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Data Warehousing Class Project Report

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Assignment #7 Class Project Report

Course Title: Data Warehousing

Course Number: ETM 538/638

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Table of Content

I- Introduction	1
II- The Data	1
III- The Need for the project	1
1- Key Business Objectives	1
2- Key business questions	1
3- Concepts the Organization is already using to analyze the data	2
IV- Procedure of analysis	2
1- Key attributes to use	2
2- Any bucketing you plan to use for key attributes	2
3- Algorithms you think are worth trying. (Only in the class are allowed)	3
4- Evaluation criteria	3
V- Applying the Algorithms	3
1- 1-R Rule (Bucketing#2)	3
2- Bayesian Naive (Bucketing#2)	4
3-Instant based Classification (Bucketing#2)	4
VI- Conclusion	5
VII- References	6
VIII- Appendix	7
Appendix A: The description of 26 attributes	7
Appendix B : Data and Pivot tables of R1	8
Appendix C : Bayesian Model Probabilities Data	9
Appendix D: Full data table for Instant-Based learning	12

I- Introduction

Data mining is widely described or defined as the discipline of: “making sense of the data”. In today’s day and age, the rise of ubiquity of information calls for more advanced and developed techniques to mine the data and come up with insights. Data mining finds applications in many different fields and industries: Whether it is in Embryology, Crops, Elections, or Business Marketing...etc. It is not a wild assumption to consider that every organization in the world has some data mining capabilities or its main activity necessitates it and they have some third party organization doing that for them. One particular area where data mining is really important is in the business world. Being able to find patterns in the data can tell whether the business survives for another couple of years or not. It can make the difference between being a fortune 500 company and bankruptcy and everybody who is interested in growth and sustainability knows that. During the whole course, we learned methodology and did assignments for practicing data mining and data warehousing. In this class project, we try to put to practice as many concepts as those learned in class and apply 3 algorithms from class (1-R, Bayesian, and Instant-based).

II- The Data

The data set that was used for this project was retrieved from IBM Watson Analytics online community platform where other datasets are made available [1]. This dataset comes from a car insurance company whose name was undisclosed. The data set has **26 attributes and 9134 records**. It has no missing values and the dependent variable is the attribute: **CLV**, standing for *customer lifetime value*. The description of 26 attributes along with their nature (numerical, categorical, answer, question, link) is shown in Appendix A.

Definition: Customer lifetime value is a marketing concept that refers to the amount of money that will be made from a customer over its lifetime as a company customer. In its calculation the analyst should be mindful of the **Cost of Customer Acquisition (CAC)**, periodic profit made from this customer over a certain period of time and the duration this customer will still be a customer of the company. **CLV** is popular concept in Banks, insurance companies (cars, health...etc.) and virtually any business.

III- The Need for the project

1. Key Business Objectives

The Key business objectives of this project is to increase the *Customer Lifetime Value (CLV)* of customers of a car insurance company. The objective will be met by analyzing the different attributes and how they impact the **CLV**. The project insights will serve in designing predictive analytical methods that will help the business owner tell whether a prospective customer will have a high lifetime value or not and based on that have our client act on some aspects to either keep the CLV high or take action to increase it.

2. Key business questions

1. Who are the customers that have the higher customer lifetime value? This can be categorized by (gender, location, age, income, vehicle type, employment...etc).

2. What type of insurance generates the most value by claims?
3. Which vehicles type and size has the most claim amount?
4. What policy type is more profitable?
5. What channel has is the most conversion rate?
6. Who are the customers that have the highest risk of recurring claims? (categorize them by education)
7. What are expiration date of different insurance policies by their coverage type?
8. What are coverage type of insurance that have most complains?
9. What is the number of complains of a certain policy types ?
10. What are the months since last inception and months since last claim for a certain no of policy types?

3. Concepts the Organization is already using to analyze the data

This dataset was made available by IBM Watson analytics for, mostly, academic reasons. The name of insurance company as specified earlier was no disclosed. The tool that is used to analyze the data is **IBM Watson Analytics which** is an advanced data analysis and visualization solution in the cloud and the concepts involved are: Natural language dialogue, Automated predictive analytics, One-click analysis, Smart data discovery, Simplified analysis, Accessible advanced analytics, Self-service dashboards.

IV- Procedure of analysis

1. Key attributes to use

In this project the key attributes to use are: **VehicleClass**, Monthly premium amount called **Premium**, and type of insurance coverage called **Coverage**. We use three different algorithms, but all of three key attributes were used in the 3-different algorithm as well.

2. Any bucketing you plan to use for key attributes

Two attributes (**Customer Lifetime Value and Premium**) that were used in all the analyses were bucketed. The bucketing happened twice. While running the Bayesian Naive algorithm we made the following buckets:

Bucketing#1	Bucketing#2
<u>Customer lifetime value (CLV)</u> Bucket A: $CVL \leq \$5,000$ per year Bucket B: $\$5000 < CVL \leq \20000 per year Bucket C: $\$20000 < CVL \leq \40000 per year Bucket D: $\$40000 < CVL \leq \60000 per year Bucket E: $\$60000 < CVL$ per year <u>Monthly premium buckets (Premium)</u> Low: premium $\leq \$100$ Medium: $\$100 < \text{premium} \leq \150 High: $\$150 < \text{premium}$	<u>Customer lifetime value (CLV)</u> Bucket A: $CVL \leq \$3,000$ per year Bucket B: $\$3,000 < CVL \leq \$6,000$ per year Bucket C: $\$6,000 < CVL \leq \$12,000$ per year Bucket D: $\$12,000 < CVL \leq \$24,000$ per year Bucket E: $\$24,000 < CVL$ per year <u>Monthly premium buckets (Premium)</u> Low: premium $\leq \$100$ Medium: $\$100 < \text{premium} \leq \150 Mid-high: $\$150 < \text{premium} \leq \200 High: $\$200 < \text{premium}$

The need for bucketing again stems from the fact that the first buckets did not give satisfying answers and therefore needed to be checked out. The results of our analyses that we present here are the ones associated with **Bucketing#2**

3. Algorithms you think are worth trying. (Only in the class are allowed)

Algorithms that are worth trying are: R1, Bayesian Naive, and Instant based classification.

4. Evaluation criteria

Depending on the algorithm, evaluation criteria might change, but the universal: Low error rate, high support and high probability should be the main evaluation criteria. Therefore, a good rule will be one that has a lot of support (big enough sample to study it), has low error and its probability of happenstance is considerable high.

V- Applying the Algorithms

1. 1-R Rule (Bucketing#2)

After getting the new buckets, we used 1-R to find the best rules to predict CLV based on the three attributes as mentioned. We did 1-R in a single condition, two conditions, and three conditions. For the single condition, we did calculate the error as you can see in Appendix B. The two and three conditions R1, we showed the best rules with the support, and accuracy as following. We used count of CLV buckets instead of average the CLV because CLV has huge range of data which will not provide insight data where the majority is from.

From the Pivot table

The best 1-condition rule:

- 1). if **Premium** = high, then CVL Bucket = D, error =56.27%
- 2). if **Coverage** = extended , then CVL Bucket = C, error = 55.22%
- 3). if **VehicleClass** = Luxury Car , then CVL Bucket = D, error = 54.6%

Note: the errors from 1-condition rule are high because there are five bucket which means it has less percent to have the same result from one condition.

The best 2-condition rule:

- 1). if **Coverage** = Premium & **Premium** = high, Then CLV = C
(support = 31, confidence = 31/48, accuracy = 64.6%)
- 2). if **Coverage** = Premium & **VehicleClass** = Luxury SUV, Then CLV = C
(support = 17 , confidence = 17/26, accuracy = 65.4%)
- 3). if **Premium** = low & **VehicleClass** = Sports Car, Then CLV = C
(support = 8, confidence = 8/12, accuracy = 66.7%)

Note: in finding support and accuracy, for each rule, we found from Pivot table by adding sup-row to show counting of each CLV in each condition.

The best 3-condition rule:

- 1). if **Coverage** = Premium & **VehicleClass** = Luxury SUV & **SalesChannel** = Agent, Then CLV = C
(support = 16 , confidence = 16/19, accuracy = 84.2%)
- 2). if **Premium** = low & **Vehicle Class** = Sports car & **EmploymentStatus** = Employed, Then CLV = C
(support = 6, confidence = 6/7, accuracy = 85.7%)

3). if **Coverage** = Premium & **Premium** = high & **SalesChannel** = Agent, Then CLV = C
 (support = 25, confidence = 25/28, accuracy = 89.3%)

Note: in finding support and accuracy, for each rule, we used the pivot tables form 2-condition and filtered the third condition to find the best rules with high accuracy.

2. Bayesian Naive (Bucketing#2)

The Bayesian model was run to find the value of CLV associated with each combination of values of the attributes (**VehicleClass, Coverage and Premium**) along with returning the probability of accurate decision for each decision.

The full data will be presented in an Excel file that will be attached with this report. Also, it can be found at the Appendix C. Following is an example of one of the best rules that we can come up with by running the Bayes Naive Algorithm.

Vehicle Class	Coverage Type	Premium	Decision	Probability
Luxury Car	Premium	mid-high	D	85.50%
Luxury SUV	Premium	mid-high	D	83.40%
SUV	Premium	mid-high	D	69.60%

Once the Bayes model is set up, The insurance company, whenever faced with a new customer profile, they can pick their data and enter them to the model and then the model will be able to predict with relatively good accuracy in what CLV bucket category this customer will be falling and hence will help the insurance company take action based on that.

3. Instant based Classification (Bucketing#2)

In the instant-based classification method, the second buckets of the data were used. Only three attributes were considered: **VehicleClass, Coverage type, and Premium Amount**. A few instances (records) of those variables were taken to run the algorithm. As seen in class, the Instant-based classification can turn out to be very time-consuming with long running times when you have large amounts of data. The full data will be presented in an Excel file that will be attached with this report.

The training set is shown in the table below. In interpretation of the results, only 14 out of 72 (**20%**) possible combinations of the data take on one **CLV** value without ambiguity. (Shown across).

It is clear from the results that this Algorithm is not adapted for all possible variables. It appears to do well when **Premium** Coverage value is selected. As the table shows.

This Algorithm despite its ability to work very well with the data takes a long running time and performed poorly, and therefore we do not recommend using it to analyze this data with no automatic system.

The recommendations we can infer from the results to make the algorithm more robust as far as analyzing out insurance company data are the following:

No.	Observation			Sequence
1	Two-Door	high	Premium	D
2	Four-Door	high	Premium	D
3	SUV	low	Premium	D
4	SUV	med-high	Extended	B
5	SUV	med-high	Premium	B
6	Luxury Car	low	Premium	D
7	Luxury Car	medium	Extended	2E
8	Luxury Car	medium	Premium	D
9	Luxury Car	med-high	Extended	2E
10	Luxury Car	med-high	Premium	D
11	Luxury Car	high	Extended	2E
12	Luxury Car	high	Premium	D
13	Sport car	low	Premium	E
14	Sport car	medium	Premium	E

- 1- Experiment with different bucketing schemes.
- 2- Make the training sample a bit bigger. (which could be very time consuming if done manually).

Vehicle Class	Premium Amount	Coverage	CLV	1	1	1	DIST
Two-Door	low	Extended	A	1	1	0	2
Four-Door	low	Basic	A	1	1	1	3
Four-Door	low	Extended	A	1	1	0	2
Four-Door	low	Basic	A	1	1	1	3
SUV	mid-high	Premium	B	1	1	1	3
Four-Door	low	Extended	B	1	1	0	2
Two-Door	low	Extended	B	1	1	0	2
Four-Door	low	Extended	B	1	1	0	2
Two-Door	low	Extended	C	1	1	0	2
SUV	medium	Basic	C	1	1	1	3
Two-Door	low	Basic	C	1	1	1	3
Two-Door	low	Basic	C	1	1	1	3
SUV	medium	Basic	D	1	1	1	3
Luxury Car	high	Premium	D	1	0	1	2
Four-Door	low	Basic	D	1	1	1	3
Luxury SU\	high	Extended	D	1	0	0	1
Luxury Car	high	Extended	E	1	0	0	1
Luxury Car	high	Extended	E	1	0	0	1
Luxury SU\	high	Extended	E	1	0	0	1
Sports Car	mid-high	Premium	E	0	1	1	2

VI- Conclusion

In this class project, an insurance company data set was analyzed. The team worked on applying all the important algorithms learned in class, and we tried to put to practice all the different concepts and techniques that were seen. The algorithms performed differently, which puts in perspective the idea of using the right algorithms for the the right application. Insights from this class project are summarized in what follows:

a) Insights regarding the methods:

- Algorithms can be application dependent.
- Bucketing can change the results of your analysis and therefore, one has got to be mindful of selecting robust and rational bucketing schemes to ensure the data is not completely skewed.
- Increasing the number of attributes used in an analysis, in most cases (in this project) increases the accuracy of prediction, but one has to be mindful to select just the right number of attributes. Overfitting issues might rise, and that will make the analysis insights basically useless.

b) Insights regarding the results of our application

- Depending on the application, our client can use any algorithm to predict the CLV of prospective customers.
- Ex: 1-R 3-condition can be used to target new customers offering premium coverage, with high monthly premium amount and reach out to them via agent will lead to C-level CLV.
- The algorithms' results can either be used by the insurance company to either improve their **Customer Relationship Management**, or even to acquire new customers.
- Once the models are set up, our client can use them to answer any of the business questions they might have.
- The attributes that our client should focus on should be: VehicleClass, Coverage, Premium amount, and Sales Channel.

VII- References

[1] "SAMPLE DATA: Marketing Customer Value Analysis," *IBM Analytics Communities*, 11-Apr-2015. [Online]. Available: <https://www.ibm.com/communities/analytics/watson-analytics-blog/marketing-customer-value-analysis/>. [Accessed: 09-Mar-2018].

[2] "IBM Watson Analytics," *IBM Watson Analytics - Overview - United States*, 10-Mar-2018. [Online]. Available: <https://www.ibm.com/us-en/marketplace/watson-analytics>. [Accessed: 09-Mar-2018].

[3] Witten, I., Frank, Eibe, & Hall, Mark A. (2011). *Data mining : Practical machine learning tools and techniques* (3rd ed., Morgan Kaufmann series in data management systems). Burlington, MA: Morgan Kaufmann.

VIII- Appendix

Appendix A: The description of 26 attributes

The attributes along with their nature are shown in the following table:

Attribute	Description	Type	Nature
Customer	Different customers with their own ID	Text and Integer	Link
State	Name of states in which insurance is sold	Text	Answer
Customer Lifetime Value (CLV)	The time period since a particular person has been paying premiums	Currency	Key-Answer
Response	No or yes response to the coverage of insurance type	Text	Answer
Coverage	The coverage type of insurance	Text	Answer
Education	The education of customers buying the insurance	Text	Answer
Effective to Date	The time period until the insurance is active	Date	Answer
Employment Status	The employment status of customer	Text	Answer
Gender	The gender of each customer buying insurance	Text	Answer
Income	The income of customers buying insurance	Currency	Answer
Location Code	The location of each customer	Text	Answer
Marital Status	The marital status of each customer	Text	Answer
Monthly Premium Auto	The insurance premiums paid for each auto	Integer	Answer
Premium	The amount paid for an insurance policy	Text	Answer
Months Since Last Claim	The number of months passed since the insurance is claimed.	Integer	Answer

Months Since Policy Inception	The insurance was first purchased	Integer	Answer
Number of Open Complaints	The number of complaints by each customer	Integer	Answer
Number of Policies	The number of policies sold by each customer	Integer	Answer
Policy Type	The types of insurance policy	Text	Answer
Policy	Name of policy	Text	Answer
Renew Offer Type	The type of offer	Text	Answer
Sales Channel	The channel through which insurance is sold	Text	Answer
Total Claim Amount	Claimed amount of each policy type of insurance	Currency	Answer
Vehicle Class	The class of vehicles being most claimed	Text	Answer
Vehicle Size	The size of vehicles that has auto insurance	Text	Answer

Appendix B: Data and Pivot tables of R1

The training Data:

Id	Casto	State	Customer	CL	Resp	Covera	Education	Effectiv	Employment	G	Incor	Incor	Location	Marital	Month	premiu	Months Since La	Months Since Policy	Number of Open Co	Number of F	Policy Ty	Policy
1	FO61281	Oregon	\$ 83,325.38	E	No	Extended	High School or Belc	2011/1/31	Employed	M	58958	d	Suburban	Married		231 high	31	74	0	2	Personal Auto	Persons
2	YCS4142	Washington	\$ 74,228.52	E	No	Extended	High School or Belc	2011/1/26	Unemployed	M	0	a	Suburban	Single		242 high	1	34	0	2	Personal Auto	Persons
3	BF23267	California	\$ 73,225.96	E	No	Extended	Bachelor	2011/2/9	Employed	F	39547	c	Suburban	Married		202 high	11	21	0	2	Personal Auto	Persons
4	KH55896	Oregon	\$ 67,907.27	E	No	Premium	Bachelor	2011/2/5	Employed	M	78310	d	Rural	Married		192 mid-high	34	18	1	2	Personal Auto	Persons
5	SK66747	Washington	\$ 66,025.75	E	No	Basic	Bachelor	2011/2/22	Employed	M	33481	c	Suburban	Single		188 mid-high	28	46	0	2	Personal Auto	Persons
6	FB95288	California	\$ 64,618.76	E	No	Extended	High School or Belc	2011/1/17	Unemployed	M	0	a	Suburban	Married		217 high	14	40	1	2	Personal Auto	Persons
7	AZ84403	Oregon	\$ 61,850.19	E	No	Extended	College	2011/2/4	Unemployed	F	0	a	Suburban	Married		238 high	19	29	0	2	Personal Auto	Persons
8	US30122	California	\$ 61,134.68	E	No	Basic	College	2011/2/28	Unemployed	M	0	a	Suburban	Single		198 mid-high	2	75	0	2	Corporate Aut/Corpor	Persons
9	JT47995	Arizona	\$ 60,556.19	E	No	Extended	College	2011/1/1	Unemployed	F	0	a	Suburban	Married		204 high	35	45	0	2	Personal Auto	Persons
10	EN65835	Arizona	\$ 58,753.88	E	No	Premium	Bachelor	2011/1/16	Employed	F	24964	b	Suburban	Married		185 mid-high	0	84	0	2	Personal Auto	Persons
11	XF89906	Arizona	\$ 58,207.13	E	No	Extended	High School or Belc	2011/1/13	Disabled	M	28295	c	Suburban	Married		219 high	25	50	0	2	Personal Auto	Persons
12	OM82306	California	\$ 58,166.55	E	No	Basic	Bachelor	2011/2/27	Employed	M	61321	d	Rural	Single		186 mid-high	0	30	1	2	Personal Auto	Persons
13	JZ23377	Oregon	\$ 57,520.50	E	No	Premium	College	2011/1/20	Employed	F	48367	c	Suburban	Married		161 mid-high	10	34	0	2	Personal Auto	Persons
14	DU50092	Oregon	\$ 56,675.94	E	No	Premium	College	2011/1/24	Employed	F	77237	d	Suburban	Married		283 high	33	93	0	2	Personal Auto	Persons
15	OY68395	Oregon	\$ 55,277.45	E	No	Basic	High School or Belc	2011/1/30	Employed	F	40740	c	Suburban	Single		198 mid-high	19	60	0	2	Personal Auto	Persons
16	CL79250	Nevada	\$ 52,811.49	E	No	Basic	Bachelor	2011/1/8	Unemployed	M	0	a	Suburban	Married		182 mid-high	8	70	0	2	Corporate Aut/Corpor	Persons
17	AH58807	Arizona	\$ 51,426.91	E	No	Basic	College	2011/1/19	Employed	F	84650	d	Urban	Married		185 mid-high	13	39	3	2	Personal Auto	Persons
18	K158952	California	\$ 51,337.91	E	No	Premium	College	2011/2/24	Employed	F	72794	d	Rural	Single		164 mid-high	3	47	1	2	Personal Auto	Persons
19	LW64678	California	\$ 51,161.07	E	No	Premium	Master	2011/2/19	Employed	F	25167	c	Urban	Married		140 medium	3	76	0	2	Personal Auto	Persons
20	QT84069	Oregon	\$ 50,568.26	E	No	Extended	Master	2011/2/28	Employed	M	82081	d	Urban	Married		249 high	1	62	0	2	Personal Auto	Persons
21	BR50492	Arizona	\$ 49,423.80	E	No	Extended	Bachelor	2011/1/14	Employed	M	85058	d	Urban	Married		137 medium	34	82	0	2	Personal Auto	Persons
22	RP30093	Oregon	\$ 49,221.43	E	No	Premium	Bachelor	2011/1/23	Employed	F	63035	d	Suburban	Married		153 mid-high	20	97	0	2	Personal Auto	Persons
23	LU42720	Nevada	\$ 48,356.96	E	No	Extended	College	2011/2/20	Employed	M	52499	d	Suburban	Divorced		138 medium	0	61	0	2	Personal Auto	Persons
24	MJ77630	Oregon	\$ 47,155.63	E	No	Extended	High School or Belc	2011/2/10	Employed	M	39891	c	Urban	Married		133 medium	12	31	0	2	Personal Auto	Persons
25	CP92616	Nevada	\$ 46,805.22	E	No	Extended	High School or Belc	2011/2/25	Employed	M	83006	d	Urban	Married		235 high	8	61	1	2	Personal Auto	Persons
26	KB44286	Oregon	\$ 46,770.95	E	No	Basic	High School or Belc	2011/2/1	Employed	F	64403	d	Rural	Single		198 mid-high	11	86	0	2	Corporate Aut/Corpor	Persons
27	DM76655	California	\$ 46,611.87	E	No	Extended	College	2011/2/6	Employed	M	22022	b	Suburban	Single		136 medium	35	1	0	2	Personal Auto	Persons
28	GV41938	California	\$ 46,302.08	E	No	Premium	High School or Belc	2011/2/6	Unemployed	F	0	a	Suburban	Married		151 mid-high	33	94	1	2	Personal Auto	Persons
29	OK56965	California	\$ 45,708.65	E	No	Basic	Bachelor	2011/1/19	Employed	F	31264	c	Urban	Divorced		198 mid-high	9	54	1	2	Personal Auto	Persons
30	ZF84966	Nevada	\$ 44,856.11	E	No	Extended	Doctor	2011/2/22	Employed	F	61675	d	Urban	Married		123 medium	35	54	0	2	Corporate Aut/Corpor	Persons
31	CF85232	Arizona	\$ 44,795.47	E	No	Extended	College	2011/2/4	Employed	M	58778	d	Rural	Married		126 medium	6	62	0	2	Special Auto	Special
32	AB31813	Washington	\$ 44,771.30	E	No	Extended	High School or Belc	2011/2/12	Unemployed	M	0	a	Suburban	Married		131 medium	20	59	0	2	Personal Auto	Persons
33	SD41771	California	\$ 44,520.14	E	No	Premium	High School or Belc	2011/1/26	Employed	M	49259	c	Suburban	Single		144 medium	30	35	0	2	Personal Auto	Persons
34	XZ262712	Washington	\$ 44,468.02	E	No	Extended	High School or Belc	2011/1/29	Employed	F	32948	c	Suburban	Single		127 medium	20	46	1	2	Personal Auto	Persons

The Pivot Table for Premium

Total	Max count	The rest	Decision	Error
510	223	287	D	0.562745
5990	2311	3679	B	0.61419
2634	1082	1552	C	0.589218
9134	3616	5518	Average	0.604116

The Pivot Table for Coverage

Total	Max count	The rest	Decision	Error
5568	2045	3523	B	0.632723
2742	1228	1514	C	0.552152
824	340	484	C	0.587379
9134	3613	5521	Average	0.604445

The Pivot Table for Vehicle Class

Total	Max count	The rest	Decision	Error
4621	1783	2838	B	0.614153
163	74	89	D	0.546012
184	79	105	D	0.570652
484	219	265	C	0.547521
1796	706	1090	C	0.606904
1886	703	1183	B	0.627253
9134	3564	5570	Average	0.60981

Appendix C : Bayesian Model Probabilities Data Vehicle Class:

Label	Coverage type	CLV	Count	CLVCount	Prob
Four-Door-Car A	Four-Door-Car	A	1060	1506	0.70385
Four-Door-Car B	Four-Door-Car	B	1783	3248	0.54895
Four-Door-Car C	Four-Door-Car	C	1333	2929	0.4551
Four-Door-Car D	Four-Door-Car	D	351	1093	0.32113
Four-Door-Car E	Four-Door-Car	E	94	358	0.26257
Luxury Car A	Luxury Car	A	0	1506	0
Luxury Car B	Luxury Car	B	1	3248	0.00031
Luxury Car C	Luxury Car	C	62	2929	0.02117
Luxury Car D	Luxury Car	D	74	1093	0.0677
Luxury Car E	Luxury Car	E	26	358	0.07263
Luxury SUV A	Luxury SUV	A	0	1506	0
Luxury SUV B	Luxury SUV	B	0	3248	0
Luxury SUV C	Luxury SUV	C	78	2929	0.02663
Luxury SUV D	Luxury SUV	D	79	1093	0.07228
Luxury SUV E	Luxury SUV	E	27	358	0.07542
Sport Car A	Sport Car	A	0	1506	0
Sport Car B	Sport Car	B	155	3248	0.04772
Sport Car C	Sport Car	C	219	2929	0.07477
Sport Car D	Sport Car	D	64	1093	0.05855
Sport Car E	Sport Car	E	46	358	0.12849
SUV A	SUV	A	1	1506	0.00066
SUV B	SUV	B	606	3248	0.18658
SUV C	SUV	C	706	2929	0.24104
SUV D	SUV	D	353	1093	0.32296
SUV E	SUV	E	130	358	0.36313
Two Door-Car A	Two Door-Car	A	445	1506	0.29548
Two Door-Car B	Two Door-Car	B	703	3248	0.21644
Two Door-Car C	Two Door-Car	C	531	2929	0.18129
Two Door-Car D	Two Door-Car	D	172	1093	0.15737
Two Door-Car E	Two Door-Car	E	35	358	0.09777

Coverage Type:

Label	Coverage type	CLV	Count	CLVCount	Prob
Basic A	Basic	A	1403	1506	0.93161
Basic B	Basic	B	2045	3248	0.62962
Basic C	Basic	C	1361	2929	0.46466
Basic D	Basic	D	593	1093	0.54254
Basic E	Basic	E	166	358	0.46369
Extended A	Extended	A	103	1506	0.06839
Extended B	Extended	B	971	3248	0.29895
Extended C	Extended	C	1228	2929	0.41926
Extended D	Extended	D	299	1093	0.27356
Extended E	Extended	E	141	358	0.39385
Premium A	Premium	A	0	1506	0
Premium B	Premium	B	232	3248	0.07143
Premium C	Premium	C	340	2929	0.11608
Premium D	Premium	D	201	1093	0.1839
Premium E	Premium	E	51	358	0.14246

Monthly Premium:

Label	Premium	CLV bucket	Count	CLVCount	Prob
low A	low	A	1505	1506	0.999335989
low B	low	B	2311	3248	0.711514778
low C	low	C	1649	2929	0.562990782
low D	low	D	418	1093	0.382433669
low E	low	E	107	358	0.298882682
medium A	medium	A	1	1506	0.000664011
medium B	medium	B	913	3248	0.281096059
medium C	medium	C	1082	2929	0.369409355
medium D	medium	D	452	1093	0.413540714
medium E	medium	E	186	358	0.519553073
mid-high A	mid-high	A	0	1506	0
mid-high B	mid-high	B	24	3248	0.007389163
mid-high C	mid-high	C	137	2929	0.046773643
mid-high D	mid-high	D	160	1093	0.146386093
mid-high E	mid-high	E	28	358	0.078212291
top A	top	A	0	1506	0
top B	top	B	0	3248	0
top C	top	C	61	2929	0.020826221
top D	top	D	63	1093	0.057639524
top E	top	E	37	358	0.103351955

CLV Bucket:

CLVBucket	CLVCount	Total	Probability
A	1506	9134	0.164878476
B	3248	9134	0.355594482
C	2929	9134	0.320670024
D	1093	9134	0.119662798
E	358	9134	0.039194219

Predictive Model:

	Class	Coverage	Premium	CLV Bucket	Product (x 10 ⁸)	Likelihood (%)
Observation:	Luxury Car	Premium	mid-high			
A	0	0	0	0.164878476	0	0.0%
B	0.000307882	0.071428571	0.007389163	0.355594482	5.778381058	0.0%
C	0.021167634	0.116080574	0.046773643	0.320670024	3685.457633	14.5%
D	0.067703568	0.18389753	0.146386093	0.119662798	21809.53613	85.5%
E	0.072625698	0.142458101	0.078212291	0.039194219	3171.571414	12.4%
					25500.77215	100.0%

Appendix D: Full Table for Instant Based Learning

	Observation			Sequence	Decision	Error
1	Two-Door	low	Extended	A-A-B-B-B-C	B	50%
2	Two-Door	low	Basic	A-A-C-C	A-C	50%
3	Two-Door	low	Premium	4A-4B-3C-D	A-B	67%
4	Two-Door	medium	Extended	2A-3B-2C-D	B	62.50%
5	Two-Door	medium	Basic	C-D	C-D	50%
6	Two-Door	medium	Premium	B-C-2D	D	50%
7	Two-Door	med-high	Extended	2A-3B-1C	B	50%
8	Two-Door	med-high	Basic	2A-3C-1D	C	50%
9	Two-Door	med-high	Premium	B-D	B-D	50%
10	Two-Door	high	Extended	2A-3B-C-D	B	58%
11	Two-Door	high	Basic	2A-3C-2D	C	58%
12	Two-Door	high	Premium	D	D	0%
13	Four-Door	low	Extended	2A-3B-C	B	50%
14	Four-Door	low	Basic	2A-2C	A-C	50%
15	Four-Door	low	Premium	4A-4B-3C-D	A-B	67%
16	Four-Door	medium	Extended	2A-3B-2C-D	B	62.50%
17	Four-Door	medium	Basic	C-D	C-D	50%
18	Four-Door	medium	Premium	B-C-2D	D	50%
19	Four-Door	med-high	Extended	2A-3B-1C	B	50%
20	Four-Door	med-high	Basic	2A-3C-D	C	50%
21	Four-Door	med-high	Premium	B-D	B-D	50%
22	Four-Door	high	Extended	2A-3B-C-D	B	57%
23	Four-Door	high	Basic	2A-3C-2D	C	57%
24	Four-Door	high	Premium	D	D	0%
25	SUV	low	Extended	2A-3B-C	B	50%
26	SUV	low	Basic	2A-3C-D	C	50%
27	SUV	low	Premium	D	D	0%
28	SUV	medium	Extended	C-D	C-D	50%
29	SUV	medium	Basic	C-D	C-D	50%
30	SUV	medium	Premium	B-C-D	B-C-D	66%
31	SUV	med-high	Extended	B	B	0%
32	SUV	med-high	Basic	B-C-D	B-C-D	66%
33	SUV	med-high	Premium	B	B	0%
34	SUV	high	Extended	2A-4B-2C-2D	B	60%
35	SUV	high	Basic	C-D	C-D	50%
36	SUV	high	Premium	B-D	B-D	50%
37	Luxury Car	low	Extended	2A-3B-C-2E	B	54%
38	Luxury Car	low	Basic	2A-2C-D	A-C	60%
39	Luxury Car	low	Premium	D	D	0%
40	Luxury Car	medium	Extended	2E	E	0%
41	Luxury Car	medium	Basic	C-D	C-D	50%

42	Luxury Car	medium	Premium	D	D	0%
43	Luxury Car	med-high	Extended	2E	E	0%
44	Luxury Car	med-high	Basic	2A-3C-3D-2E	C-D	70%
45	Luxury Car	med-high	Premium	D	D	0%
46	Luxury Car	high	Extended	2E	E	0%
47	Luxury Car	high	Basic	2E-D	E	30%
48	Luxury Car	high	Premium	D	D	0%
49	LuxurySUV	low	Extended	2A-3B-C-D-E	B	62%
50	LuxurySUV	low	Basic	4A-3B-3C-2D-E	A	70%
51	LuxurySUV	low	Premium	4A-4B-3C-3D-2E	A-B	75%
52	LuxurySUV	medium	Extended	D-E	D-E	50%
53	LuxurySUV	medium	Basic	C-D	C-D	50%
54	LuxurySUV	medium	Premium	B-C-3D-2E	D	57%
55	LuxurySUV	med-high	Extended	D-E	D-E	50%
56	LuxurySUV	med-high	Basic	2A-3C-3D-E	C-D	67%
57	LuxurySUV	med-high	Premium	B-2D-2E	D-E	60%
58	LuxurySUV	high	Extended	D-E	D-E	50%
59	LuxurySUV	high	Basic	D-E	D-E	50%
60	LuxurySUV	high	Premium	2D-E	D	33%
61	Sport car	low	Extended	2A-3B-C	B	50%
62	Sport car	low	Basic	2A-2C-D	A-C	60%
63	Sport car	low	Premium	E	E	0%
64	Sport car	medium	Extended	C-D-E	C-D-E	33%
65	Sport car	medium	Basic	C-D	C-D	50%
66	Sport car	medium	Premium	E	E	0%
67	Sport car	med-high	Extended	2A-3B-C-D-4E	E	63%
68	Sport car	med-high	Basic	2A-3C-2D-E	C	62.50%
69	Sport car	med-high	Premium	D-3E	E	25%
70	Sport car	high	Extended	2A-3B-C-D	B	57%
71	Sport car	high	Basic	2A-3C-4D-4E	D-E	70%
72	Sport car	high	Premium	D-E	D-E	50%