

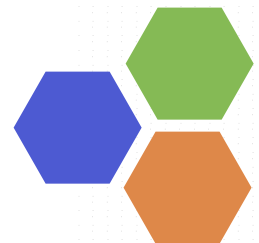
PREDICTING CUSTOMER CHURN

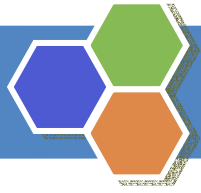


**WHICH CUSTOMER
IS LIKELY TO LEAVE?**



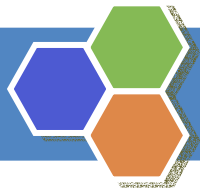
Cecily Rekart
Craig Lowenstein
Crystal Trainor
Ernest Chrappah
Maieka Hansard





AGENDA

- 1 Background
- 2 Why Predicting Customer Churn Matters
- 3 Data Modeling & Analysis
- 4 Recommendations
- 5 Questions and Answers



PREDICTING CUSTOMER CHURN

◆ Background

- Competition is intense: 0% balance transfers

Aggressive Acquirers	Relationship Managers
Nextcard	American Express
GetSmart	Discover Card



- High rates of customer defection: 20%-30%
- Highly profitable
- Cost \$80 to acquire a customer that will generate \$120 a year if he/she keeps the card

◆ Firm

- Major credit card company with travel offices in UK, France, Britain, and Germany

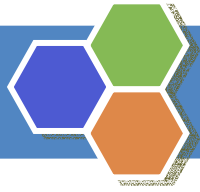
◆ Problem

- Which Current Customer Is Likely To Leave?

WHY PREDICTING CHURN MATTERS

- ◆ 0% offers cost the industry £1bn a year in lost revenue in UK.
- ◆ 20% annual churn rate means half of your customer base will be gone in 4 years!
- ◆ Costs 7 times to acquire a new customer than to keep an existing customer
- ◆ Devise strategies for “rate tarts”
- ◆ Win-back high value customers





DATA MODELING & ANALYSIS

Data Source: Professor P. Kannan, Harvey Sanders Associate Professor of Marketing. Director, Center for Excellence in Service, UMD.

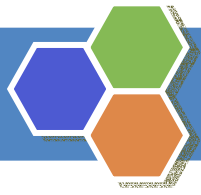
Explanatory Analysis: Examined data by sorting, pivot tables, scatter plots, correlations, and histograms

Variable Reduction: Started out with 405 observations and 182 predictor variables. Utilized 11 predictors. Narrowed predictors through domain knowledge, elimination of null values, and creation of interaction variables.

Other activities: Logged variables to normalize data, recoded the data into format usable by analysis tool, looked at stepwise through logistic regression to find most relevant variables

Model/Statistical technique Used: Discriminant Analysis because -

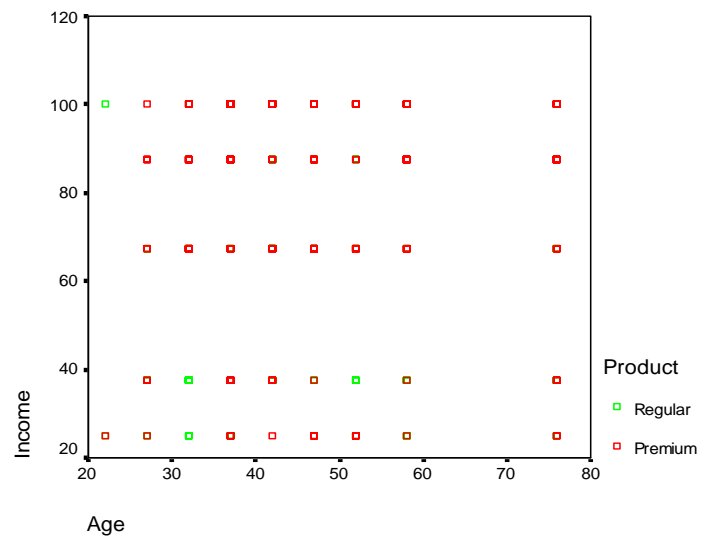
- Insufficient data to run classification trees
- Asymmetrical misclassification cost (7:1)
- Prior probabilities
- 30% more efficient than logistic regression given multivariate normal data

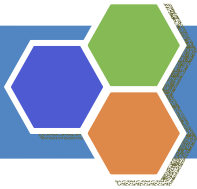


VARIABLES IN OUR MODEL

- ◆ Income
- ◆ Age
- ◆ Product
- ◆ Amount Spent
- ◆ # Transactions
- ◆ Marital Status
- ◆ Statement Ease
- ◆ Marketing Quality
- ◆ Anniversary Date
- ◆ Loyalty
- ◆ Gender

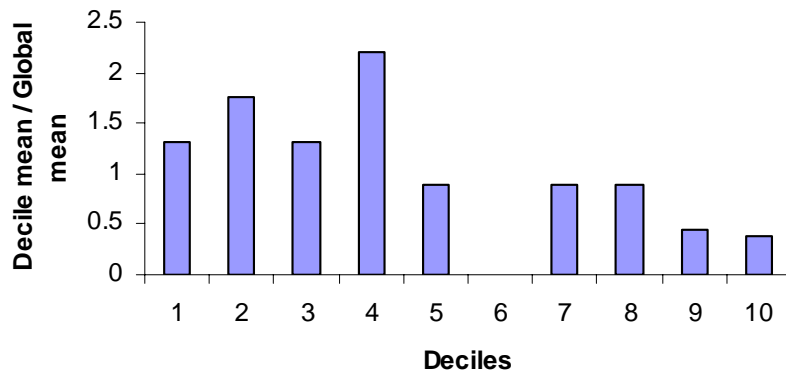
Variables	Classification Function	
	1	0
Constant	-146.1769714	-145.9470673
Log(Age)	56.04314804	55.95493698
MARITAL STATUS	-6.37859583	-6.39721918
Log(INCOME)	21.88240623	21.65524483
PRODUCT	9.39768505	9.12808704
Log (ANNDATE)	-7.50112486	-7.17833376
TOTAL_SPEND24	-0.03029263	-0.02248576





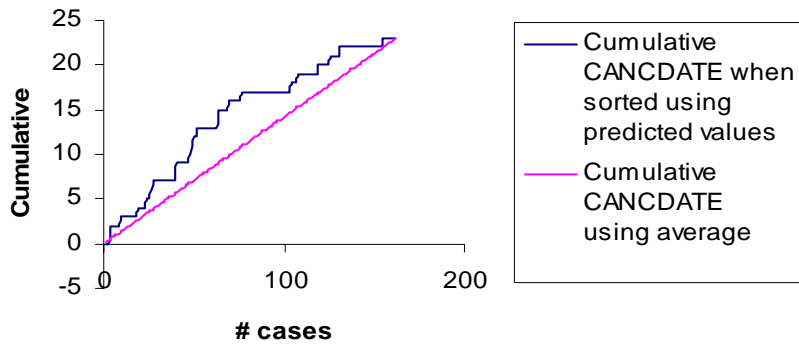
DISCRIMINANT ANALYSIS RESULTS

Decile-wise lift chart (validation dataset)

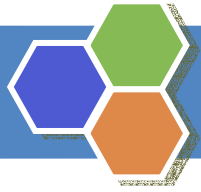


Actual Class	Predicted Class	
	1	0
1	22	1
0	127	12

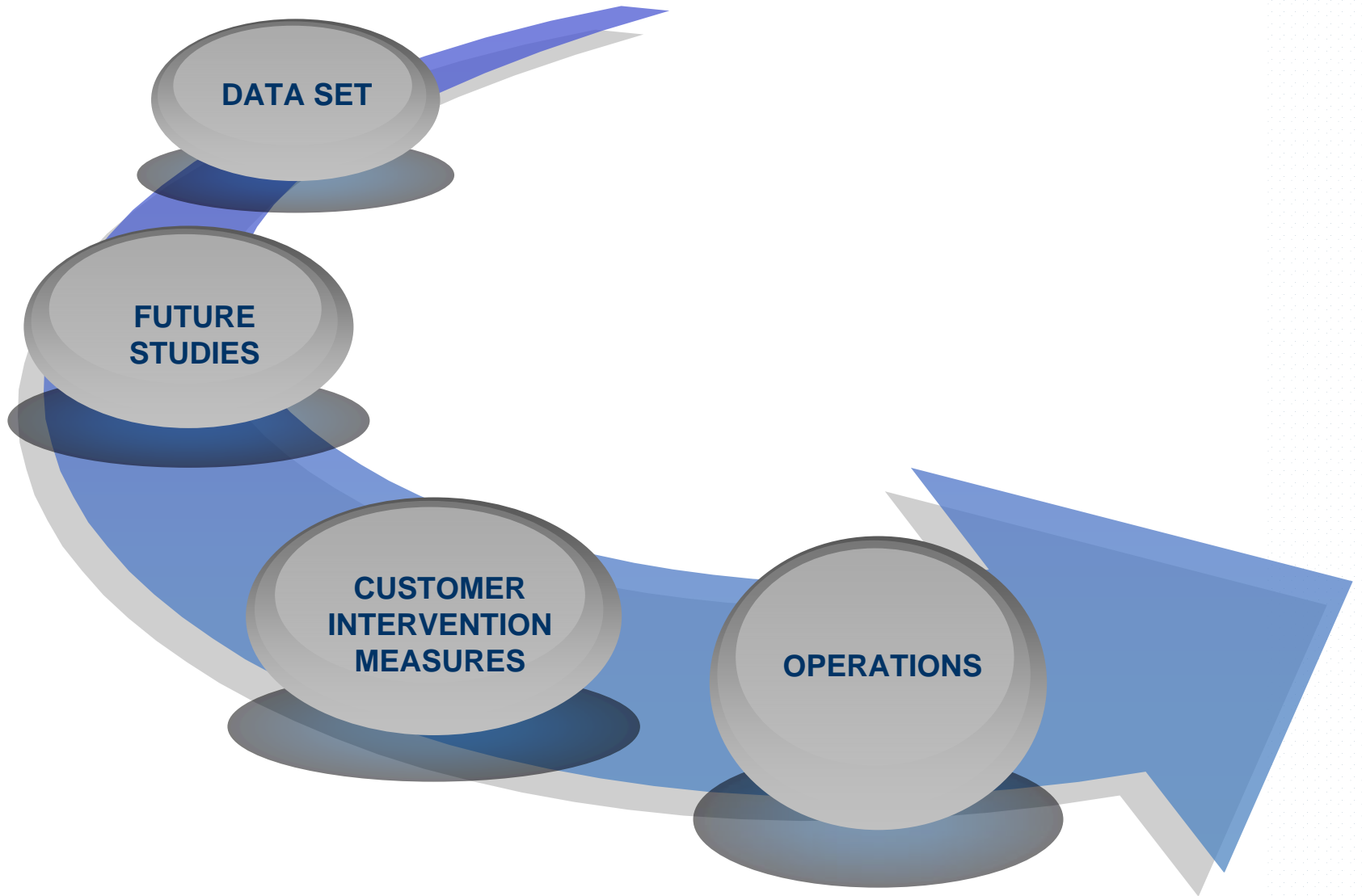
Lift chart (validation dataset)



Error Report			
Class	# Cases	# Errors	%Error
1	23	1	4.35
0	139	127	91.37
Overall	162	128	79.01



RECOMMENDATIONS

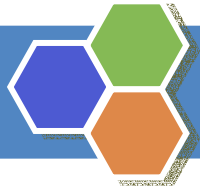


WHICH CUSTOMER IS LIKELY TO LEAVE?

- ◆ Age: 40's
- ◆ Shorter Tenure
- ◆ Regular Product
- ◆ Lower Income
- ◆ Spend Less
- ◆ Single

	Stay	Leave
Premium	86.14%	13.86%
Standard	80.30%	19.70%

Variables	Classification Function	
	1	0
Constant	-146.1769714	-145.9470673
Log(Age)	56.04314804	55.95493698
MARITAL STATUS	-6.37859583	-6.39721918
Log(INCOME)	21.88240623	21.65524483
PRODUCT	9.39768505	9.12808704
Log (ANNDATE)	-7.50112486	-7.17833376
TOTAL_SPEND24	-0.03029263	-0.02248576



RECOMMENDATIONS

- ◆ **Data Set –**
 - ◆ **Collect more ratio data**
 - ◆ **Track carrying balance, payoff trends**

- ◆ **Conduct future studies – *Why* are customers leaving?**

- ◆ **Operationalize the Model**

- ◆ **Intervention Measures**
 - **Incentives**

PREDICTING CUSTOMER CHURN



Thank You!

