PGDM (RM), 2016-18
Customer Relationship Management
RM- Subject Code 502
Trimester – V, End-Term Examination: December 2017

Time allowed: 2 Hrs 30 Min
Max Marks: 50

Roll No: ______

Instruction: Students are required to write Roll No on every page of the question paper, writing anything except the Roll No will be treated as **Unfair Means.** All other instructions on the reverse of Admit Card should be followed meticulously.

Sections	**No. of Questions to attempt**	**Marks**	**Marks**
A	3 out of 5 (Short Questions)	5 Marks each	3*5 = 15
B	2 out of 3 (Long Questions)	10 Marks each	2*10 = 20
C	Compulsory Case Study	15 Marks	15
		Total Marks	**50**

Section A:

1. How are CRM activities similar /different from marketing activities? Please deliberate.
2. What makes CRM the preferred approach to marketing in the Information Age?
3. What is the distinction between traditional database marketing and a customer value –based approach toward database marketing?
4. Describe some of the key CRM software applications and their functions.
5. "Evolution of CRM practices over time". Comment.

Section B

1. Companies want relationships with customers. But do customers want relationships with companies? Please deliberate.
2. Do call centers in general improve customer satisfaction? Are customers increasingly accepting the use of call centers and the Internet as the only available interfaces with the firm?
3. "Practicing CRM without technology is not possible." Do you agree with this statement?

5

Section C

Credite Est (name disguised) is a regional mid-tier bank in France, serving roughly 600,000 customers. The company, which has been growing organically since its inception in 1965, has a quantitative approach to operations. Therefore, the use of quantitative methods in marketing via data mining is second nature to the company. The following example highlights a specific data-mining project of the bank.

As is typical for financial services operations, the bank has a very diverse set of customers in terms of customer profitability. Besides using a segmentation scheme based on behavioral characteristics (e.g., product ownership), the company has an activity-based-costing system in place that allows individual customer-level contribution margins to be identified. The project in question had the business goal to acquire new prospects by using the technique of profiling. Specifically, the objective was to identify the characteristics of profitable customers in Credite Est's mass-market segment. Once these characteristics are more closely identified, it could then efficiently target similar profiles in the prospect pool. The nature of this project required the bank to go beyond using firm-level data because behavioral (transaction) data are not available for prospects by definition. Since the company does all data-mining projects in house, it has considerable experience in the process management of such a project.

The response variable for current customers is customer contribution margin. The company sorted customers by operating contribution and chose to profile the top 20% of them. Transaction information is not available for prospects. This is why the bank has to rely on information available for both existing customers and prospects. One type of information is geodemographic data, such as socioeconomic status of a region, average age, type of housing, and so on. They can be purchased from direct marketing agencies and then appended to individual records of existing customers. That is, depending on ZIP code, geodemographic information is added to existing customer records. The model attempts to predict customer operating margin as the dependent variable with geodemographic information as the independent variables. The rationale behind this process is to find the profile that best characterizes high-value clients, which is subsequently applied to prospects' information. Credite Est appended a total of 65 variables to existing customer records. They were procured from the French list manager CIFEA, as well as from Claritas.

Upon creating a single data file including all appended information, the next step is to start with exploratory analyses. A key concern with appended data is the amount of potentially missing information. All appended variables had almost 50% missing data. The next step was to assess whether the missing data could be meaningfully replaced. These operations improved the overall rate of missing values from 42% to 21%. The next step was to investigate univariate statistics (means, standard deviations, frequencies, outliers) for all variables to ensure the included variables have sufficient integrity. This step brought a reduction in variables from 65 to 54. The next step was to calculate all bivariate correlations (or mean analyses in case of categorical variables) of the existing independent variables with the dependent variable—customer value. This was an iterative process where independent variables were subjected to transformations and where new variables were created. For example, there were three variables which indicated whether a household has children in age brackets 0–4, 5–11, and 12–18. From that, a new variable was created that was a simple dummy indicator: children versus no children. In the end, this data evaluation process resulted in a total of 17 variables that had a reasonable correlation with the dependent variable. These were retained for the next step, the response model. 6

The methodology chosen by the modelers was logistic regression. Since the goal was to either target or not target a certain individual in the prospect pool, classifying the dependent variable as 0/1 was appropriate. In the previous step, only those variables were retained with a minimum level of bivariate correlation. However, now the issue of multicollinearity came into play. Multicollinearity occurs when two variables convey essentially the same information, making one of them redundant. Thus, an important step was to make a theory based elimination of those highly collinear variables. The final model was chosen on grounds of predictive ability while containing a low number of missing values. It contained five predictors of customer value: bourgeois cluster, technology cluster, children index, house value index, and managerial job position. The ability of the model to correctly classify was 75.5% in the estimation sample and 69.8% in the holdout sample, i.e., roughly 20% points higher than based on chance alone. This result was deemed successful, and thus it was decided to utilize this model for a prospecting campaign.

The final model was rolled out in a sequential fashion to the target prospect audience. The goal was to iteratively refine the model in future rounds. As a first step, Credite Est purchased addresses from list brokers that had nonmissing values for at least three out of five variables in the final model. The prospects were scored with the model and then ranked by likelihood of being a high value customer. From the resulting pool of 10,000 prospects, half were targeted with a money-market product, and halfwith a lending product. The objective was to assess the receptivity of the two samples for the respective products. In addition, a baseline scenario was conducted whereby the same prospecting campaigns were conducted for a random sample of households. Although both target mailings were significantly more successful than the baseline scenario, this was only the first step in a further refinement of the model and the offer. In particular, besides assessing response rate, it was now important to track and document the value of the acquired customers—the original goal of the project.

1. Identify and discuss the key steps in the data mining process. (8 marks)
2. Use the learnings of this case to layout a data mining process for a retailer. (7 marks)

7