A STUDY OF CUSTOMER RETENTION AND CHURN RATE MANAGEMENT THROUGH DATA MINING AND CUSTOMER PROFILING OF MALAYSIAN MOBILE USERS

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ABSTRACT

This study aims to investigate the needs and wants of prepaid mobile service subscribers in Malaysia and identify usage patterns of industry churners, ultimately to offer the right product and value to target customers within a highly competitive market. This paper discusses the challenges faced by mobile companies in relation to high churn rates (sometimes called attrition rate), maintaining customer loyalty and the presence of stiff competition. Data was collected through database extraction from a telecommunication company in Malaysia which includes available demographic and behavioral data of the subscribers. Apriori association algorithm was employed to determine product bundling and C&R decision trees were used for customer profiling. It was discovered that there were three main product bundles subscribed by the prepaid mobile consumers. A brief look at the behavioral usage pattern of churners was also discussed. These information help mobile service providers to be more aware of their customer needs and to intelligently predict potential market churners.

1. INTRODUCTION

In recent years, the mobile penetration rate in Malaysia has increased significantly. Hence it is not surprising to see consumers possessing on average two or more mobile phones, especially when there are many alternative service providers offering great pricing deals and bundle packages for mobile phone users; particularly prepaid users (The Edge Malaysia, September 2009).

Service providers are investing huge capital towards enhancing their respective network and offerings, such as the value added 3G data service and the latest mobile broadband to grow and maintain average revenue per user (ARPU) numbers (The Edge Malaysia, September 2009). Such investments are necessary, as consumers are demanding for more tailored products and better services at greater value (Lu, 2001). Affluent consumers are well aware of their demands, and are more proactive in informational search for services that provides them value-added services. They have no hesitation to change or switch service providers especially when they are in a noncommittal service contracts such as prepaid packages.

The telecommunication industry experience annual churn rates of over 15 percent and 14.8 percent of service providers reported loss of over 50 percent of their customers every year (NST Online, 12 October, 2009). Naldi M. (2008) defines churn as "the erosion of the customer base due to migration or switching". An earlier research conducted by Lu (2001)

states that it costs almost 5-10 times more to recruit a new customer than to retain an existing one. For this reason, churn management and customer retention in the telecommunication industry becomes an integral part of their marketing strategy (Kuusik & Varblane, 2008; Lejeune, 2001). Furthermore, it is a challenge for companies to predict which customers are likely to leave the company and their reasons for doing so. At the same time, it is equally difficult to implement cost-effective incentives to make them stay (Chang, 2009).

This paper aims to identify the optimal product bundles which could provide marketers an insight to effective targeting of subscriber for package promotions. Additionally the research carried out will also identify the possible contributing factors that separate active users from churners; while looking into the possibility of significant behaviors that may contribute to the possible churning. As such, this study seeks to examine the needs and wants of mobile phone customers in Malaysia through product bundling and customer profiling. At the same time this study would identify significant behaviors that may contribute to possible churn rates and identify optimal product bundling for effective targeting purposes.

2. LITERATURE REVIEW

Consumers would stay with a brand or a service provider when they are satisfied with the service quality and the overall user experience (Vlachos & Vrechopoulos, 2006). As much as it would cost a lot for service providers to recruit new customers, it costs about as much for a consumer to try new services. The cost discussed here, are specifically indirect cost (time and convenient cost), such as notifying contact of change of new mobile numbers. The time lost and inconvenience faced during the transition, are not pleasant user experiences.

Kotler and Keller (2009) asserts that "understanding the needs and wants of the target customer enables service providers to offer the right product and value to sustain long term relationship with its consumers". Additionally, effective research and analysis facilitates marketers to effective product bundling hence providing greater value to customers which in turn, adds to the increase in user experience (Koderisch et al., 2006). Grouping customers with similar needs and buying behaviors into segments, with the intention of identifying effective product bundle offers are groundwork to the success of marketing and sales activities (Kassim, 2006). In spite of this, new segmentation methodologies are constantly developed with the use of data mining which provides a new outlook into profiling customer buying behavior. (Lejeune, 2001, Ong & Andrews, 2011).

These customers' needs and wants can be identified through effective product bundling; utilizing rich data for data mining. Data mining ameliorate ways of segmenting customers, for association and prediction, which consequently translate the findings into their respective wants through product profiling (Lejeune, 2001). Several service industries have begun tapping and adopting data mining to better understand and to reach out effectively to their consumers' wants and retaining subscribers (Ong & Andrews, 2011). It is through product bundling (profiling) service providers can categorize consumers accordingly under behavioral segmentation – in this case, usage rate, call plan type, brand loyalty and others (Ong & Andrews, 2011; Legaretta & Miguel, 2004). Essentially, marketers can then cross sell and up sell available products and services that fits into the value product basket of these subscribers, hence increasing the exit barriers of subscribers subsequently resulting in lower churn rate.

Booz-Allen and Hamilton (2001, cited in Sophcli et al 2003) defines two types of customer churn i.e. "voluntary churn" where customers choose to switch carriers or terminate their use

of wireless [or other] services, and "involuntary churn" where service is deactivated due to missed payments, bad debts, etc. In this research paper, behavioral patterns and user experiences of prepaid service subscribers are observed. Essentially, user experience is the overall process experience while consuming a product/service, thus it important for service providers to ensure subscribers experience positive and high user experience when consuming their services. Consequently this will translate into higher retention rate for the telecommunication company.

As it is difficult to predict potential customer churn, churn management would be an important element for telecommunication companies to implement, focusing on data mining techniques to find the best model of predictive churn (Ruta et al, 2009). Mobile operators must also consider customer retention as part of their business strategy. Both churn management and customer retention go hand in hand (Asaari & Karia, 2000). Churn management involves developing techniques to identifying 'who' will likely to churn and 'how' should firms react effectively to these potential churners (Hung et al, 2006). Often, some firms may quickly counter these customers with attractive incentives. This counter reaction is merely promotion which only allows firms to keep their profitable customers temporary and in hope to increase customer loyalty (Kumar, 2005). This being said, a long-term customer however, is not necessarily a loyal customer (Lejeune, 2001).

In developing customer loyalty, mobile firms must consider recognizing who their customers are, build relationships by keeping in constant contact with customers and rewarding customers by making relationships more valuable in consumer's minds (Clow, 2010). For this reason mobile operators must incorporate strategies that would maintain their loyal customer base and to develop such strategies would very much depend on the analysis of the data mined (Johnson & Siriket 2002; Pavlos & Adams, 2008). Data mining strategies will enable mobile companies to have a thorough knowledge on customer expectations. Knowing customer expectations is considered the first critical step in delivering quality service. Poor knowledge of customer expectations will undoubtedly cause a loss in profits and customer churn. Ultimately the firm will not be able to survive in a fiercely competitive market (Zeithaml, 2009)

3. METHODOLOGY

Data was collected through a database extraction from a telecommunications company in Malaysia. 10,000 data, which encompass available demographic and behavioral data of the telecommunications company's subscribers was extracted for the purpose of this study. Below is a list of data obtained from the database:

Table 3.1 – Demographic and Usage data

Variable Label	Variable Description
Customer_ID	Unique customer id
Gender	M = Male, F = Female
Age	Age in years
L_O_S	Length of service in months
Dropped_Calls	No of dropped calls during 6-month period
Churn	Past churners versus existing subscribers (active / churned)
International_mins_Sum	Total no of international-call minutes in 6-month period
National mins	Total no of national minutes in 6-month period
Total_call_cost	Actual call cost + cost of international calls

Data on 12 products offered by the telecommunication company was also extracted for the purpose of product bundling. Below is a list of the products variables that were extracted (coded 1 – subscribed and 0 – not subscribed).

Table 3.2 – Product data

Variable Label	Variable Description
VoiceCall	Normal voice calls between phones
SMS	Short messaging service
VoiceMail	Voice messaging service
CallerRingtones	Caller ringtones to identify different callers
MMS	Multimedia messaging services
MissedCallNotification	Notification of missed calls
CLIP	Caller identification presentation
IDD	International direct dialling
Data	Mobile web browsing capabilities
CallWaitingHold	Service that allows choice of acceptance or ignoring incoming calls while on the other line
AirtimeShared	Sharing of credit within same service providers
SmartSIM	SIM based application that allows backup storage of data from phone.

Analysis of the data was broken down into three phases using SPSS 19.0 and Modeler 13.0. Firstly, the 12 products were subjected to an association algorithm (Apriori algorithm was used in Clementine 12.0 to extract out the highest association of products that can be bundled together). Next, using the highest confidence of product bundles, a node was created to generate the rule sets. From these rule sets, decision tree analysis (C&R; Classification and Regression tree was used for binary outcomes) segments the demographic and behavioral variables in terms of importance to the bundle purchase. With this information the telecommunication company will be able to identify bundles of products that are most sellable with the purpose of package promotions. From this, analysis of churners was also evaluated using C&R Trees. This helps to identify the demographic factors that separate the active users from the churners. This will in turn allow the company to identify the significant behaviors that may contribute to possible churners and successfully mitigate these cases with new packages to retain their customers.

4. ANALYSIS RESULTS

4.1 Respondents Profile and usage behavior

Out of the 10,000 available data, 49.6% were males and 50.4% were females. The majority of people who are subscribers of the telecommunication company are mainly aged 35 years old and below. The database contains 55% of active subscribers and 49% of users who have churned. The average values of length of service in months, number of dropped calls, total number of international-call minutes in 6-month period, total no of national minutes in 6-month period, and total call cost by gender, churn and age groups are presented in the table below:

Table 4.1 Mean value of behavioral variables by gender, churn and age groups.

Demographic Factors	%	LOS	DC	Mean Int'l	Mean Nat'l	TC
Gender						
Male	50.4	33.3	3.0	173.7	1064.6	189.4
Female	49.6	33.2	3.0	175.7	1060.9	189.4
Age						
<16 years old	12.3	33.6	2.9	176.4	1074.5	190.0
17 – 21 years old	16.2	33.2	2.9	175.9	1074.4	191.1
22 – 27 years old	19.1	33.2	3.0	173.0	1080.0	189.9
28 – 35 years old	21.6	33.3	3.0	178.0	1050.7	189.7
Above 35 years old	30.7	33.3	3.0	171.8	1049.5	187.6
Churn						
Active	55.0	33.8	2.5	172.6	1087.7	189.8
Churned	45.0	32.6	3.7	177.2	1032.3	188.9

Legend:
LOS – Length of service in months
DC - number of dropped calls during a 6- month period
Int'l - total no of international-call minutes in 6-month period
Nat'l- total no of national minutes in 6-month period
TC – Total Cost of usage

4.2 Directed Graph Association of Churners

The directed graph below shows the association of churners to certain characteristics. As shown in Figure 3.2.1, churners are largely associated with people who subscribe more to voice mail and to SMS services and are also largely the male population.

4.3 Product Bundling

Apriori association algorithm was employed in the process of determining which products bundle together in meeting the specified confidence rules. Apriori starts out by generating simple rules involving two items and then testing them against the data. This rule is then added to include other antecedents that have a strong association to those rules. Therefore, to find an association between the products, 12 items corresponding to the products were fed into the apriori algorithm node with a two-way directional analysis possibility. A minimum confidence of 85% and a maximum of 5 antecedents were set as the criteria for apriori association algorithm.

The results revealed (Table 4.2) 10 association rules that were produced and present within the data. Out of these 10 rules, 3 products that were used as the consequence for the rules stood out which includes, the call waiting or hold, MMS and Data. The products that are associated with these three was largely also associated with the corresponding antecendents. For example in RULE 1 from the table below; those who subscribed to both SmartSIM, IDD and Data also subscribed to CallWaitingHold (Support of 11.28% meaning that 11.28% of

Figure 4.2.1 – Directed graph of Churners Vs. Products and Gender

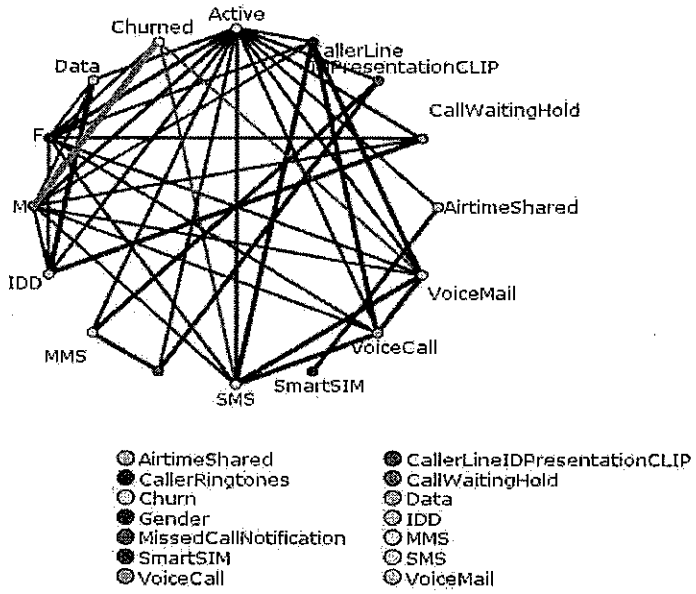


Table 4.2 Product Bundles of Call Waiting/Hold, MMS and Data

Rule	Consequent	Antecedent	Support (%)	Confidence (%)
1	CallWaitingHold	SmartSIM, IDD, Data	11.28	86.082
2	CallWaitingHold	IDD, Data	33.25	86.045
3	CallWaitingHold	MMS, IDD, Data	10.94	86.015
4	MMS	SmartSIM, CLIP MissedCallNotification	10.64	85.526
5	CallWaitingHold	CLIP, IDD, Data	10.82	85.49
6	CallWaitingHold	AirtimeShared, IDD, Data	11.81	85.351
7	CallWaitingHold	MissedCallNotification, IDD, Data	10.98	85.337
8	Data	IDD and CallWaitingHold	33.55	85.276
9	MMS	CLIP, MissedCallNotification	29.94	85.271
10	MMS	AirtimeShared, CLIP, MissedCallNotification	11.02	85.027

the entire data finds this 3-way association). Confidence of 86.082% explains that 86.082% of the people who subscribed to both SmartSIM and Data resulted in also subscribing to CallWaitingHold. For each rule, the Support and Confidence figures will largely affect the rule generation for the association of products.

From the bundles, rule sets are generated from the antecedents that links with the consequences of the top three products that has the strongest association with all other corresponding products (Table 3.2). These rule set will then be used to do profiling using decision trees.

4.3 Profiling using Decision Trees

From the rule sets generated, C&R decision tree algorithm was used to determine the important variables used to segment the subscribers of the product bundles. Using this algorithm a decision support framework is developed that will give a clearer picture of the general demographic or behavior of the subscribers. The variables that were used to do the segmentation were chosen based on literature and observation of general trends of telecommunication subscribers. All variables in Table 3.1 were used for segmentation except Customer ID and Total_call_cost (this variable was suppressed for this analysis to isolate the spending habit of the subscribers). The results of the segmentation of the product bundles using the C&R Tree is presented in Figures 4.3.1 – 4.3.3. Tables 4.3.1 – 4.3.3 shows the summary of profiles in each bundle.

4.4 Segmentation of churners

From the bundles, churn appeared to be an important variable in determining the segmentation subscriber of the product bundles. The results suggest that the subscribers of the bundles each have a possibility of churning. To understand the reasons for churn, the study continues by looking into the segments profiles of churners. Using the C&R tree algorithm again, the churners are then subjected to a segmentation process using the same variables in table 2.1 except Customer ID and Total Cost (this variable was suppressed for this analysis to isolate the spending habit of the subscribers). Figure 4.4.1 shows the segmentation process by C&R tree algorithm in determining the segment for churners.

From the results we note that number of dropped calls is an important factor that determines the possibility of churning followed by duration of national calls made, age category, number of international calls made respectively.

5. CONCLUSION

Customer profiling has provided many important opportunities for firms in terms of increased profits and sustainability. Although these recommendations may help mobile industries in terms of understanding customer needs and wants, handling churn rates and dealing with competitors, mobile companies must be aware of some of these challenges.

One of the major challenges faced by service firms as compared to manufacturing firms is in positioning and promoting their offerings due to the intangibility of their services (Schiffman, 2010). Thus it is important for mobile operators to develop strategies that encompass visual images and tangible reminders of their service offerings (Schiffman, 2010). These strategies include advertising and other communication strategies that clearly communicate a firms service attributes and benefits to consumers, including strategies designed to encourage word-of-mouth communication (Zeithaml, 2009).

Another challenge is in terms of the changing nature of consumer behavior, attitudes and preferences which at times can be difficult to predict. These changes can threaten existing products and can also offer opportunities for firms to develop products consistent with new values and behaviours (Peter, 2010). Many firms have adapted to this by offering products in line with such consumer changes such as in the beer industry offering "lite beer" in lieu of consumer's changing health conscious life-styles. (Peter, 2010)

Other challenges faced by mobile operators include high churn rates, low customer retention and stiff competition from other mobile operators. Thus a combination of customer relationship management, churn management systems and data mining techniques can be offered as tools to manage these challenges (Asaari and Karia, 2000).

This paper provides mobile phone operators the potential for other possible marketing based activities that would further propel the company towards market share growth and development. It is proposed that mobile operators focus on database extraction in terms of demographic and behavioral data for the purpose of customer profiling. This would then allow mobile operators to link customer profiles to product offerings via product bundling. With a deeper understanding of customer needs and wants by way of customer profiling and analysis, mobile companies would be able to launch successful campaign management with specific marketing campaigns aimed at specific demographic profiles (Richter, 2010). Consumer behavior information and sources of individualized profile data can be used to simultaneously explain and predict consumer's behavior and also helps to facilitate individualized consumer and organization interaction (Evans, 2010) Hence the link between customer profiling and product bundling would be greatly beneficial to mobile firms.

6. LIMITATIONS AND FURTHER RESEARCH

One of the limitations of this study is that data was obtained from only one telecommunication company. Hence there may be a possibility that the results may be particular to that company. A comparative analysis of data collected from other telecommunication firms is needed in future research to provide a different outcome. It would also provide a better understanding of why customers choose to switch to other mobile service providers and at the same time provide valuable information on the competitor's service offerings.

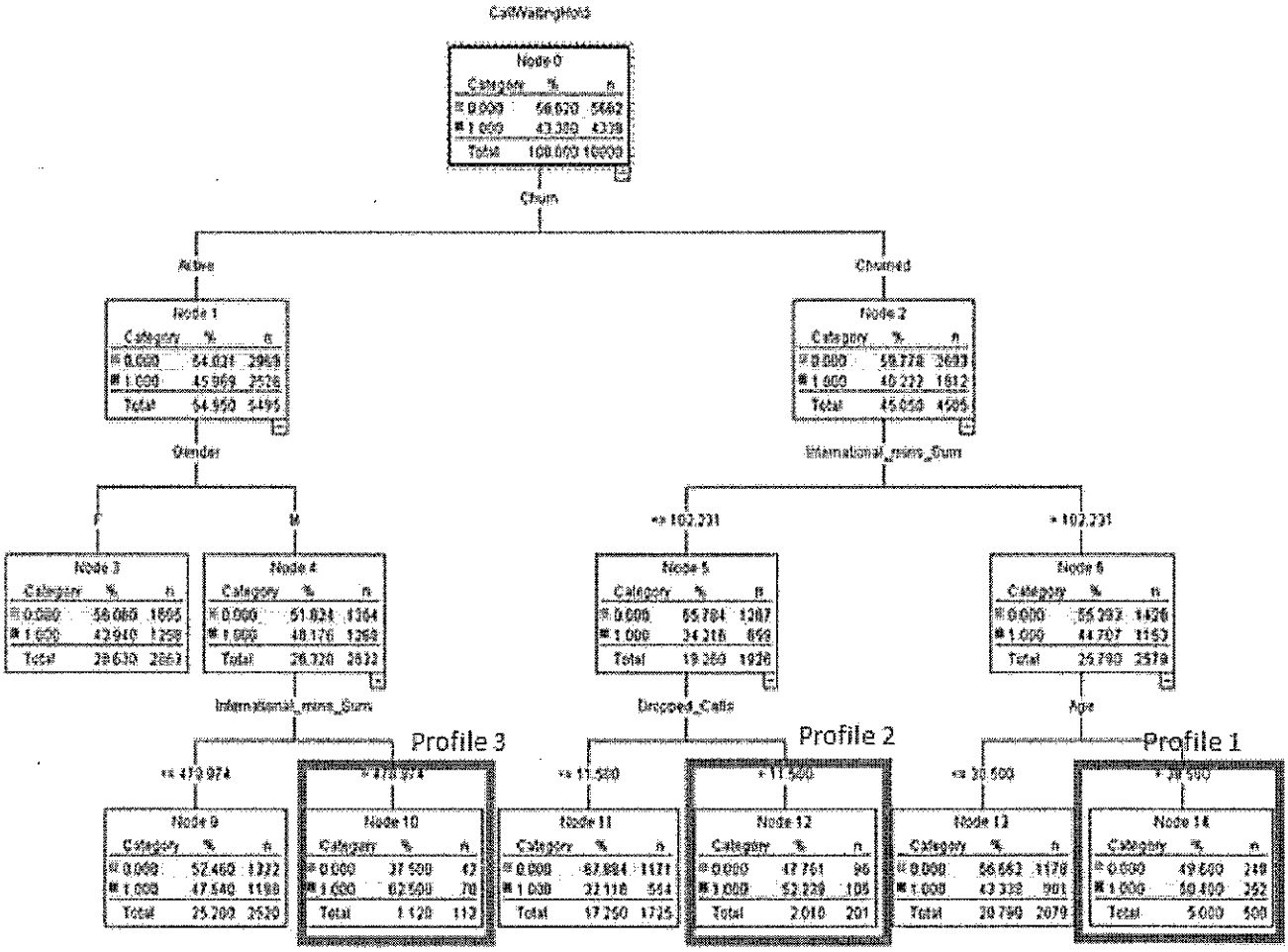
The population of study concentrates only on the needs and wants of prepaid mobile service subscribers which limits the results thus an analysis of the needs and wants of post-paid mobile service subscribers could also be useful in future research. This would provide an opportunity to analyse any gaps between the two types of service subscribers. Mobile firms can then plan for improved service strategies for these markets.

Another opportunity for research would be in analyzing the needs and wants of business-to-business mobile subscribers. Mobile operators would benefit from further data and analysis of their business clients and thus provide these businesses with the best telecommunication offerings and solutions.

This study could be extended by understanding how mobile operators could create value for its customers and then analyze the customer's perception of value in terms of the mobile

operator's offerings. A study of the differences between these factors and the potential for mobile operators would be useful in closing the gap between product offerings and customer perception before the products are marketed to the general public.

Figure 4.3.1 – Segmentation of Call Waiting/ Hold bundle

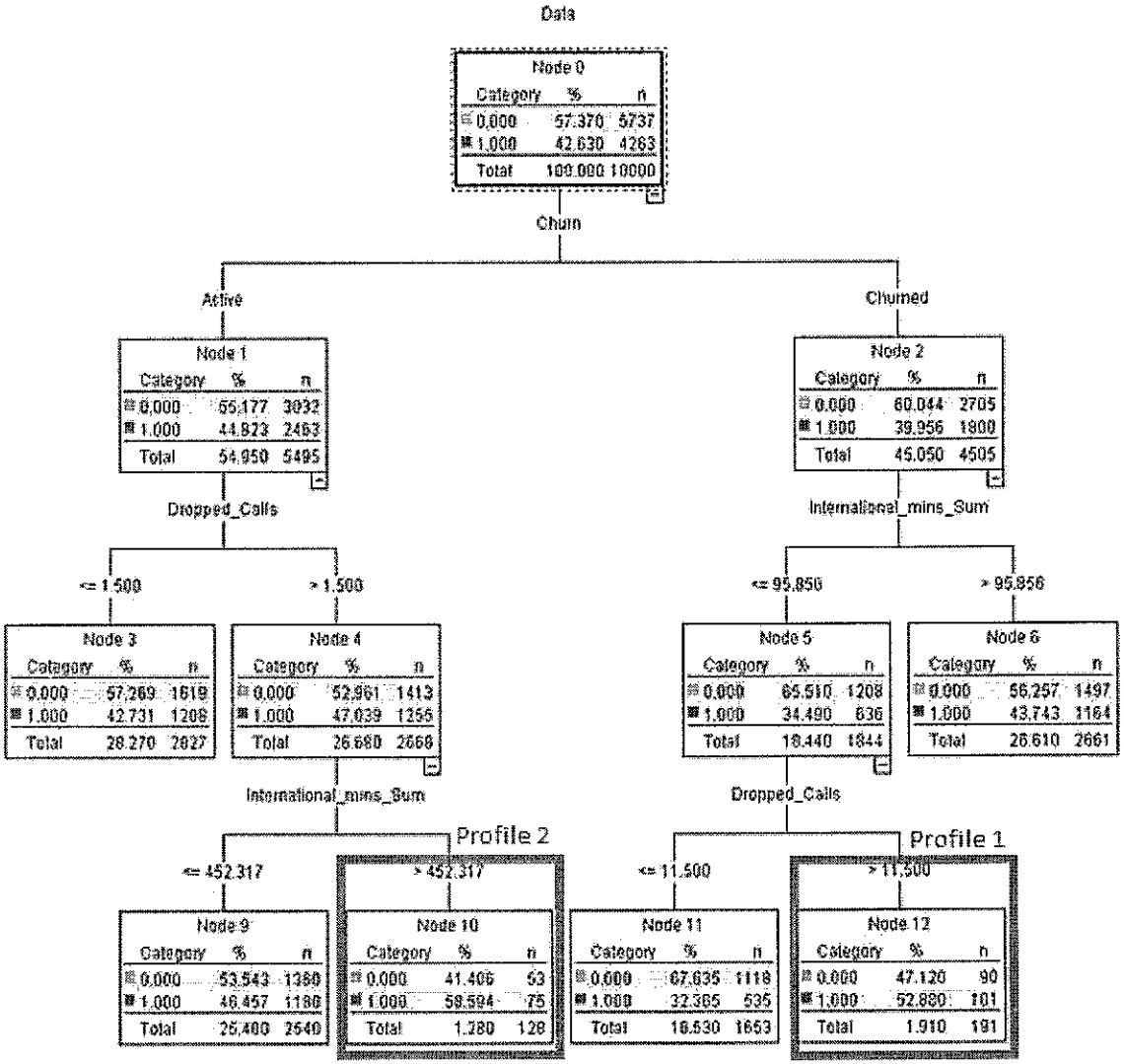


From the Figure 4.3.1 above, three distinct profiles of subscribers to this bundle (CallWaitingHold) are identified and summarized in the table below (Table 3.3.1):

Table 4.3.1 – Profiles of customers subscribing to CallWaitingHold bundle

Profile	Variables	Characteristics
1	Churners	Yes
	Total of International Calls (mins)	>102.231 minutes
	Age	>38.5 years of age
2	Churners	Yes
	Total of International Calls (mins)	<102.231 minutes
	Number of dropped calls	>11.5
3	Gender	Male
	Churners	No
	Total of International Calls (mins)	>478.974 minutes

Figure 4.3.2 – Segmentation of Data bundle

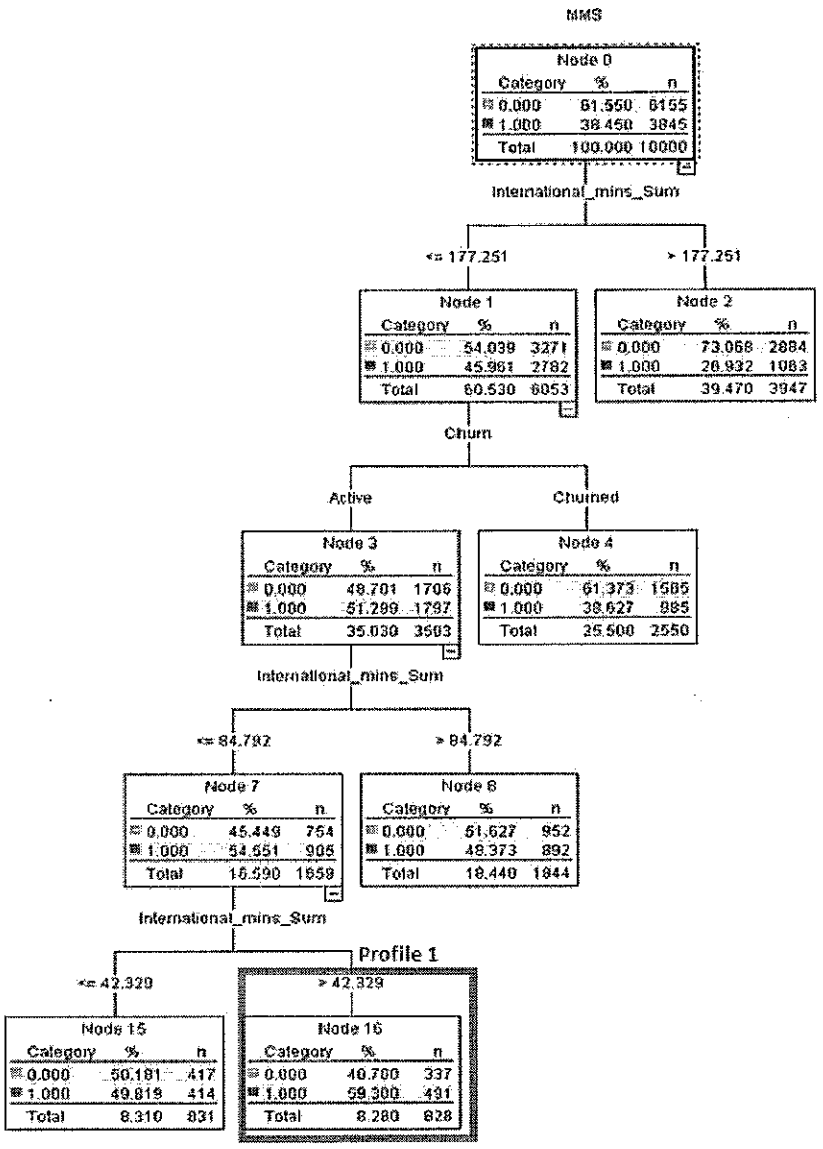


From the Figure 4.3.2 above, two distinct profiles of subscribers to this bundle (Data) are identified and summarized in the table below (Table 4.3.1):

Table 4.3.2 – Profiles of customers subscribing to Data bundle

Profile	Variables	Characteristics
1	Churners	Yes
	Total of International Calls (mins)	>95.856 minutes
	Number of dropped calls	>11.5
2	Churners	No
	Number of dropped calls	<1.5
	Total of International Calls (mins)	>452.317 minutes

Figure 4.3.3 – Segmentation of MMS bundle



From the Figure 4.3.3 above, one distinct profile of subscribers to this bundle (MMS) are identified and summarized in the table below (Table 4.3.1):

Table 4.3.2 – Profiles of customers subscribing to MMS bundle

Profile	Variables	Characteristics
1	Churners	No
	Total of International Calls (mins)	Between 42.329 and 84.792 minutes

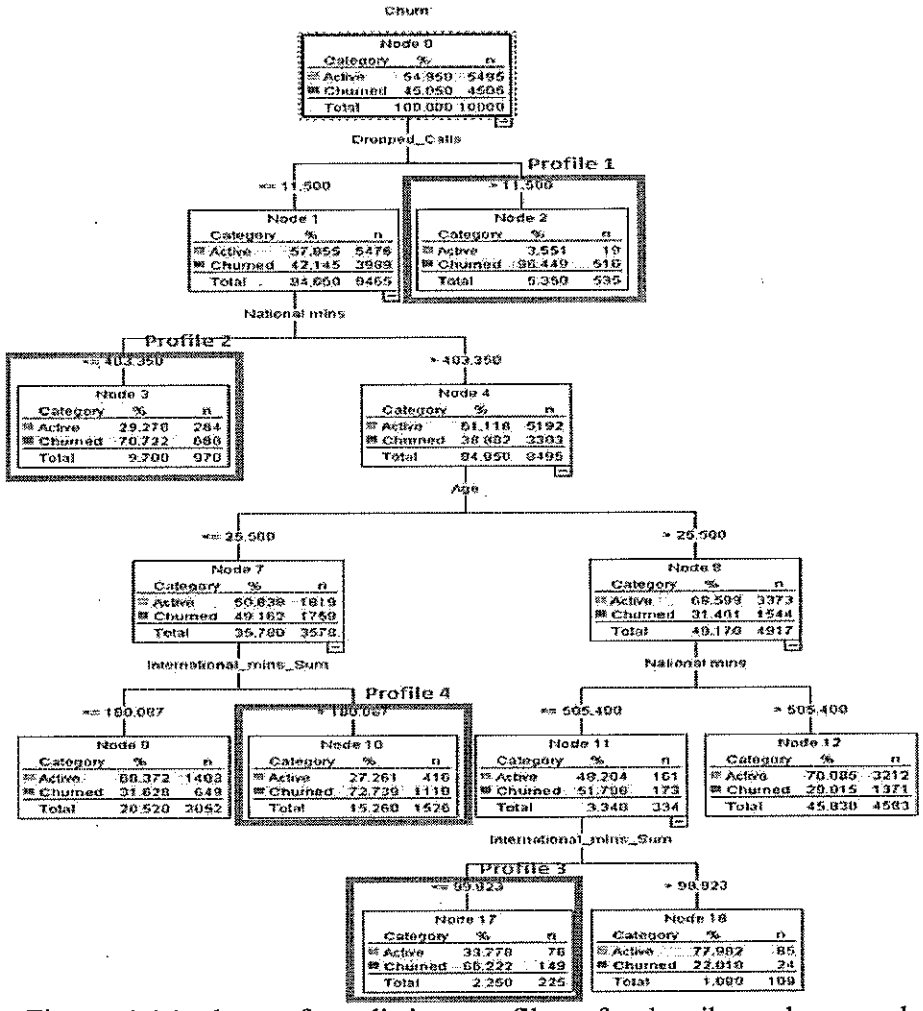
Combining information from Figures 4.3.1 to 4.3.3 and tables 4.3.1 to table 4.3.3, the following summarizes the importance of variables used for bundle segmentation.

Table 4.3.4 – Variable Importance in bundle segmentation

Rule	Bundle	Importance Variables
1	CallWaiting/Hold	Int'l, DC, Churn, Age, Gender, LOS
2	Data	Churn, DC, Int'l, Age, LOS
3	MMS	Churn, Int'l

**Variables that appear first indicate relative importance to other variables; Age and LOS were added for more information on character differences although not as significant as other variables*

Figure 4.4.1 – Segmentation of Churners



From the Figure 4.4.1 above, four distinct profiles of subscriber who are churners are identified and summarized in the table below (Table 4.3.1):

Table 4.3.1 – Profiles of customers subscribing to CallWaitingHold bundle

Profile	Variables	Characteristics
1	Number of dropped calls	>11.5
2	Number of dropped calls	<11.5
	Total of National Calls (mins)	<403.35 minutes

2	Number of dropped calls	<11.5
	Total of National Calls (mins)	Between 403.35 and 505.40 mins
	Age	>25.5 years
	Total of International Calls (mins)	<99.923 minutes
4	Number of dropped calls	<11.5
	Total of National Calls (mins)	>403.35 minutes
	Age	<25.5 years
	Total of International Calls (mins)	>180.087 minutes

Table 4.4.1 below summarizes the importance of variables used for identifying churners as it complements the results shown above:

Table 4.4.1: Variable importance of churners segmentation

Rule	Variable	Importance Variables
1	Churn	DC, Nat'l, Age, Int'l

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