: CoIL2000 Challenge

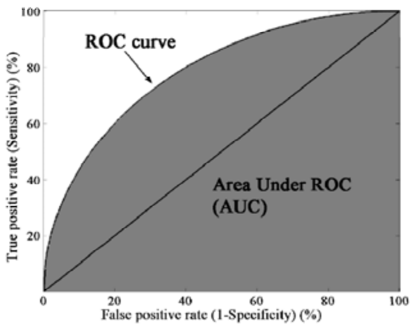
Performance Evaluation Criteria

The number of actual respondents among top 800 prospects

Lift chart

ROC chart

Area under ROC



Case Study: CoIL2000 Challenge

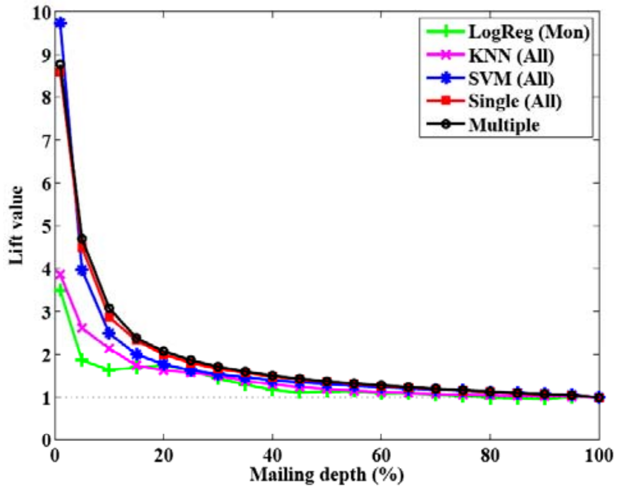
Top 800 Prospects

Data source	All	Demo	Freq	Mon	Ensemble
LogReg	52.80	66.43	46.70	75.53	65.37
K-NN	75.00	41.65	61.49	47.71	63.07
SVM	76.50 [3]	61.37	44.63	65.67	69.20
Single	84.97 [2]	73.57	52.17	59.43	-
Multiple	-	-	-	-	88.27 [1]

The best with α=0.10

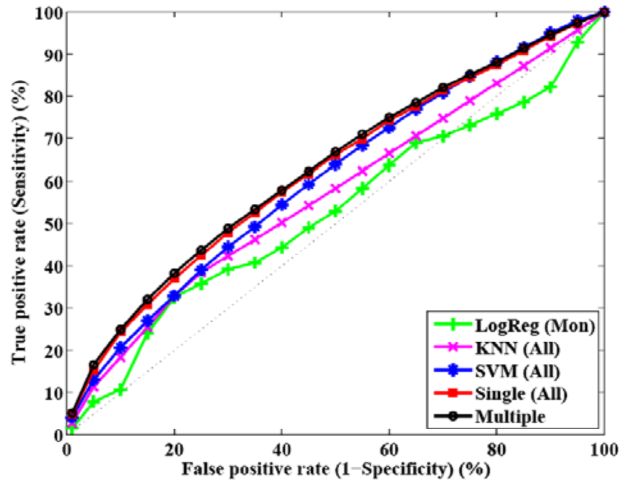
Case Study: CoIL2000 Challenge

Lift Chart



Case Study: CoIL2000 Challenge

ROC Chart



Case Study: CoIL2000 Challenge

Area under ROC

Data source	All	Demo	Freq	Mon	Ensemble
LogReg	49.08	56.90	52.67	54.63	53.76
K-NN	57.00	47.94	49.63	53.17	53.52
SVM	60.61 [3]	57.75	57.23	50.67	59.12
Single	62.29 [2]	58.34	48.98	33.86	-
Multiple	-	-	-	-	63.02 [1]

The best with α=0.10

Conclusion

Semi-supervised Learning for Response Modeling

To exploit information of the unlabeled customers

Graph-based learning

- Graph representation of data
- Convex optimization
- Single graph algorithm
- Multiple graph algorithm to deal with various sources of information

Case study on CoIL Challenge 2000 data set

- 3 sources → 3 graphs
- Comparison with supervised learning algorithm
- Semi-supervised learning outperform supervised learning

Semi-supervised learning should be considered as a viable option for response modeling where a large number of unlabeled data are available

Future Research Directions

Computational Complexity

Missing Not At Random (MNAR)

Voluntary Response

Other Semi-supervised Learning Algorithms

Class Imbalance

Feature Selection

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- Conference Overview
- Conference Registration
- Call for Papers
- Abstract Submission
- Schedule at-a-glance
- Conference Program
- Conference Venue
- Sponsors

Conference Overview

The Sauder School of Business of The University of British Columbia will host the 2008 INFORMS Marketing Science Conference to be held from Thursday, June 12 to Saturday, June 14, 2008 at the Sheraton Wall Centre Hotel in Vancouver, British Columbia, Canada. This event brings academics, practitioners and policymakers from around the world together in one of the world's most beautiful cities to present, hear, and discuss new research in a broad range of marketing science topics.

Conference Organizing Committee is composed of the Marketing faculty of the Sauder School of Business:

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Darren Dahl (co-chair)
Dan Putler (co-chair)
Jack Chen
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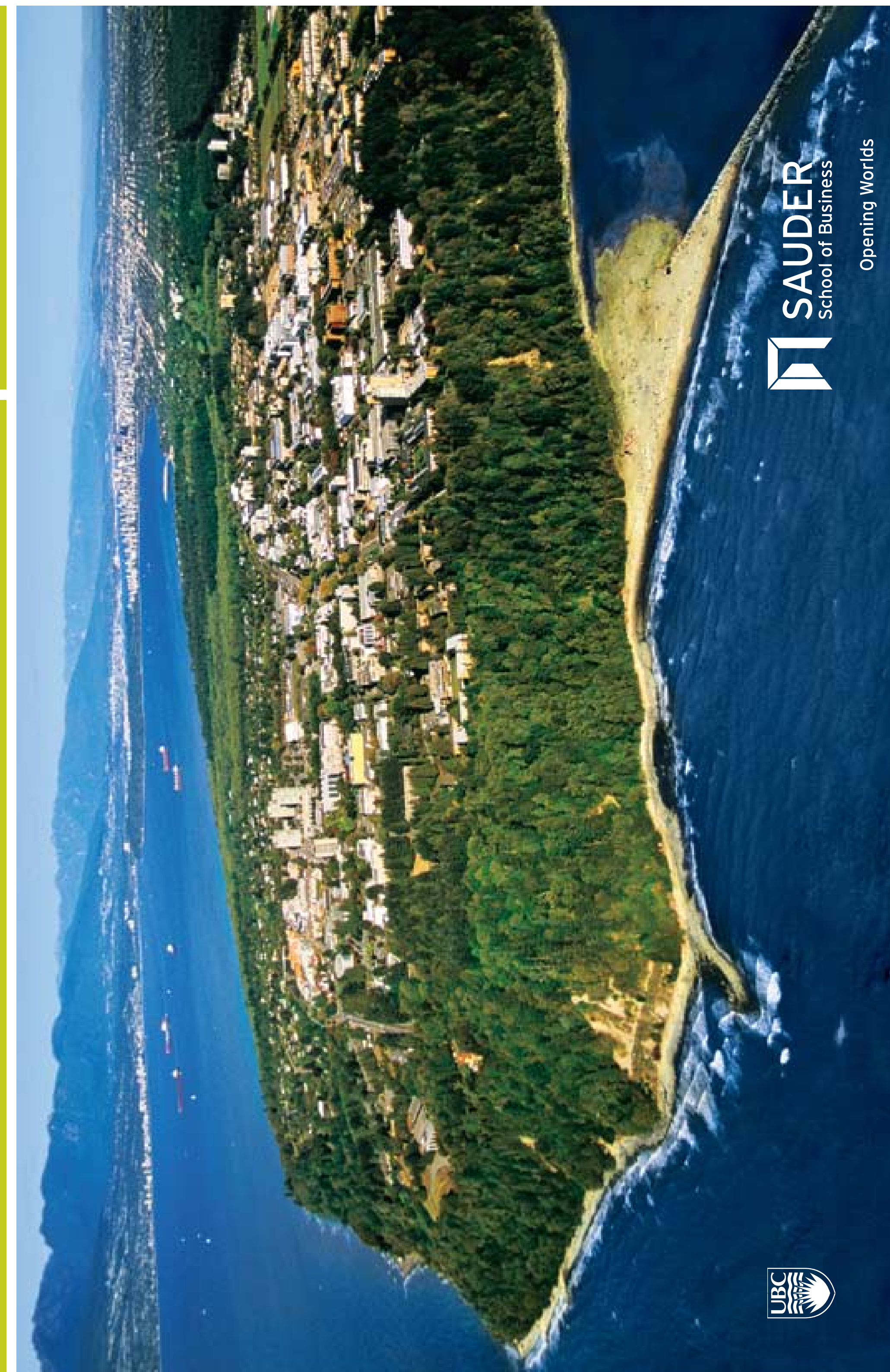

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2008 INFORMS Marketing Science Conference

Day	Room ➔	Junior D	Junior C	Grand D (Pavil D-Fri)	Port Alberni	Grand C (Pavil C-Fri)	Grand B (Pavil B-Fri)	Grand A (Pavil A-Fri)	Port Hardy	Junior B	Junior A	Port McNeill	Parksville	Orca	Finback	Granville	Galiano
	Track ➔	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
THURSDAY	10AM - 6:30PM	REGISTRATION															
THURSDAY	TA 1-2:30PM	Empirical Analysis of Online Auctions	Expanding Frontiers of Diffusion Research	Loyalty Programs	New Approach. Word-of-Mouth	Issues in New Product Adoption	Modeling Movie Box-Office	Brand Choice & Market Structure	Reference Points, Timing & Concession	Models of Customer Churn	Modeling Dynamic Market Competit.	Sales Manage-ment I	Price Eval., WTP & Pricing Options	Issues in Branding	Theoret. Models of Advertis. & Promo.	Internatio-nal Marketing Issues	Direct Marketing & Targeting
THURSDAY	2:30-3PM	BREAK															
THURSDAY	TB 3-4:30PM	Static & Dynamic Equilib-rium Models	Marketing & Financial Performance I	Bidding Behavior in B2B & B2C Online Auctions	Word-of-Mouth in Online Environ-ments	New Product Diffusion – Applica-tions	Entertain-ment Demand	Applied Choice Models	Self-Prediction, Control & Need Satisfaction	CRM-Customiza-tion & Customer Portfolio	Issues in Competi-tion Modeling	Sales Manage-ment II	Willingness to Pay Measure-ment	Brand Strategy	Issues in Advertis-ing	Best Practices Effective Global Marketing	Multi-Product Marketing
THURSDAY	TC 4:45-6:15PM	Dynamic Structural Models	Financial Market's Reaction to Marketing	Private Labels	Social Influence & Self-Construal in Consu-mption	New Product Diffusion - Cross Country Studies	Movie Marketing	Choice – Methods & Data	Mood, Brand Familiarity & Decision Frames	CRM-System Implemen-tation	Dynamic Aspects of Competi-tion	eComm – Multi-Channel	Bundling & Pricing	Branding	Advertis-ing Strategy	Marketing Strategy & Firm Performan.	Retail Manage-ment
THURSDAY	6:30-8PM	WELCOME RECEPTION															
FRIDAY	7AM-5PM	REGISTRATION															
FRIDAY	7:30-8:30AM	BREAKFAST															
FRIDAY	FA 8:30-10AM	Search Engines & Marketing I	Service Marketing	Marketing Meets Design	Influences on Purchase	Managing New Product Intro.	Word-of-Mouth in Movie Marketing	Choice – Statistical Methods	Consumer Decision Making	Dynamic Effects in Predictive Modeling	Channel Competi-tion	eComm – Recomm-endation Systems	Factors Influencing Price Perception	Branding Issues	Adverti-sing Issues	Org. Theory Issues in Marketing	Retail Category Manage-ment
FRIDAY	10-10:30AM	BREAK															
FRIDAY	FB 10:30-12PM	Online Customi-zation	Variance Components in Choice Experiments	Special Session on Marketing & Health	Network Effects & Social Influence	New Product Forecasting	DVD & Entertain-ment Media Marketing	Choice – Marketing Mix Response	Influences Consumer Choice Process	Customer Lifetime & Wallet-share	Strategic Alliances	eComm – The Long Tail Effect	Pricing	Factors Infl. Brand Equity & Image	New Media Adverti-sing	Market Orientation, Cus. Loyal. & Competit.	Location Issues in Retailing
FRIDAY	12-1:30PM	LUNCH															
FRIDAY	FC 1:30-3PM	Adverti-sing by "Words"	Sales Force Design & Compensa-tion Strategy	Managerial Decision Making	Social Networks & Market Efficiency	Emerging Issues in Software & Tech. Mkts	Pharmaceu-tical Marketing	Choice - Applications	Craving & Justification in Hedonic Consump.	Predictive Modeling – Applica-tions	Pricing Competi-tion	eComm – Online Info Search	Price Perception	Brand Measure. & Manage-ment	Adverti-sing & Sponsor-ship	Financial Markets & Marketing	Retail Store Choice & Competit.
FRIDAY	3-3:30PM	BREAK															
FRIDAY	FD 3:30-5PM	Search Engines & Marketing Science	Frontiers in Marketing Channels	Alternative Preference Measure-ments	Network Externali-ties & Self-Selection	Organiza-tional Dynamics & Innovation	Health Marketing	Multiattribute Models	Importance Culture & Ethnicity in Consumer Behavior	Predictive Modeling – Methods	Time Series Market Analysis	eComm – Consum-er Choice & Learning	Price Promos & Price Discrimina-tion	Brand Identity, Persona-lity & Extensions	Adverti-sing & Market Competi-tion	Strategy & Consumer Behavior	Retail Store Environ-ment
FRIDAY	6-7PM	RECEPTION															
FRIDAY	7-10PM	GALA DINNER															
SATURDAY	7AM-4PM	REGISTRATION															
SATURDAY	7:30-8:30AM	BREAKFAST															
SATURDAY	SA 8:30-10AM	Social Networks & Marketing I	Price Rigidity	Social & Cause Marketing	Consum-er Response to Promos.	New Product Design & the Design Process	Structural Equation Modeling	Structural Econometric Models of Consumer Choice	Consumer Perception: Packaging, Stimuli & Haptics	Customer Lifetime Value	Channel Manage-ment	Blog-Research	Understand-ing & Improving Customer Satisfaction	Brand Equity	Measuring Adverti-sing Effective-ness		
SATURDAY	10-10:30AM	BREAK															
SATURDAY	SB 10:30-12PM	Social Networks & Marketing II	Words Matter	Marketing & Public Policy: Public Interest	Models of Sales Promotion	Commer-cializing Innovations & Launch. New Prod.	Bayesian Method-ology	Conjoint Analysis Methods	Assessing Risk & Ambiguity Aversion	Product Manage-ment	Channels & Customer Choice	Customer Relation. in a Multi-channel Environ.	Issues in Customer Satisfaction Research	Brand Equity & Corporate Citizenship	Adverti-sing Pricing		
SATURDAY	12-1:30PM	LUNCH															
SATURDAY	SC 1:30-3PM	Social Networks & Marketing III	Marketing Engineering – Integrating Data Mining Tools	Marketing Science Beyond Business	Service Organiza-tion Manage-ment	New Product Develop. – Product Design	Statistical Method-ology	Market Segmenta-tion	Behavioral Choice Models	Product Line Manage-ment	Channel Structure	Issues in B2B Marketing	Customer & Employee Relation-ships in Services	Brand Manage-ment	Consumer Response to Adverti-sing Comm.		
SATURDAY	3-3:30PM	BREAK															
SATURDAY	SD 3:30-5PM	Social Networks & Marketing IV	Gift Giving & Fashion	No Session	Service Evalua-tion	The Role of Network Externali-ties in Diffusion	Methodol-ogy: Data Manage-ment & Collection	Segmenta-tion Research	Models of Consumer Learning	Factors Influencing Product Line Innovative	Altering Channel Relation-ships	Marketing Metrics	B2B Customer Relation-ships	**Meet the Editors:** Thursday, Pavilion D TA17– 1:00- 2:30PM TB17– 3:00- 4:30PM			

Friday, June 13th, 2008 3:30-5:00PM (FD)

FD09 – Junior Ballroom B

Predictive Modeling-Methods

Chair: Makoto Abe

Semi-supervised Learning for Response Modeling
Sungzoon Cho, Hyunjung Shin, Seong-seob Hwang, Douglas MacLachlan, Hyoung-joo Lee

Contextual Determinants of the Predictive Accuracy of Binary Prediction Models
Bas Donkers, Aurélie Lemmens, Peter C. Verhoef

Optimizing the Value of Incentives for New Customers
Jeanette Heiligenthal, Bernd Skiera

Counting your Customers' One by One: A Hierarchical Bayes Extension to the Pareto/NBD Model
Makoto Abe

FD10 – Junior Ballroom A

Time Series Market Analysis

Chair: Hernan Bruno

Structural Dynamics of Competition and its Effects on Long-term Customer Profitability
Jens Keller, Sven Reinecke

Dynamic Customer Management on Duration Time Structure
Geonha Kim, Dae Ryun Chang

The Impact of Pricing on Customer Profitability: Evidence From an Industrial Market
Hernan Bruno, Bruce Hardie, Shantanu Dutta

FD11 – Port McNeill

eCommerce-Consumer Choice and Learning

Chair: Wenzel Drechsler

The Effect of Internet Adoption on Catalog Customers' Buying Behavior
Junzhao Ma, Eric Anderson, Karsten Hansen

The Impact of Internet Adoption on Customer Purchasing Behavior in Direct Marketing
Xiaojing Dong, Kirthi Kalyanam, Pradeep Chintagunta

Does Opening a Physical Store Change Customer Behavior?
Yantao Wang, Eric Anderson, Karsten Hansen

The Impact of Visualizing a Product's Price History at Price Comparison Sites on Consumer Decisions
Wenzel Drechsler, Martin Natter

FD12 – Parksville

Price Promotions and Price Discrimination

Chair: Amit Pazgal

Market Segmentation for Pricing Strategy
Yoshiyuki Okuse

Endogenous vs. Exogenous Wholesale Prices During Instant Rebates
Simon Sigue

Endogenous and Exogenous Determinants of Inter-Category Price Sensitivity- A Spatial Approach
Joy Joseph, Aman Nanda

Innovative Pricing Strategies Under Strategic Consumer Behavior
Amit Pazgal, Yossi Aviv

FD13 – Orca

Questions on Brand Identity, Personality, and Extension

Chair: Robert Kreuzbauer

The Interchangeability of Brand Extensions
Joseph Chang, Bob Wu

Designing Coolness: Brand Building in the Global Fashion Industry
Rajesh Chandy, Om Narasimhan, Paola Cillo, Jaideep Prabhu

Brand Personality: Transference and Preference
Sharon Hodge, Kathryn Olinger

Basic Social Motives of Brand Identity Signaling
Robert Kreuzbauer, Chi-yue Chiu, Vivian Vignoles

FD14 – Finback

Advertising and Market Competition

Chair: Nawel Amrouche

Advertising and Market Structure: A Digital Video Recorder Field Experiment
Carl Mela, Bart Bronnenberg, Jean Pierre Dube

Copycat Advertising and Strategic Theme Release
Chun (Martin) Qiu, Demetrios Vakratsas

Search Advertising
Sridhar Moorthy, Avi Goldfarb

Feedback Stackelberg Equilibrium Strategies When the Private Labels Competes with the National Brand
Nawel Amrouche, Guiomar Martín-Herrán, Georges Zaccour

FD15 – Granville

Strategy and Consumer Behavior

Chair: Wilfred Amaldoss

Unbundling Music: Can Selling Individual Songs Reduce Competitive Intensity Among Music Producers?
Sherif Nasser, Nicholas Economides

Turf Wars: Brand Extension in Markets with Preference Based Segmentation
Yogesh V. Joshi, David Reibstein, John Zhang

Software Piracy in the Presence of Open Source Software
Rajiv Sinha, T.S. Raghu, Fernando Machado

Strategic Implications of Reference Groups: An Experimental Investigation
Wilfred Amaldoss, Sanjay Jain

FD16 – Galiano

Retail Store Environment

Chair: Julien Schmitt

Shelf Layout Effects for Sustainable Products
Erjen van Nierop, Erica van Herpen, Laurens Sloot

Extreme Makeover: Financial and Perceptual Effects of a Remodeled Servicescape Over Time
Bram Foubert, Elisabeth Brüggen, Dwayne Gremler

Investigation of the Impact of Store Layout on Category Sales and Store Profitability
Yu Ma, Minakshi Trivedi, Dinesh Gauri

Associations Between Purchases and In-store Behavior: An Extension of the Market Basket Analysis
Julien Schmitt, Ganael Bascoul