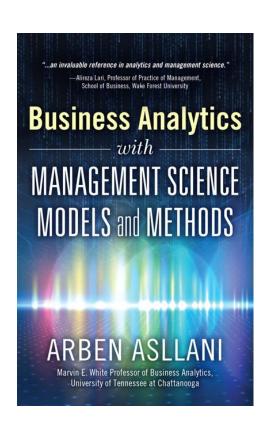
Business Analytics Prescriptive Models



Based on

Business Analytics
With
Management Science
Models and Methods
by
Arben Asllani

CHAPTER 8

Marketing Analytics with Linear Programming

Business Analytics with Management Science Models and Methods

Chapter Outline

- Chapter objectives
- Marketing analytics in action: HPdirect.com
- Introduction
- RFM Overview
- RFM Analysis with Excel
 - Using pivot table to summarize records
 - Using VLOOKUP to assign RFM score
- LP models with single RFM Dimension
- Marketing analytics and big data
- Wrap up

Chapter Objectives

- Understand the role of marketing analytics as part of business analytics
- Explain the recency, frequency, and monetary value approach model as a descriptive marketing analytics tool
- Demonstrate how to use Excel to classify customers into recency, frequency, and monetary value clusters
- Apply linear programming models to determine segments of customers which must be reached in order to maximize the profits under budget constraints
- Discuss the challenges of implementing marketing analytics in the era of big data

Marketing Analytics in Action



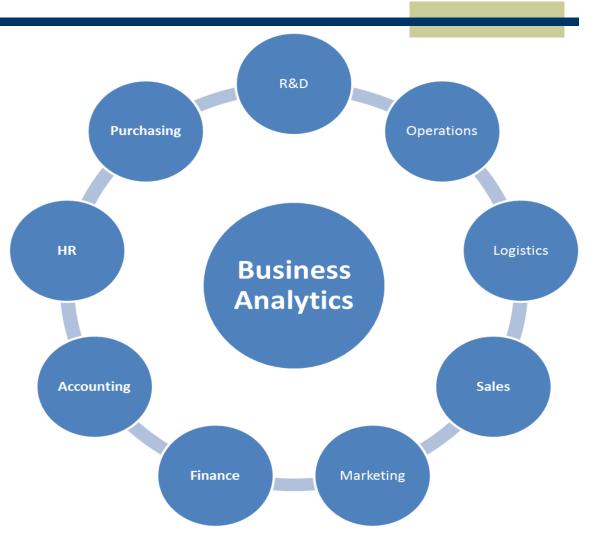
- HPDirect.com was established in 2005 with the goal to utilize the Internet to increase sales
- Building such capability proved to be challenge
 - Need to increase their volume of online sales, conversion of visits to transactions, return visits, and order size
 - These goals can translate to more frequent purchases, more recent transactions, and more money spent by customers in each transaction
- Data scientists at HP Global Analytics used mathematical programming and other optimization techniques
 - The proposed models helped improve the average conversion rate from 1.5% to 2.5% and increased the order size by 20%

Introduction

- The use of linear programming models for marketing purposes.
- Specifically, how LP models can be used to augment the analysis of data generated by customer transactions from predictions to optimizations.
- Explosion of customer data due to automatic capturing of online and offline customer transactions.
- Data provide valuable information about customers, their buying patterns and customer behavior.
- Data can be used by marketing analysts to design better marketing campaigns and increase their return on investment.

The domain of Business analysis

- Marketing analytics is an important part of business analytics.
- It can be used to make better business decisions using real market feedback.



Three dimensions of Marketing Analytics

Descriptive marketing analytics is used to analyze the effectiveness and efficiency of investments in marketing, marketing contribution to the sales pipeline, return on investment for different marketing channels, and the number of lead, prospects, or actual potential customers. Is important in marketing campaigns because it is used to help firms identify and improve current response rates, conversion rates, and campaign profitability.

Prescriptive marketing analytics covers a series of important decisionmaking tools for marketing managers. Can be used to reallocate future funds for marketing campaigns, provide the best possible mix of marketing channels, and optimize social media scheduling by identifying the best times of the month or day to post an update, when to make a new offer, or when to upgrade to a new account level.

Descriptive

- Investment in marketing
- Dollar value of pipeline contribution
- Channel ROI
- Number of people who entered the sales funnel

Marketing Analytics

Prescriptive

- Reallocation of marketing spend
- Marketing mix optimization
- Optimization of social media scheduling

Predictive

- Number of active conversations
- Social media sentiment score
- Forecast the number of leads in funnel that will convert to customers

Predictive marketing analytics is important for marketing campaigns. It can be used to predict future response rates, conversion rates, and campaign profitability. For example, to monitor and identify active conversations in social media, assign a sentiment score to each social media site and predict the conversion rate of lead customers to buying customers

RFM, CLV

- The recency-frequency-monetary value (RFM) framework
 - To capture and store data:
 - (R) the date of most recent purchase
 - (F) frequency or number of purchases during a given time period
 - (M) average monetary value or amount of purchase
 - Used in combination with descriptive, predictive, and prescriptive analytics
- Customer Lifetime Value (CLV)
 - Is the net present value of cash flow expected during a customer's tenure with a firm
 - Used as objective function for marketing mathematical programming models
 - CLV is generally higher when a customer purchases frequently, has purchased recently, and the average monetary value is higher

RFM Overview

- Chief marketing officers are forced to achieve business goals within budget constraints
- Optimization models can identify if a RFM segment is worthy of pursuing, which create a balance between errors
 - Type I error: when organizations ignore customers who should have been contacted because they could have returned and repurchased
 - Type II error: when organizations reach customers who are not ready to purchase
- The RFM approach is often used as a promotional decisionmaking tool in which "promotional spending is allocated on the basis of people's amount of purchases and only to a lesser degree on the basis of their lifetime of duration."

Recency Value

- Recency: the time of a customer's most recent purchase.
 - A relatively long period of purchase inactivity can signal to the firm that the customer has ended the relationship.
- Recency values are assigned to each customer and these values represent the following categories on a scale from 1 to 5:
 - Not recent at all
 - 2. Not recent
 - 3. Somewhat recent
 - 4. Recent
 - 5. Very recent
- The specific cutoff points depend on the specific marketing campaign and are decided by the marketing team based on the type of purchase.

Frequency value

- Frequency: the number of a customer's past purchases.
- Frequency values are assigned to each customer and these values represent the following categories on a scale from 1 to 5:
 - 1. Not frequent at all
 - 2. Not frequent
 - 3. Somewhat frequent
 - 4. Frequent
 - 5. Very frequent
- The specific cutoff points for each category and the number of frequency categories are decided by the marketing team based on the type of purchase.

Monetary Value

- Monetary value is based on the average purchase amount per customer transaction.
- In this chapter the average amount of purchase is used and categories are defined as:
 - Very small buyer
 - 2. Small buyer
 - 3. Normal buyer
 - 4. Large buyer
 - 5. Very large buyer
- The specific cutoff points can be decided based on the type of purchases.
 - Using the quintile values for the average price can be an alternative approach for the cutoff points.

(ch8_OCR_RFM.xlsx)

Using Pivot Table to

\$52.55

\$37.48

\$31.99

6/25/2014

6/25/2014

6/25/2014

00001712

00001899

00002175

23

24

25

Appendix A

Explanation of pivot table and functions

		51	umma	rize		K	30	CO1	ras	1	10.010	2110 10		. •
_	4	А	В	С										
1	L	Customer ID	Transaction Date	Sales	1	Α		В	С	D				
2	2	00000320	6/30/2014	\$22.88	3				Frequency	-	2344 00002349	5/29/2013	2	\$25.17
3	3	00000767	6/30/2014	\$11.57	4			2/12/2013	4	450.25	2345 00002350	12/15/2013	5	\$44.26
4	1	00000549	6/29/2014	\$23.58	5			1/13/2013 6/20/2014	2 15		2346 00002351	3/25/2013		\$25.37
5	5	00001533	6/28/2014	\$22.49	7	00000007		2/5/2013			2347 00002352	2/22/2014	2	\$25.23
6	5	00000810	6/28/2014	\$23.99	8	00000008	3	3/7/2014			2348 00002353	3/30/2014	3	\$34.16
7	7	00000968	6/28/2014	\$39.48	9	00000009) :	2/11/2014	4	\$38.14	2349 00002354	9/11/2013	6	\$55.11
8	3	00001502	6/28/2014	\$36.48		00000011		1/11/2013			2350 00002355	2/1/2014	2	\$29.19
9)	00002312	6/28/2014	\$44.99		00000013		5/27/2014	7	*	2351 00002356	6/7/2014	7	\$40.00
1	0	00000211	6/27/2014	\$72.47		00000017 00000018		1/6/2014 2/4/2013	12 1		2352 00002357	3/25/2013	1	\$36.74
1		00000499	6/27/2014	\$50.97		00000019		5/5/2014			2353 (blank)			
1		00001056	6/27/2014	\$70.39	15	00000020)	1/2/2013	1		2354 Grand Tota	al 6/30/2014	6680	\$47.46
1	3	00001387	6/27/2014	\$62.36	16	00000021	L 4	4/14/2013	3	\$37.53	2355			-
1	4	00001533	6/27/2014	\$62.08		00000022		1/2/2013		7	2356 Count	2349		
1		00002031	6/27/2014	\$36.98		00000023		1/2/2013	1	,	2357 Min	1/2/2013	1	\$11.00
1		00000529	6/26/2014	\$38.97		00000024		1/2/2013 2/21/2013	1 2	,	2358 Max	6/30/2014		\$517.97
1		00000767	6/26/2014	\$23.58		00000025		1/13/2013	2		2359 Average		2.84	\$44.01
1		00001203	6/26/2014	\$54.36		00000027		1/2/2013	1					
1		00001470	6/26/2014	\$41.98	23	00000028	3	7/27/2013	2	\$64.30	Botto	om Pa	art of '	the
2		00000382	6/25/2014	\$23.99		00000029		1/2/2013	1					
2		00000713	6/25/2014	\$28.49		00000030		2/12/2013	2		PIVOI	Table	e and	
2		00000713	6/25/2014	\$20.49		00000031		1/2/2013	1		Sum	mary	Statio	stics
	_	00000033	0/23/2014	Ş20.43	21	00000032	_	1/2/2013	1	\$21.77	Culli	iiiaiy	Juli	

Partial Top Results of the Pivot Table

Using Vlookup to Assign RFM Score

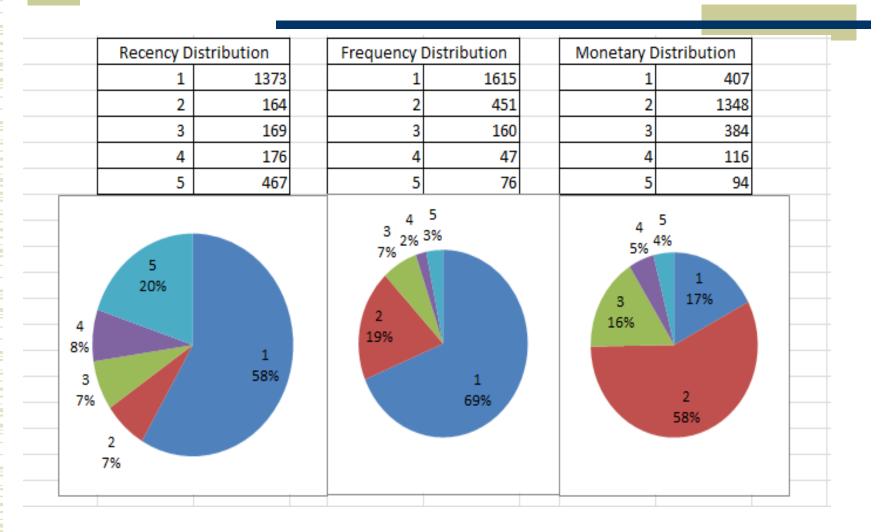
Recency Cutoffs		Frequency Cutoffs		Monetary Cutoffs		
1/1/2013	1	0	1	\$0	1	
4/1/2013	2	3	2	\$25	2	
7/1/2013	3	6	3	\$50	3	
11/1/2013	4	9	4	\$75	4	
2/1/2014	5	12	5	\$100	5	

RFM Cutoff Points

	В	С	D	E	F	G	Н	1	J	K	L	M	N	О	Р	Q	R
	L																
_	2																
	Recency	Frequency	Monetary	R-score	F-Score	M-Score											
	12/12/2013	4	\$36.13	4	2	2				Recency	Cutoffs		Frequenc	y Cutoffs		Monetan	y Cutoffs
	1/13/2013	2	\$48.56	1	1	. 2				1/1/2013	1		0	1		\$0	1
	6/20/2014	15	\$82.40	5	5	4				4/1/2013	2		3	2		\$25	2
	7 2/5/2013	1	\$22.77	1	1	. 1				7/1/2013	3		6	3		\$50	3
	3/7/2014	2	\$24.38	5	1	. 1				11/1/2013	4		9	4		\$75	4
- 1	2/11/2014	4	\$38.14	5	2	2				2/1/2014	5		12	5		\$100	5
1	0 11/11/2013	6	\$41.03	4	3	2											
1	1 5/27/2014	7	\$31.52	5	3	2											
1	2 1/6/2014	12	\$37.15	4	5	2	<'=VL	OOKUP(D1	2,\$Q\$5:\$R\$	\$9,2)							
1	3 2/4/2013	1	\$20.99	1	1	<'=VL0	OKUP(C1	3,\$N\$5:\$O	\$9,2)								
1	4 5/5/2014	6	\$39.35	5	<	LOOKUP(B1	4, \$K\$5:\$L	\$9,2)									
1	5 1/2/2013	1	\$28.96	1	1	. 2											
1	6 4/14/2013	3	\$37.53	2	2	2											

Applying Vlookup to Generate R-F-M Scores

Distributions of Customers by Recency, Frequency, and Monetary Value



Optimizing RFM-Based Marketing Campaigns

LP Models with single RFM dimension:

- LP model for Recency case
- LP model for Frequency case
- LP model for Monetary case

LP Model for the Recency Case

(ch8_RFM_with_LP_single_dimension.xlsx)

Maximize:
$$Z_r = \sum_{i=1}^5 N_i (p_i V_i - C) x_i$$

subject to:

$$\sum_{i=1}^{5} N_i C x_i \le B$$

 $x_i = \{0, 1\}$ $i = 1, 2, ..., 5$

where:

$$x_i = \begin{cases} 1 \text{ if customers in recency i are reached by marketing campaign} \\ 0 \text{ otherwise} \end{cases}$$

 $N_i = number of customers in category i$

 $p_i = probability that customer with recency i will respond to campaign$

 V_i = average amount spent by customer with recency i

C = average cost to reach customer during campaign

B = available budget for the campaign

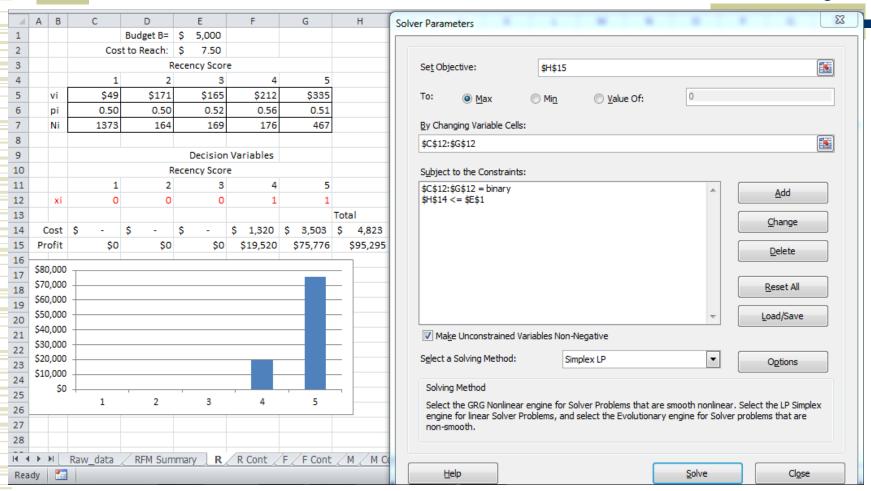
LP Model for the Recency Case

A	Α	В	С	D	Е	F	G	Н	1
1	Cust ID	Recency	Frequenc	Monetary	R-score	F-Score	M-Score	Response Rate	Sales
2	1	12/12/2013	4	\$36.13	4	2	2	0.20	\$144.50
3	2	1/13/2013	2	\$48.56	1	1	2	0.86	\$97.11
4	6	6/20/2014	15	\$82.40	5	5	4	0.62	\$1,236.05
5	7	2/5/2013	1	\$22.77	1	1	1	0.82	\$22.77
6	8	3/7/2014	2	\$24.38	5	1	1	0.12	\$48.76
7	9	2/11/2014	4	\$38.14	5	2	2	0.87	\$152.57
8	11	11/11/2013	6	\$41.03	4	3	2	0.94	\$246.18
9	13	5/27/2014	7	\$31.52	5	3	2	0.13	\$220.65

A	K	L	M	N	0	Р	Q	R	S	Т
1										
2	Recency Cutoffs		Vi	pi	Ni					
3	1/1/2013	1	\$49.02	0.50	1373	<	-=COUNTIF(\$E\$2:\$E	\$2350,L3)	
4	4/1/2013	2	\$171.06	0.50	<=A	VER	AGEIF(\$E\$2:	\$E\$235	0,L4,\$H\$2:	\$H\$2350)
5	7/1/2013	3	\$164.62	<=A\	/ERAGE	IF(\$E	\$2:\$E\$2350	,L5,\$I\$2	:\$1\$2350)	
6	11/1/2013	4	\$211.57	0.56	176					
7	2/1/2014	5	\$335.36	0.51	467					
8										

Calculating parameters for LP Recency Model

Solving the LP Model for the Recency



Optimal Solution for the Recency Model with 0-1 Decision Variables

LP Model for the Recency Case

(x is continuous variable)

Maximize:
$$Z_r = \sum_{i=1}^5 N_i (p_i V_i - C) x_i$$

subject to:
$$\sum_{i=1}^5 N_i C x_i \le B$$

$$x_i \le 1$$

$$x_i \ge 0 \qquad i = 1, 2, ..., 5$$

where:

 x_i = proportion of customers to be reached in group i

 $N_i = number of customers in category i$

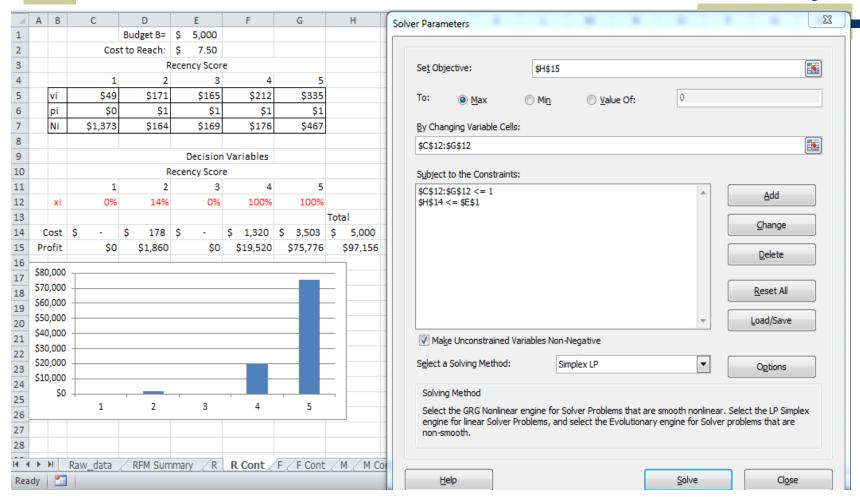
 $p_i = probability that customer with recency i will respond to campaign$

 V_i = average amount spent by customer with recency i

C = average cost to reach customer during campaign

B = available budget for the campaign

Solving the LP Model for the Recency



Optimal Solution for the Recency Model with continuous Decision Variables

LP Model for the Frequency Case

Maximize:
$$Z_f = \sum_{i=1}^5 N_i (p_i V_i - C) x_i$$

subject to:
 $\sum_{i=1}^5 N_i C x_i < R$

$$\sum_{i=1}^{5} N_i C x_i \le B$$

 $x_i = \{0, 1\}$ $i = 1, 2, ..., 5$

where:

$$x_i = \begin{cases} 1 \ if \ customers \ in \ frequency \ i \ are \ reached \ by \ campaign \\ 0 \ otherwise \end{cases}$$

 $N_i = number of customers in category i$

 $p_i = probability that customer with frequency i will respond$

 V_i = average amount spent by customer with frequency i

C = average cost to reach customer during campaign

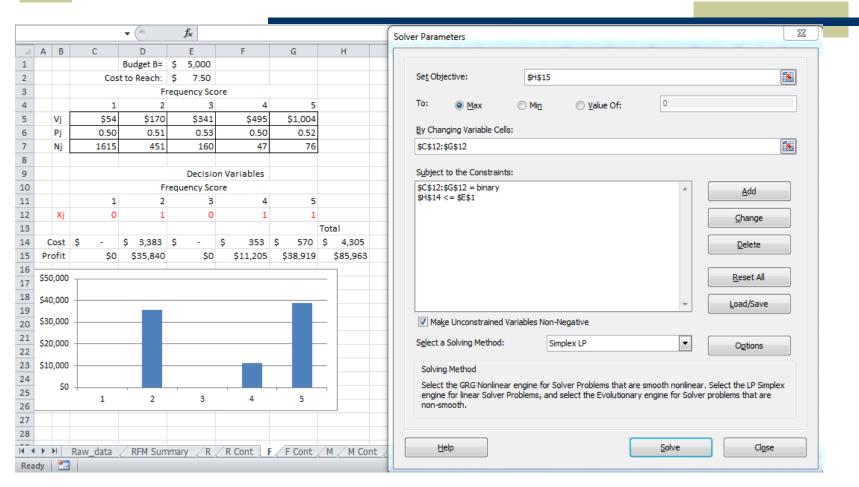
B = available budget for the campaign

LP Model for the Frequency Case

Parameters for LP frequency Model

Frequenc	y Cutoffs	Vj	Pj	Nj
0	1	\$53.51	0.50	1615
3	2	\$169.50	0.51	451
6	3	\$341.29	0.53	160
9	4	\$495.37	0.50	47
12	5	\$1,003.52	0.52	76

Solving the LP Model for the Frequency



Optimal Solution for the Frequency Model with 0-1 Decision Variables

LP Model for the Frequency Case (x is continuous variable)

Maximize:
$$Z_f = \sum_{i=1}^5 N_i (p_i V_i - C) x_i$$

subject to:
$$\sum_{i=1}^5 N_i C x_i \le B$$

$$x_i \le 1$$

$$x_i \ge 0 \qquad i = 1, 2, ..., 5$$

where:

 $x_i = proportion of customers to be reached in group i$

 $N_i = number of customers in category i$

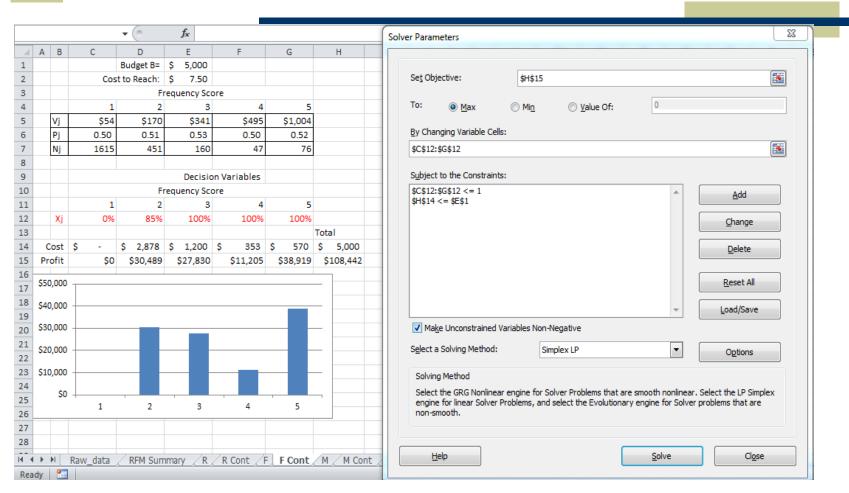
 $p_i = probability that customer with frequency i will respond$

 V_i = average amount spent by customer with frequency i

C = average cost to reach customer during campaign

B = available budget for the campaign

Solving the LP Model for the Frequency



Optimal Solution for the Frequency Model with Continuous Decision Variables

LP Model for the Monetary Case

Maximize: $Z_m = \sum_{i=1}^5 N_i (p_i V_i - C) x_i$ subject to:

$$\sum_{i=1}^{5} N_i C x_i \le B$$

 $x_i = \{0, 1\}$ $i = 1, 2, ..., 5$

where:

$$x_i = \begin{cases} 1 \ if \ customers \ in \ monetary \ i \ are \ reached \ by \ campaign \\ 0 \ otherwise \end{cases}$$

 $N_i = number of customers in category i$

 $p_i = probability that customer with monetary i will respond$

 V_i = average amount spent by customer with monetary i

C = average cost to reach customer during campaign

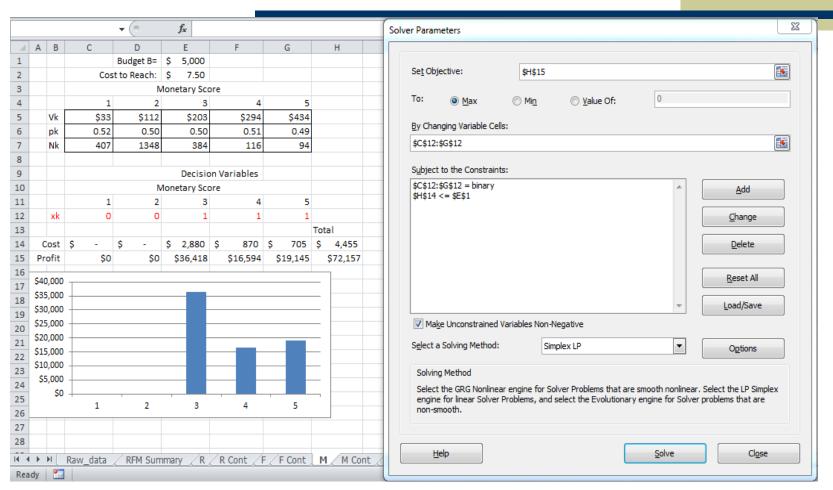
B = available budget for the campaign

LP Model for the Monetary Value Case

Parameters for LP Monetary Model

Monetary	y Cutoffs	Vk	Pk	Nk
\$0	1	\$32.57	0.52	407
\$25	2	\$111.92	0.50	1348
\$50	3	\$203.20	0.50	384
\$75	4	\$293.81	0.51	116
\$100	5	\$4333.88	0.49	94

Solving the LP Model for the Monetary Value



Optimal Solution for the Monetary Model with Binary Decision Variables

LP Model for the Monetary Case (x is continuous variable)

Maximize: $Z_m = \sum_{i=1}^5 N_i (p_i V_i - C) x_i$ subject to: $\sum_{i=1}^5 N_i C x_i \le B$ $x_i \le 1$

 $x_i \ge 0$ i = 1, 2, ..., 5

where:

 x_i = proportion of customers to be reached in group i

 $N_i = number of customers in category i$

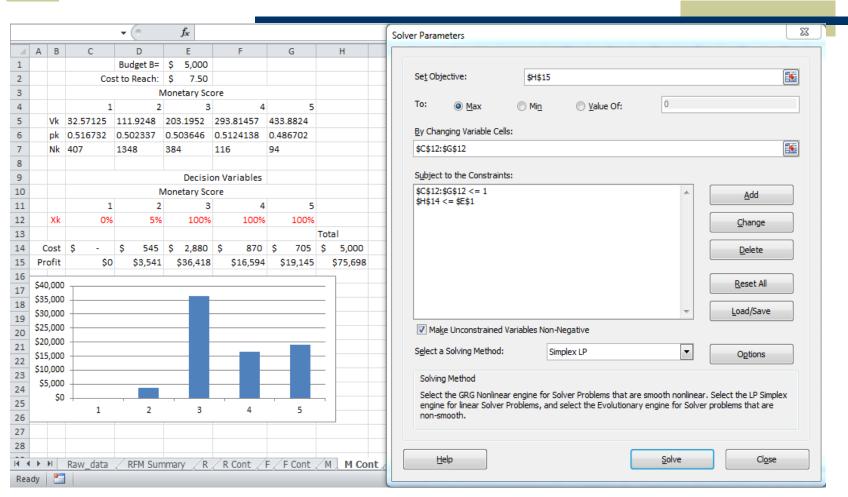
 $p_i = probability that customer with monetary i will respond$

 V_i = average amount spent by customer with monetary i

C = average cost to reach customer during campaign

B = available budget for the campaign

Solving the LP Model for the Monetary Value



Optimal Solution for the Monetary Model with Continuous Decision Variables

Marketing Analytics and Big Data

- Big data marketing analytics tend to be mostly generated by customers in the form of structured data from sales transactions and unstructured data from social media networks.
- The results of marketing models are driven by the accuracy of data and also by other market forces, especially by the competitors' reactions
- A successful marketing analytics project requires a supportive analytics culture, support from:
 - the top management team
 - appropriate data
 - analytics skills
 - necessary information technology support

Wrap up

Descriptive Analytics with RFM

- Pivot Table to Summarize Records
- Lookup Function to Assign RFM Scores
- Countif(s) or Sumif(s) to Gain Insights

Predictive Analytics with RFM

- Correlation
- Regression
- Cluster Analysis

Prescriptive Analytics with RFM

- Combine RFM and LP to Maximize Revenue
- LP Models with One Dimension (R, F, or M)
- LP Models with Two Dimensions (RF, RM, or FM)
- LP Model with Three Dimensions (RFM)

Overview of Marketing Analytics with RFM

End of The Lecture

Thank You