Predictive Modeling in Automobile Insurance: A Preliminary Analysis

by

Stephen P. D'Arcy

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Contact information:

Stephen P. D'Arcy
Professor of Finance
College of Business
University of Illinois
1206 S. Sixth Street
Champaign, IL 61820
Telephone: 217-333-0772
E-mail: s-darcy@uiuc.edu

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Abstract

This project applies the *Data to Knowledge* (D2K) systems developed by NCSA to the Detail Claim Database (DCD) of the Automobile Insurers Bureau of Massachusetts to generate predictive models to enhance insurance claim investigation practices. Data mining is a relatively new tool for insurance companies. However, advances in applications of data mining have been hindered by the lack of research that can be shared within the industry. Although insurers have conducted many data mining projects for a variety of applications, including underwriting, rating and claim investigation, they have generally resisted disclosing the details of this research in an attempt to maintain a competitive advantage. In many cases, when insurers have tried to utilize the results of these studies in their operations they have encountered regulatory resistance due to a lack of full disclosure of the supporting documentation. This project seeks to redress some of the problems limiting the advance of data mining and predictive modeling in the insurance industry by conducting a study that can be shared within the industry and all the details can be published. This study provides a significant advance over the few prior studies that used this data set by utilizing the state-of-the-art data mining tools developed at NCSA.

This project examines the data set for patterns of claim behavior based on the records of the almost one-half million automobile bodily injury claims included in the DCD. An updated D2K system has been applied to these data to establish which factors can be effectively utilized in the claims process in order to generate a predictive model to help insurers identify which claims are most likely to generate cost savings by investigating the claim more extensively in an attempt to deter fraudulent claiming behavior.

Overview

Technological advances have allowed the insurance industry to begin to apply data mining techniques to the vast data bases the industry routinely collects in the course of conducting its business. Data mining has been effectively used to determine significant characteristics for use in underwriting applicants, to support the use of credit score factors in rating, and to identify claims that should be investigated for fraudulent activity. Many insurers have undertaken data mining projects, several consulting firms have established specialty areas to develop predictive models based on data mining activity for insurers, and a cottage industry of companies performing analytics and predictive modeling for insurance companies and other industries has developed. Predictive modeling appears to represent a significant new avenue for the insurance industry.

Several problems, though, need to be addressed before data mining can be applied most effectively within the insurance industry. First, despite the extensive efforts by a large number of parties, there have been very few published results of these studies. As one professional colleague (who asked not to be identified) commented,

> "Unfortunately, insurance companies are very sensitive and reluctant in sharing their data. I have done data mining and predictive modeling for the last 10 years, and have worked with more than 20 different clients. But none of them is willing to share the data publicly. For every project I have worked on so far, we have always signed an agreement with the clients that we cannot use the data for other purposes, not even for research."

Companies know the value they can obtain from data mining their information, and do not want to lose this competitive advantage by giving away the results of their work. While this is understandable behavior, its near universal application has prevented this area from advancing to its full potential. By conducting each project separately, there is no benefit gained from the experience of other companies. By requiring each project to stand on its own, subtle interactions that are not significant based on a single study would be ignored, even though they might be considered relevant if the results of numerous analyses could be combined.

A second problem is that the studies are performed by a small group of experts, and shared with a small group of customers. This drastically limits the understanding of data mining and predictive modeling to only a subset of the people who could actually benefit from these techniques and unnecessarily limits the situations to which they will be applied. If most individuals within an insurance company are not aware of data mining techniques, they will not realize the potential applications of this technology to their everyday work. If the impetus for data mining is for an expert to discover the application, and then convince a practitioner that a large enough benefit can be obtained to justify the initial cost of a project, most potential applications will not be addressed. However, if the results of data mining projects in one company, or in one part of a company, can be disseminated, then other applications will become obvious. This would advance the pace and productivity of this research.

A function of the limited sharing of data mining applications is the over reliance on a specialized jargon appropriate for this field. Since most data mining research is shared only with other specialists, if at all, then the terminology does not need to be understood by a wider audience. Thus, even when data mining results are shared, the terminology restricts the understanding of the results, or even the significance of the approach, to other experts.

Finally, one special attribute of the insurance industry is its regulatory structure. Insurance is one of the most heavily regulated industries in this country. Insurers must obtain regulatory approval for a wide variety of functions, including policy forms, rates, investments, and underwriting and sales practices. If an insurer wants to use a specific characteristic in setting rates, in many cases it must convince a regulator that this is an appropriate factor. Currently, credit scoring is a particularly sensitive issue in many regulatory jurisdictions. Through data mining insurance companies have found that certain personal characteristics that are related to credit score are also related to insurance claims experience. In some cases regulators are allowing these factors to be used; in others they are not. One element contributing to the problems is that insurers and the modeling companies want to keep the results of their data mining confidential. This confidentiality leads to misunderstandings and incorrect conclusions about the effect of including credit scoring on certain segments of the population.

In this project we apply the data mining techniques developed by NCSA to insurance data from the Automobile Insurers' Bureau of Massachusetts. This data set is described by Derrig (2003):

> "The Detail Claim Database (DCD) is mandated by the Commissioner of Insurance for use by all companies operating in Massachusetts. It includes reports from all Massachusetts automobile bodily injury claims closing January 1, 1994 and subsequent. The DCD receives in excess of 160,000 claims filed annually and contains information not normally reported in insurance statistics, including injury information and related treatment expense statistics for medical and legal providers. The DCD is a progressive and unique creation of the Governing Committee of the Automobile Insurers Bureau of Massachusetts, and it is unparalleled in its level of detail and overall participation by any data collection effort elsewhere in the country. This system is viewed as a new cornerstone in the battle against insurance fraud in Massachusetts."

The most important feature of the DCD is that the results of research on this data set can be freely shared by researchers, leading to cooperative advances in the development of predictive models. This data set has been made available to a limited number of researchers and has been the basis for several previous applications of data mining [Brockett, Derrig, Golden, Levine and Alpert (2002), Derrig and Weisberg (2003), Tennyson and Salas-Forn (2002) and Viaene, Derrig, Baesens and Dedene (2002)]. This sharing has led to collaboration and advances in this field.

NCSA has developed a state-of-the-art data mining application process termed *Data To Knowledge* (D2K) [Hsu, Welge, Redman and Clutter (2002)]. This system has been applied in a number of business applications, including insurance. A recent innovation is an updated version of this program that is designed to be user-friendly for the less technical practitioner. This advance should be extremely helpful for this project, which seeks to make insurance data mining techniques both more widely applicable and more easily understandable.

Literature Review

The prior published research using the Massachusetts claim database has focused on several specific aspects of this data. Brockett, Xia and Derrig (1998) apply a feature mapping process to classify potential fraud cases in bodily injury claims. Tennyson and Salsas-Form (2002) look at a small sample of claims to determine if auditing was used primarily for detection of fraud or deterrence of future fraud. Derrig and Weisberg (2003), in their most recent study using the DCD, report on the results of an experiment to provide fraud indicators generated from data mining to claim investigators to determine if that information leads to more effective detection of fraudulent claims. Brockett, Derrig, Golden, Levine and Alpert (2002) apply principal component analysis of RIDIT scores to automobile insurance claims. Viaene, Derrig, Baesens and Dedene (2002) compare several binary classification techniques to automobile insurance claims to determine which approach is most effective, but find no single method works best.

Massachusetts Detail Claim Database

This database, mandated by the Commissioner of Insurance, consists of all automobile bodily injury claims closing on or after January 1, 1994. The Automobile Insurers Bureau (AIB) of Massachusetts maintains this database, which is accessible for all member companies of the AIB. The database provided for this research consists of 491,591 claim observations with 95 variables from five categories included:

1. Policy Information
2. Claim Information
    a. Accident date
    b. Report date
    c. Type of injury
    d. Type of treatment
3. Outpatient Medical Provider Information (up to 2 providers)
    a. Provider type (Medical Doctor, Medical Organization, Medical Institution, Chiropractor, Chiropractic Organization, Physical Therapist, Physical Therapy Organization, N/A)
    b. Amount billed
    c. Amount paid (PIP or BI)
4. Attorney Information
5. Claim Handling Information
    a. Type of investigation
        i. Independent Medical Exam (IME)
        ii. Medical Audit (MA)
        iii. Special Investigation (SI)
    b. Result of Investigation
        i. No change recommended
        ii. Billing or treatment curtailed
        iii. Damages mitigated
        iv. No show (the claimant failed to show up for an IME)
        v. Refused (the claimant refused to have an IME)
        vi. Claim denied (as the result of an SI)
        vii. Claim compromised (a compromise was worked out after an SI)
    c. Amount of Savings Estimated from Each Type of Investigation

There are several recognized shortcomings of the DCD. The amounts listed for savings from investigations are based on formulae that likely understate the full value of any savings achieved, especially regarding bodily injury coverage. The type of medical provider is omitted in many cases. Investigations undertaken and second outpatient medical provider information are considered to be underreported. These problems are typical of most data mining studies, and underscore the importance of accurate data for this type of research.

For the purpose of this research, the database was randomly divided into two components, a training dataset of 400,000 observations and a testing dataset of 91,591 observations. Based on the training database, of the three types of investigations, IMEs were the most common (16.72%), followed by MAs (11.02%) and then SIs (4.17%). The average estimated savings from each type of investigation is $348.71 for Independent Medical Exams (IME_SAVE), $367.08 for Medical Audits (MA_SAVE) and $1805.39 for Special Investigations (SI_SAVE). These values for savings do not consider the cost of the investigation itself.

Empirical Results

Initial Indicators Study by the D2K Decision Tree tool

1. Motivation – To test the relationship between the independent nominal (dummy) variables and three dependent variables, IME_SAVE, MA_SAVE and SI_SAVE.
2. Methodology and Tools - Decision Tree and D2K Itinerary for Decision Tree
3. Approach - Dependent variables were taken as IME_Saved, MA_Saved and SI_Saved. Independent variables are 7 out of 52 nominal variables. They were Policy Type, Coverage, Em_Treat, Health_I, Injury Type, MP1_Type and MP2_Type. All other nominal variables are either location, ID numbers or investigation information.

The possible values for all selected variables are listed as follows:

- Policy Type: P (personal) and C (commercial)
- Coverage: (BI), (U-1), (U-2) and (PIP/MED)
- Em_Treat: Y (Emergency and /or Inpatient Treatment or No Treatment – No Outpatient Treatment), N (Out Patient Treatment Only) and B (Outpatient Treatment and Emergency and /or Inpatient Treatment)
- Health_I: Y (Yes), N (No) and U (Unknown)
- Injury Type: 1-22, 30 or 99 according to the different types of injury.
- MP1_Type: MD, MO, MI, CH, CO, PT, PO and N/A.
- MP2_Type: Same as above

The D2K decision tree itinerary was applied separately for each of the seven selected nominal variables. The whole dataset includes 491,591 observations, which were randomly separated into 400,000 observations for a training dataset and 91,591 observations to be used as a testing dataset by the D2K decision tree itinerary. The training dataset was used to generate the possible trees. The testing dataset was used to generate the external error for each of the possible trees to select the best tree and the optimal depth (number of levels). The maximum depth of the trees is the number of the nominal variables included, which in this case is two for the policy type variable (personal/commercial) or eight for medical provider (seven types plus N/A). The absolute difference of the estimated and actual value of each dependent variable tested was used as the measure of the tree's evaluator.

For each of these seven nominal variables, there are some missing data. The missing data is treated as a random distribution, so the trees were generated from the available data without considering the impact of any specific relationships between any of the nominal variables and the likelihood of data to be omitted.

The decision tree results for the significant relationship between the selected dependent and independent variables were summarized in the Table 1. Y indicates a significant relationship; N indicates no significant relationship between the dependent variables and the selected nominal variables.

Tables 2, 3 and 4 list the D2K decision tree results for the savings obtained through an Independent Medical Exam (IME), Medical Audit (MA) and Special Investigation (SI) considering the 24 different injury types. In Table 2, the 24 injury types are shown in the 1st column. Each row provides the mean, standard deviation, minimum, maximum and the internal error (D2K decision tree factor) for each injury type. The last three columns show the number of IMEs that were requested for this injury type, the total number of claims with that injury type, and the percentage of the claims for which an IME was requested (IME Requested/Total). Each injury type is listed in a separate row, but some rows do not have any individual values for some of the statistics. For these injury types, the D2K decision tree did not find a significant difference to separate the injury types (in this case injury types 3,5,6,7,9,14,18,19) so they are combined together as a group. For example, the value 351.289 is the mean savings for all these injury types combined. At the bottom of Table 2, the external errors with and without the optimal tree are listed as 93.379 and 93.5752. This means that if injury type were not used as an indicator of potential savings from requesting an IME, then the error term would be 93.5752. This error value was reduced to 93.379 by using the optimal tree based on injury type. The optimal decision tree has a depth of 17 (16 individual injury types and the combined group of the 8 remaining types), out of a potential tree depth of 24 (the total number of injury types). Injury type is a significant variable for predicting the IME_Saved, as indicated by the **Y** listed at the bottom of the table.

Other useful information can also be determined from Table 2. About 16.72% (66,876 out of 400,000) of the claims reported IMEs requested (as listed on the bottom row). The average IME savings for investigating claims for injury type 22 (psychological condition) is 957.50, which is the highest mean for any injury type. Investigating claims for injury type 12 (loss of body part) had no savings when an IME was requested, but there were only three instances where an IME was requested for this type of injury. Injury type 14 (jaw joint dysfunction) had an IME requested most frequently (27.54%) and injury type 16 (fatality) was the least likely to have an IME (logically).

In Table 3, D2K decision tree suggested only injury type 1 (minor visible injuries) was significantly different from the other injury types based on Medical Audits. An MA was requested 11.02% of the time (44,099 out of 400,000), which is less than for IMEs. Injury type 4 (strain and sprain – neck) had an MA most frequently (16.08%) and injury type 16 (fatality) was audited least frequently (2.56%). The expected MA saving is 198.748 on injury type 1 and 382.357 on all others injury types.

As shown in Table 4, based on special investigations, the optimal decision tree has 13 depths, out of a possible 24. Injury types 2, 6, 7, 8, 9, 11, 14, 17, 19, 21, 22 and 30 are grouped together for SI savings. The SI investigation percentage is 4.17% (16,668 out of 400,000), less than for IME and MA. Injury 12 (loss of body part) and 20 (pregnancy related) are expected to generate no SI saving. For injury type 15 (loss of sense) the mean savings from an SI was 12,857.14, which is the highest. The range of SI savings (from 0 to 12,857.14) for different injuries is larger compared with IME (from 0 to 957.5) and MA (from 198.748 to 382.357).

Table 5, 6 and 7 show the results of medical provider type (MP1_Type) on the savings. For IME, as shown in Table 5, the optimal tree has 5 depths. Providers MI, MO, MD and CH are grouped together for the IME savings. N/A is for data missing (ID 000000, 990000 or 999999). The average IME savings for different types of providers range from 301.494 (PT) to 379.414 (PO). The range is narrow compared with the other variables tested.

In Table 6, the optimal tree for MA has 8 depths, which means the D2K decision tree considering MA savings for all seven types providers and the unknown providers (N/A) are each significantly different from each other. MA investigations for the unknown providers (N/A) are expected got the less MA savings at 132.418. MO is the highest MA saving provider type at 519.719. For PO providers, 51% of the claims had MAs requested, which is much higher than other types. The average MA savings for PO is also higher than the average level. These results indicate that requesting an MA when the primary medical provider is a Physical Therapy Organization can produce significant savings.

As shown in Table 7, considering MP1_Type, the optimal tree for SI is 5. The D2K decision tree grouped MO, MD, MI and PT for SI savings. The Unknown provider has the lowest SI investigation percentage (1.58%) with highest average SI savings (2,551.82). PO had the highest percentage of claims on which an SI was requested (15.77%), which is much higher than the average (4.77%). The lowest average SI savings is for the group MO, MD, MI and PT at 1,488.02.

Table 8, 9 and 10 are for the type of second medical providers. N/A includes data missing which indicates either that there was only one outpatient medical provider on that claim or the second one was not reported. The level of requested investigations, for IME, MA or SI, were all lower for the N/A case, which suggests that claims with more than one provider were more likely to be investigated than cases where there was only a single medical provider.

The optimal IME tree has a depth of 2 (Table 8). The D2K decision tree grouped N/A, CO, PO, PT, MI and MO for IME savings. The average IME savings and the average IME investigation percentage for each type providers are similar. The optimal MA tree (Table 9) and SI tree (Table 10) both have 8 depths. MO, MD and PO are frequently investigated for both MA and SI. MI, CO, N/A are less commonly investigated for both MA and SI. However, the investigation results for MA and SI are quite different. N/A is both the smallest MA savings type (266.27) and the largest SI savings type (2425.37).

The decision tree approach for each of the seven nominal variable analyzed individually provides an initial indication of which characteristics are most important for each of three types of investigation. Investigations performed for certain injury types and certain types of medical providers have been shown to produce a high level of savings. Additional work combining different attributes (injury type and medical provider, or the type of the primary and secondary medical provider) will be investigated to see if additional differences can by identified.

Multiple Linear Regressions by the D2K Linear Regression itinerary

1. Motivation - Finding the linear relationship for the dependent variables of IME_SAVE and the independent variables.
2. Methodology and Tools - Multiple Linear Regressions and D2K Itinerary for Linear Regression
3. Approach - Five input nominal variables are IME_Req, MedAudit, SI_Done, Injury_Type, MP1_Type. Four input number variables are Tot_Paid, MP1_Bill,

TREATLAG, REP_LAGT. The dependent variable is IME_Saved. The five input nominal variables are treated as 38 nominal input features according to the 38 possible values. Therefore, there are 42 input variables.

The dataset was separated into training dataset (400,000) and testing dataset (91,591). The forward stepwise method was practiced to test the linear models. The D2K Linear Regression program started the linear regression from one variable case. All possible single variable regressions were completed by the training dataset. Then the testing dataset selected one of the best regression formulas with the most significant variable, which minimized the external error. Based on the single regression, D2K Linear Regression program added one additional variable to the selected single variable regression by trying all variables one by one. The testing process was the following step. All two-variable regressions were tested by the testing dataset. The optimal regression minimized the external error (including the external error of single variable regression). This training and testing process continued until the optimal regression that minimized the external error was determined.

The regression stopped at 16th step due to the computer resource. The optimal linear model is the 15-variable regression model determined at step 16. Model variables with the coefficients in the determined order are provided in the table 11. The constant term is 352.96. The coefficient for no IME requested was -351.78, meaning that the total savings would be approximately zero (352.96-351.78) if no IME were requested. The number variables of Total Paid, MP1_Bill and REP Lag are positively related to the IME saved. The nominal (dummy) variables of IME Request, SI Done, Injury Type 14, 18, 19, 99 and MP1 Type=N/A increase the IME saved. The nominal variables of MP1 Type=CH, PT and Injury Type 7, 11, 16 decrease the IME saved.

Additional Analyses

A series of additional analyses were performed using SAS to gain a better understanding of the dataset. The most significant results are illustrated in the following figures. Figure 1 illustrates the relationship between the types of Primary Medical Provider and Health insurance. The claims are grouped by the health insurance status- yes, no or unknown. For each claims group, the percentages of Primary Medical Provider's Type were shown at y-axis. In the No health insurance group, most claimants chose CO type provider. In the Yes group, most claimants prefer MO type provider. The type of medical provider is strongly influenced by the presence of health insurance.

Figure 2 illustrates the attorney representation frequency according to the different types of providers. According to the bars, the PO, CO and CH providers have the highest attorney representation, over 80%. MD, MI and MO have a lower attorney representation, around 60%.

Figures 3 and 4 illustrate the distributions of Amount Billed and Amount Paid for CH providers in PIP claims. In Figure 3, the x-axis is the actual value of the amount billed or paid. In Figure 4, the amounts are grouped into ranges. The blue area is for the paid; the pink area is for the bill. The distribution of the amount of the bill has the general shape of a Normal distribution. The paid distribution has two mass points of 0 (45.65%) and 2000 (1.47%), indicating that 45.65% of the bills had no medical payments (BI claims do not cover medical bills), and 1.47% of the bills are covered with a $2000 payment, the tort threshold in Massachusetts and the primary coverage for PIP in the presence of private health insurance.

Figure 5 and 6 illustrate the distributions of Amount Billed and Amount Paid for MD providers. The blue area is for the paid; the pink area is for the bill. Comparing with CH providers, the distributions for both Bill and Paid are more discrete. The two mass points for paid distribution are 0 (38.86%) and 2000 (0.98%). These percentages are smaller than for the CH providers. Unlike the distribution for CH providers, these distributions appear to be shaped more like a lognormal distribution, with more values concentrated around 0 compared with CH providers.

Figures 7 and 8 illustrate the distributions of Attorney representation frequency according to the number of claims a medical provider was involved with for CH (Figure 7) and MD (Figure 8) providers. Each point in the figure represents a provider. The x-axis coordination is the number of claims in the dataset for this provider; the y-axis coordination is the attorney representation frequency for this provider. When the claim numbers increase, the attorney frequencies for the CH appear to increase, and then level out around 90%; for MDs, the attorney frequency appears to decrease for the providers with the greatest number of claims, at least for the outliers.

Figures 9, 10, 11 and 12 show the accident month distributions for different Injury Types. The x-axis represents the accident month; the y-axis represents the number of claims that occurred in that month. Several types of injuries (type 5 – strain and sprain back or neck, type 6 – strain or sprain other than back or neck, and type 30 – no visible injury) display an unusual seasonal pattern, with significant increases in October, November and December. In contrast, Figure 12 displays the number of claims by month for all injury types except 5, 6 and 30, which stayed much more level for the whole year. The seasonal pattern for injury types 5, 6, and 30 appear highly unusual and may suggest some suspicious claim behavior to generate end of year cash.

Figure 13 illustrates the accident month claim distributions according to different type of providers. The x-axis represents the accident month; the y-axis represents the number of claims that occurred in that month. The distributions for different provider types are represented by different color lines. The CH, CO and PO lines increase significantly at the end of the year. The lines for MD, PT and MI stayed at a relatively steady level for the whole year.

Figures 14 and 15 illustrate the distributions of average Amount Billed and Amount Reduced for each claim. Each point in the figure represents a provider. The x-axis coordination is the number of claims for this provider; the y-axis coordination is the average bill (Figure 14) or average reduction (Figure 15) for this provider. The points can be grouped by the distance to the center trend line. The larger distance group in the bill figure suggests higher reduced probability for investigating this group.

Figure 16 illustrates the positive linear relationship between the Amount Billed by the primary medical provider and the Amount Reduced. Each point in the figure represents a provider. The x-axis coordination is the average Amount Billed for this provider; the y-axis coordination is the average Amount Reduced for this provider. This relationship indicates that the greatest savings are on the largest bills, which is a very logical conclusion.

Future Work

To deal with the fact that the amount of savings achieved from the different types of investigations is likely to be underestimated in the data, the decision trees are going to be regenerated using dummy variables representing a favorable result (anything other than No Change Recommended) instead of the numerical value previously tested. The current classification N/A (for Not Available) for medical provider is going to be separated into cases in which there is a medical provider but the type is not shown, versus the situation where there is no medical provider information at all. The effect of multiple outpatient medical providers will be investigated to determine if particular combinations of providers (such as two physical therapists, or a chiropractor and a physical therapist) indicate greater potential savings from investigations. In order to get more sensitive indicators, injury types will be combined (strains and sprains, minor injuries, serious injuries, major injuries or fatalities) for machine learning techniques.

The seasonality effect for certain types of injures (as illustrated in Figures 9-12) will be used to identify those injury types that may be linked to fraudulent claiming behavior, and incorporated into further D2K decision trees. Additional work will incorporate information regarding attorney representation, accident location and the timing of seeking medical treatment to generate more significant predictive models.

Additional multiple regressions will be run for MA and SI savings, and greater computer resources will be used to allow for more steps and more variables in the process. These runs will identify the most important variables, or combination of variables, that affect the savings from investigations.

To date the programs have been run on the entire dataset. Future analyses will be run separately by coverage to isolate differences between PIP and BI claims.

Conclusion

Predictive modeling provides a set of valuable tools for insurance companies for a variety of purposes, from pricing to underwriting to claims handling. This work represents a start on this process for determining the optimal strategy for investigating claim to reduce medical costs, but there is a long way to go to get fully coherent and meaningful results. Comments and suggestions on this work would be greatly appreciated.

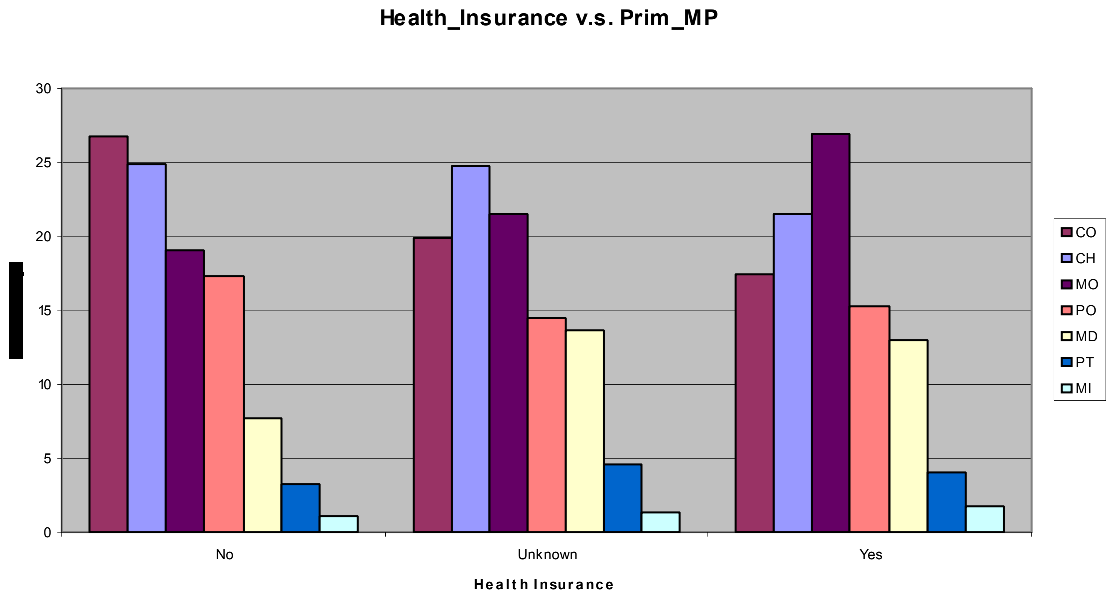


Figure1

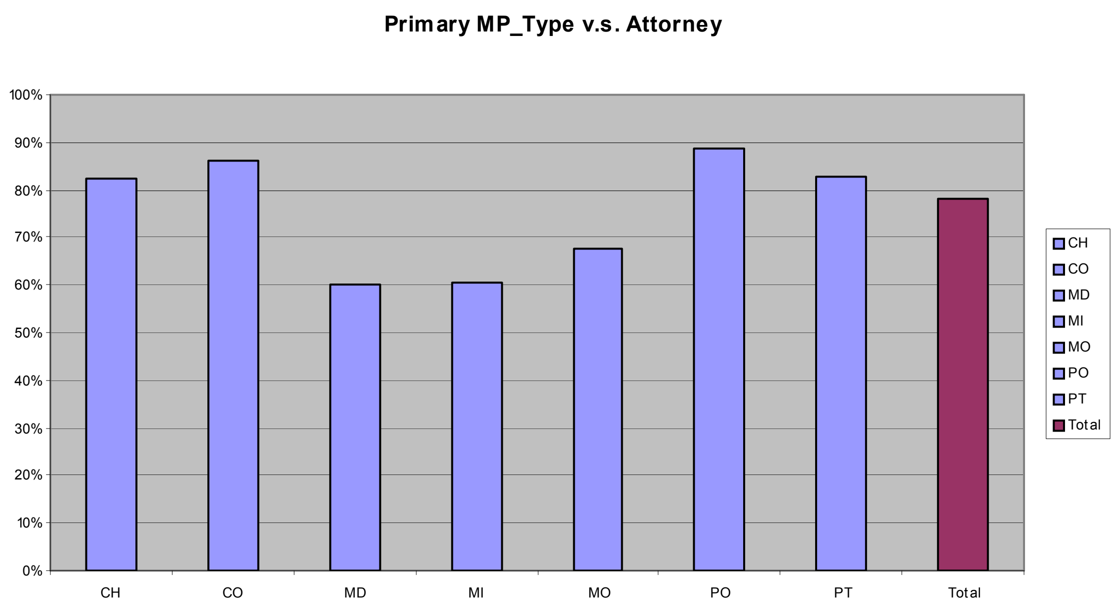
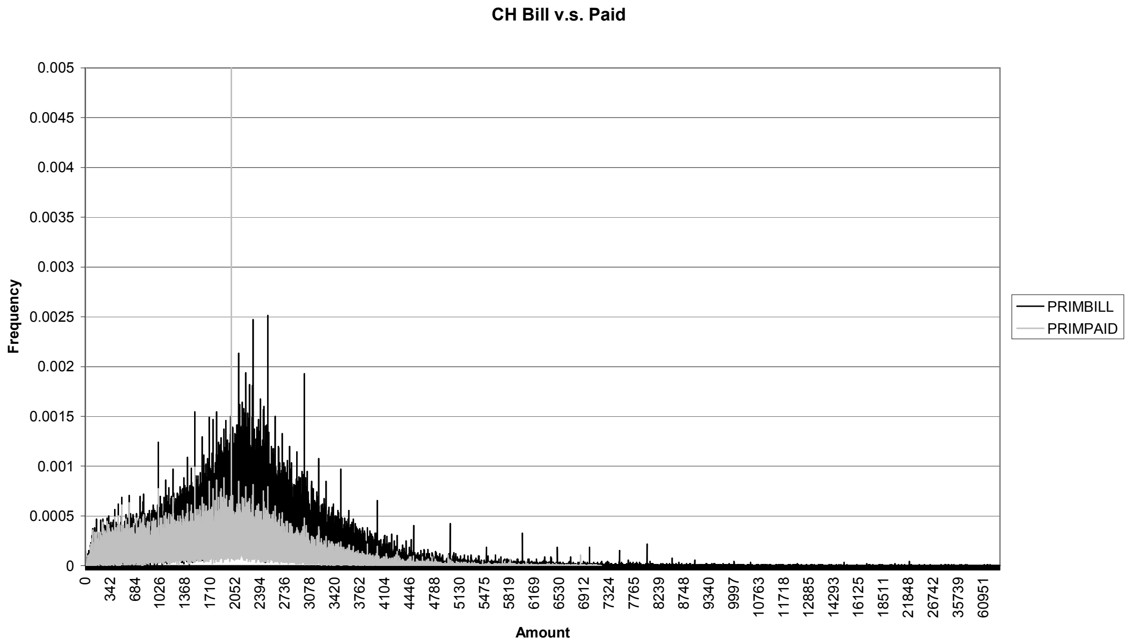
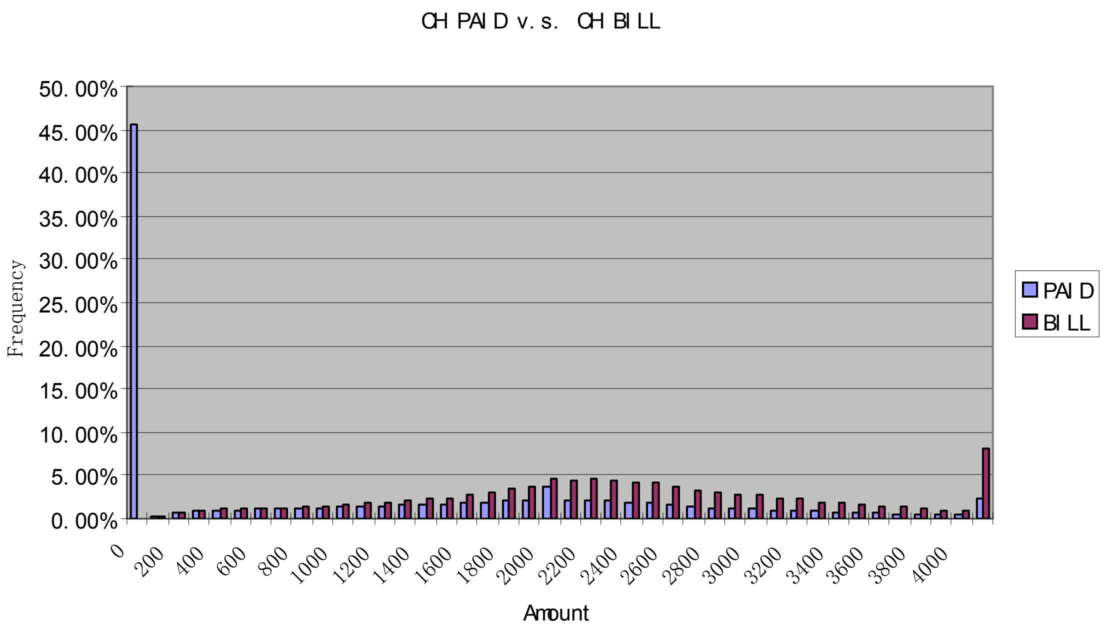


Figure2



Figure

3



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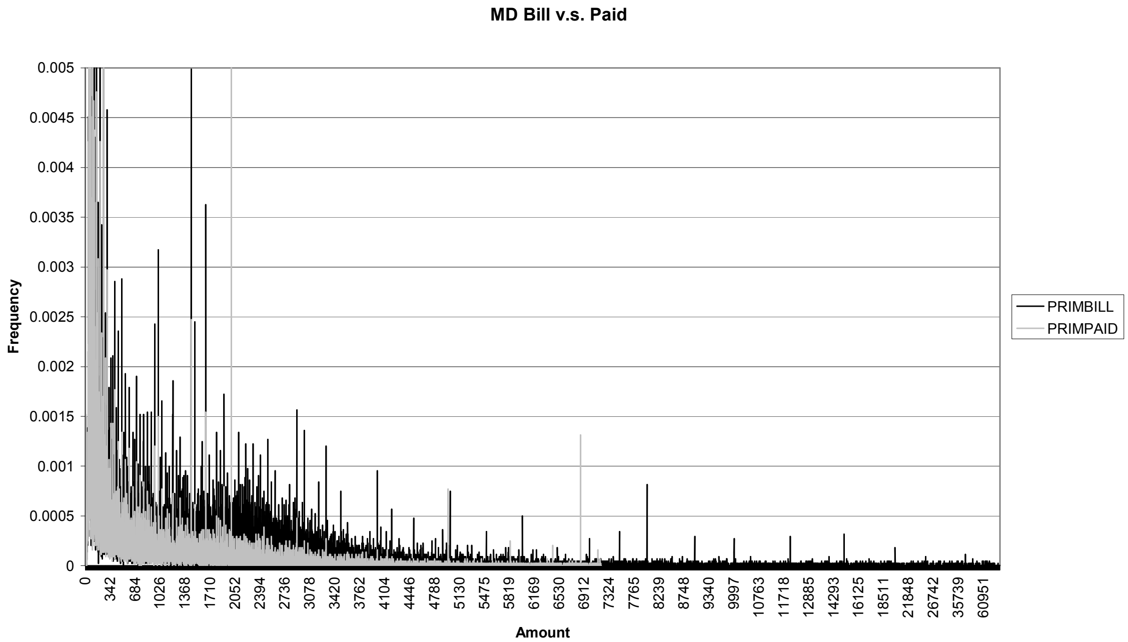


Figure

5

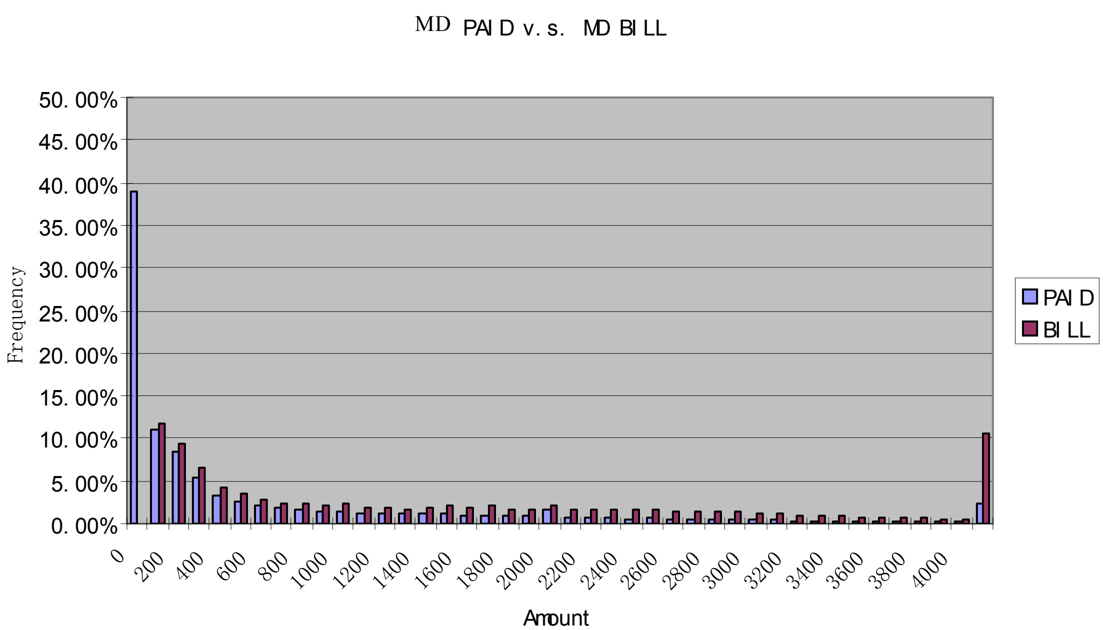
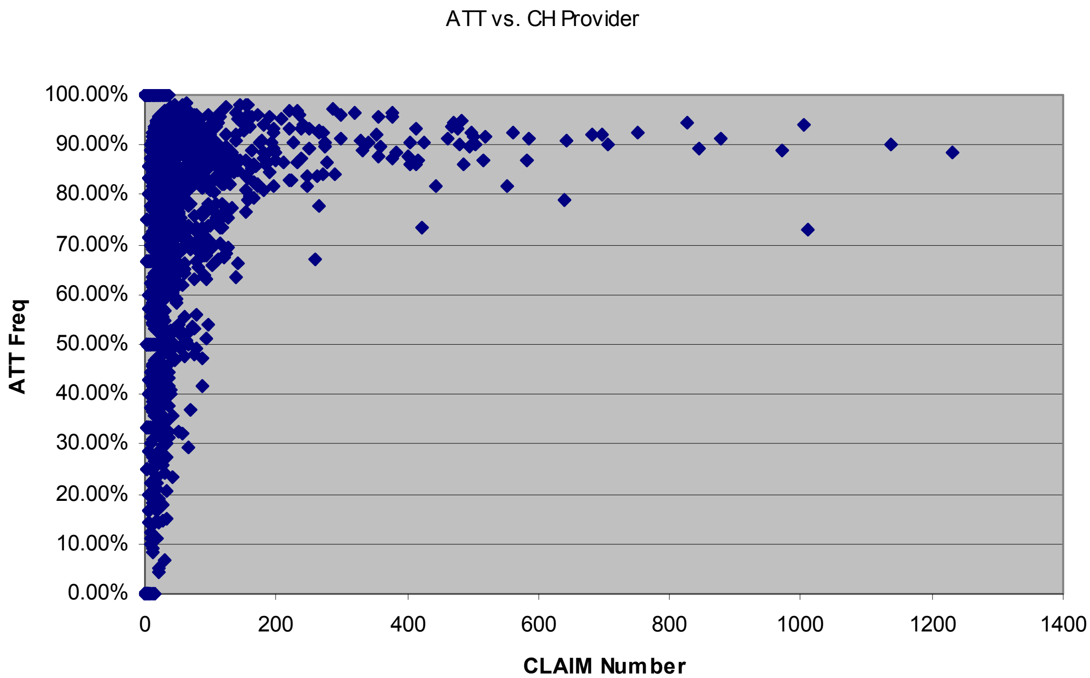


Figure6



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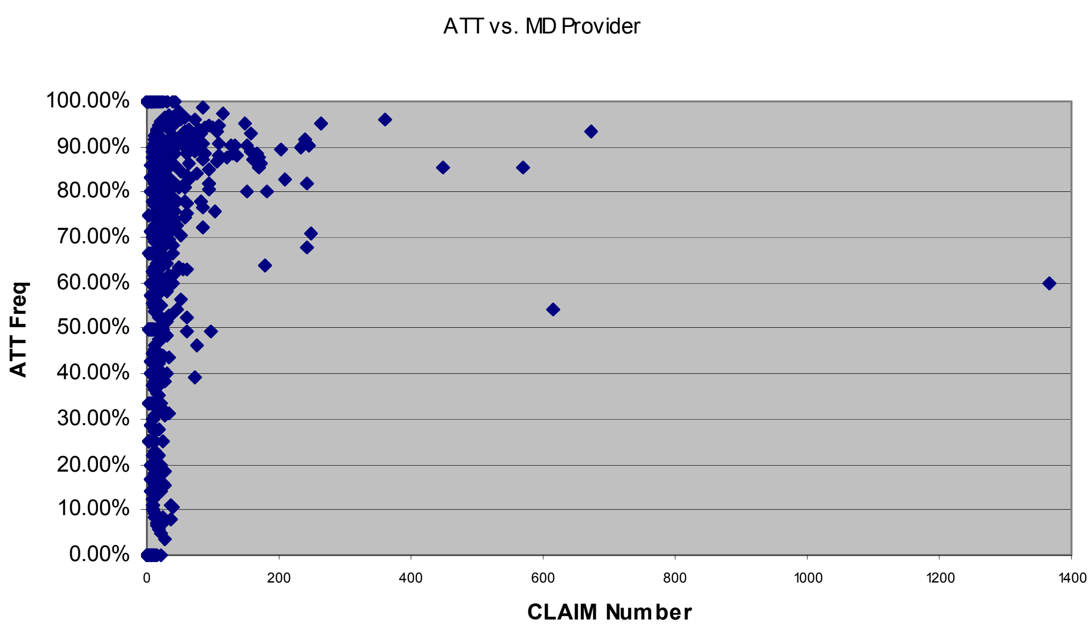

Figure8

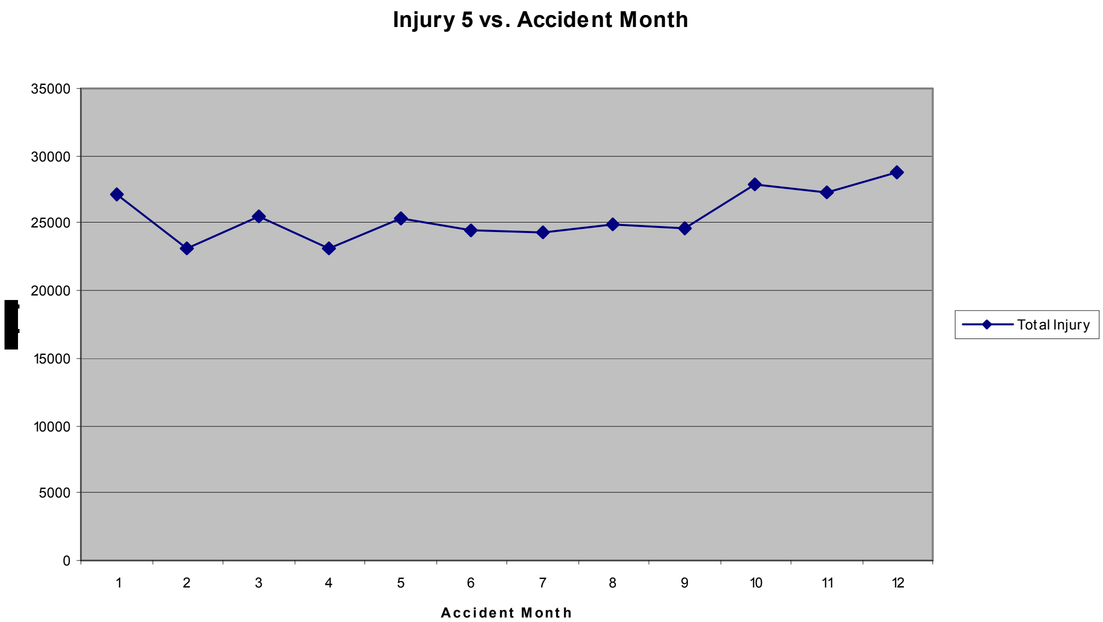

Figure9

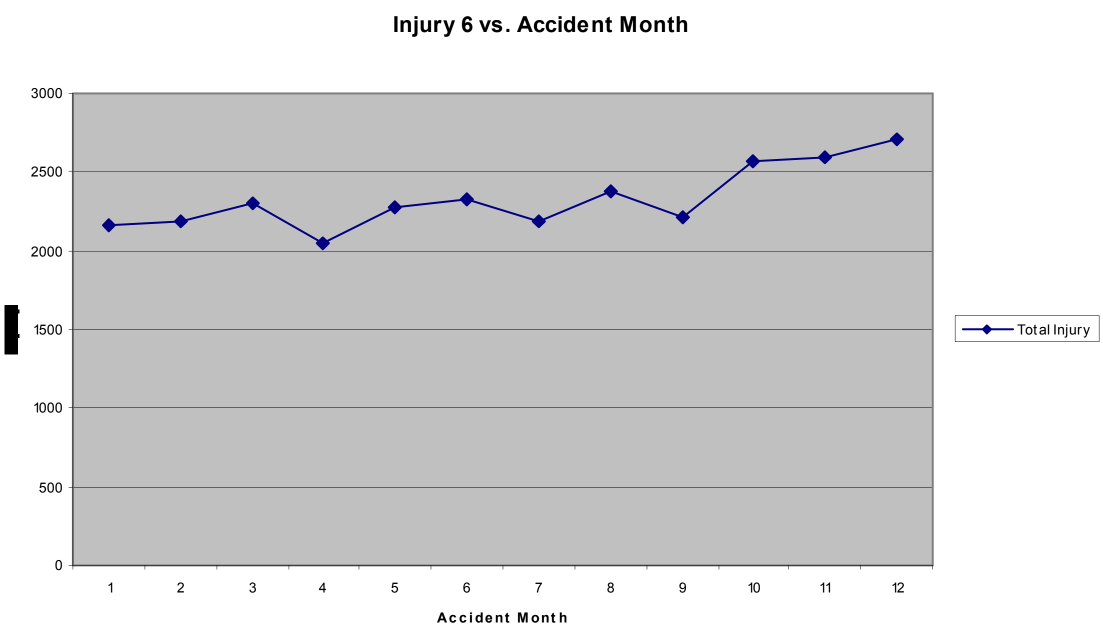

Figure10

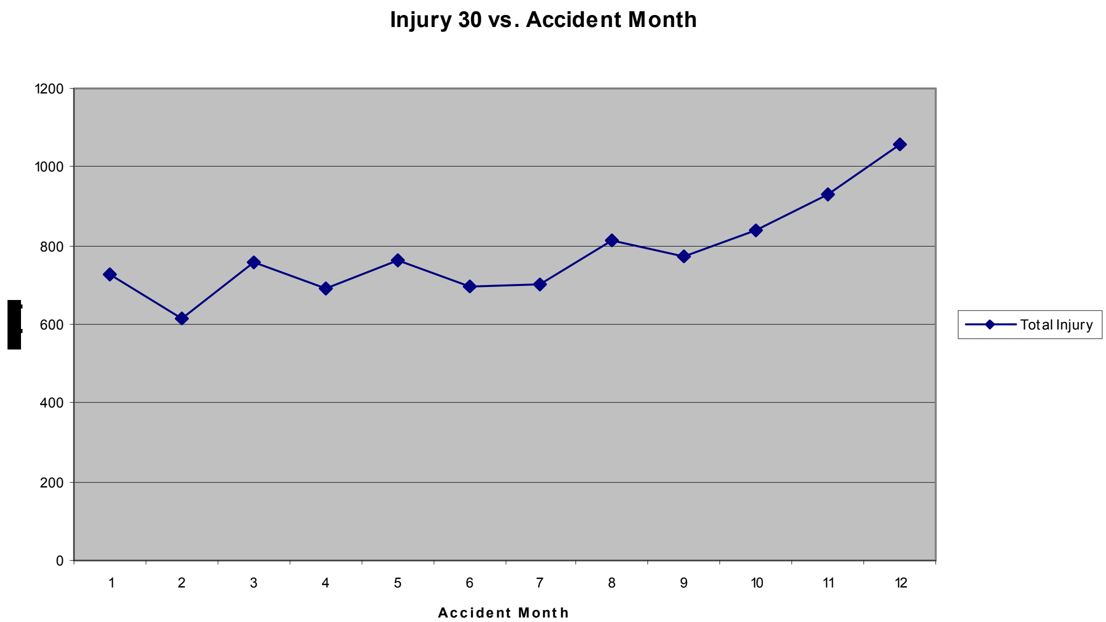

Figure11

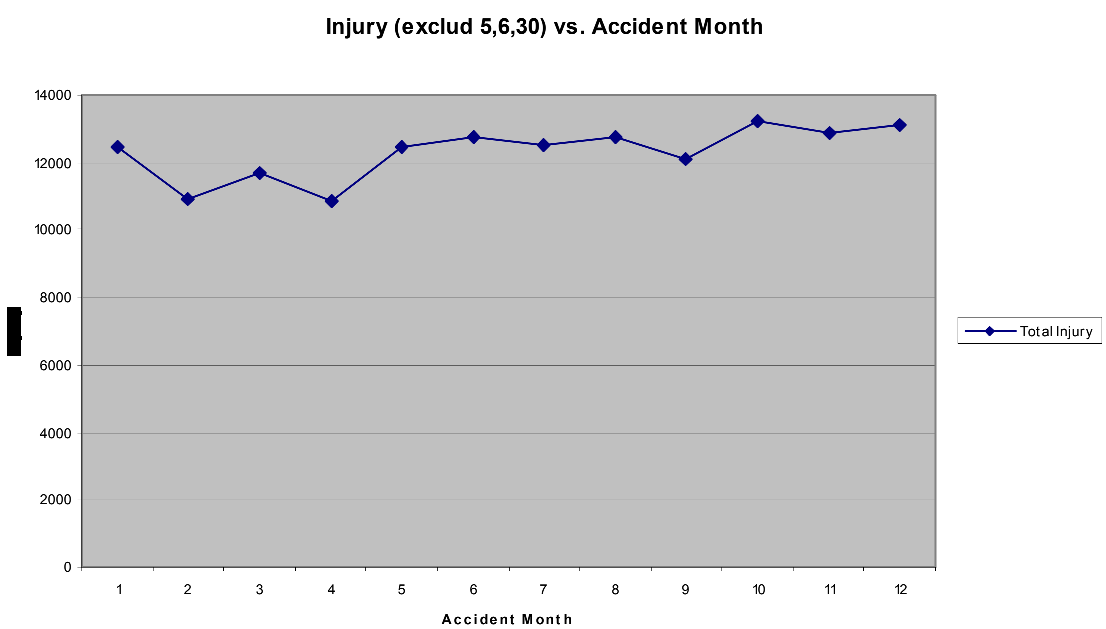

Figure12

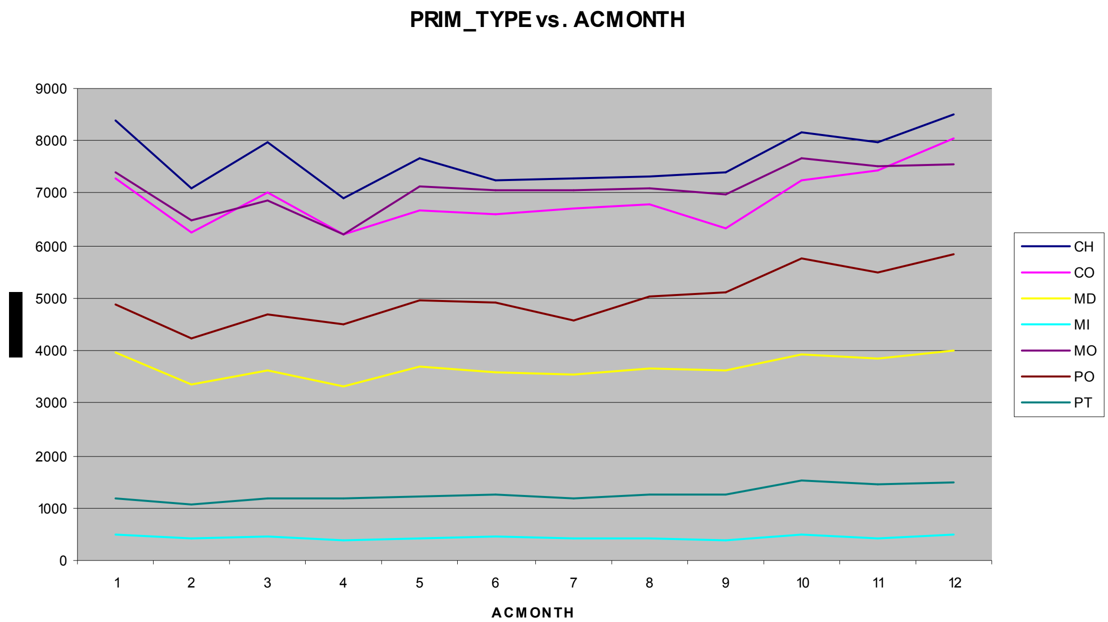

Figure13

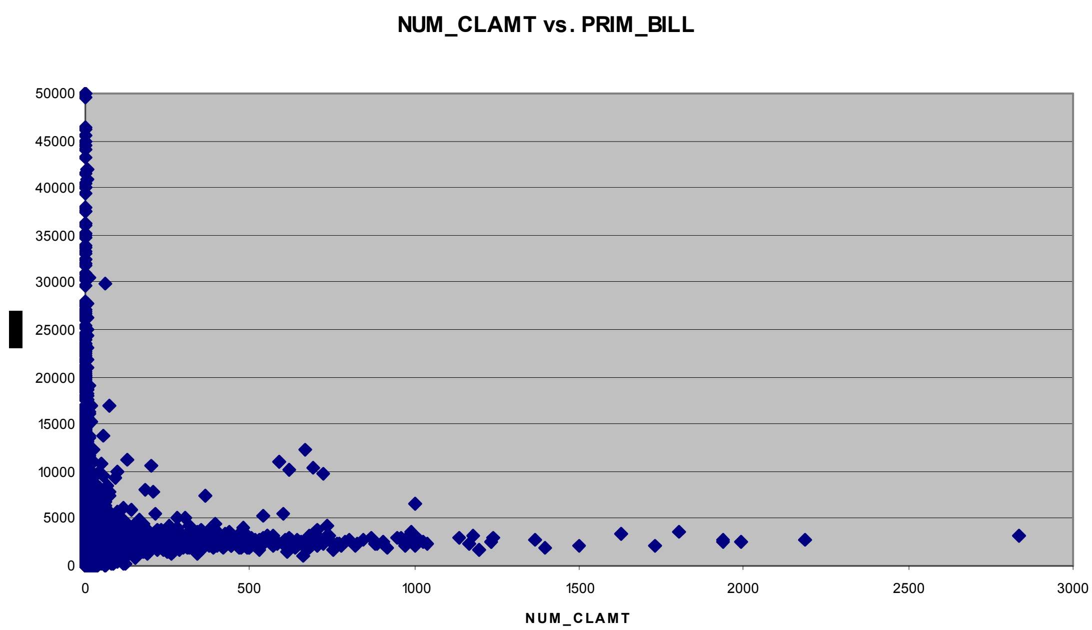

Figure14

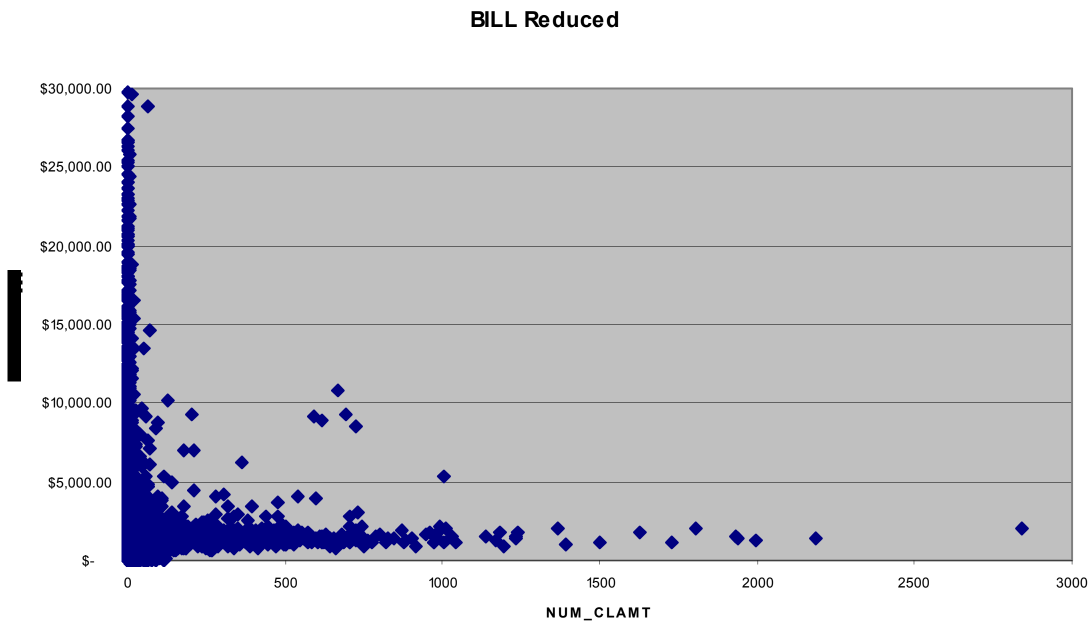

Figure15

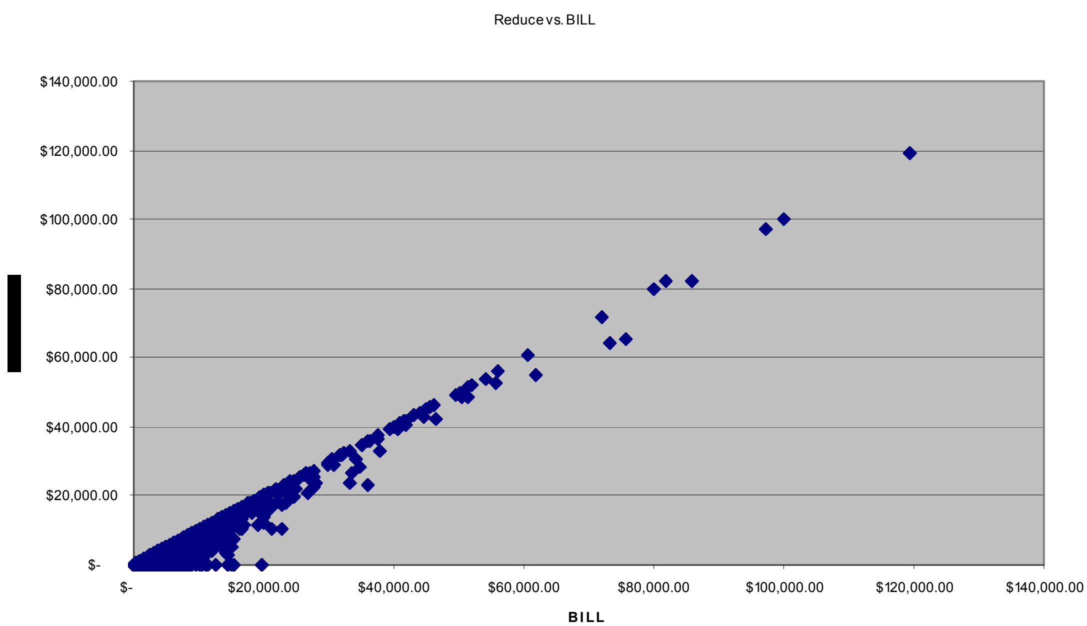

Figure16

Nominal Variables	IME_Save	MA_Save	SI_Save
Policy_Type(4)	Y	N	N
Coverage(9)	N	Y	Y
Em_Treat(10)	Y	Y	Y
Heath_I(11)	Y	Y	Y
Injury_Type(13)	Y	Y	Y
MP1_Type(26)	Y	Y	Y
MP2_Type(34)	Y	Y	Y

Table1

	Save					Population		
Injury_Type(13)	Mean	Std	Min	Max	ERR	IME_Req	Total	Percentage
1	241.206	929.946	0	20000	397.751	3589	36826	9.75%
2	210.455	1017.826	0	12500	372.311	268	3405	7.87%
4	355.934	1378.653	0	60000	551.39	5015	33019	15.19%
8	339.79	2334.105	0	37000	612.858	671	8766	7.65%
10	309.458	1848.312	0	35000	538.289	671	4723	14.21%
11	22.778	114.531	0	500	52.469	18	295	6.10%
12	0	0	0	0	0	3	79	3.80%
13	513.333	1309.894	0	4000	889.778	15	117	12.82%
15	238.095	1064.794	0	5000	453.515	21	119	17.65%
16	594.3	1768.613	0	5900	1061.14	10	1329	0.75%
17	318.085	1275.81	0	10000	553.682	94	899	10.46%
20	835.464	2726.453	0	11191	1432.22	28	386	7.25%
21	774.179	2344.773	0	10000	1323.36	67	284	23.59%
22	957.5	3071.881	0	15000	1595.83	30	269	11.15%
30	230.118	753.679	0	7500	372.348	651	7576	8.59%
99	631.269	2368.755	0	50000	941.054	1068	14020	7.62%
3						184	3134	5.87%
5						49076	249283	19.69%
6						3697	22785	16.23%
7						418	6598	6.34%
9						92	1147	8.02%
14						149	541	27.54%
18						513	2302	22.28%
19	351.289	1363.615	0	100000	542.206	528	2098	25.17%
						66876	*400000*	16.72%
		With Injury_Type	Without Injury_type	Considering as an Indicator				
Tree Evaluator_Absolute		93.379	93.5752	**Y**				
Optimal_Tree Depth		17						
Max_Tree Depth		24						

Table 2

	Save					Population		
Injury_Type(13)	Mean	Std	Min	Max	ERR	MA_Req	Total	Percentage
1	198.748	906.586	0	30870	272.908	3670	36826	9.97%
2						338	3405	9.93%
3						126	3134	4.02%
4						5309	33019	16.08%
5						27931	249283	11.20%
6						2699	22785	11.85%
7						650	6598	9.85%
8						877	8766	10.00%
9						114	1147	9.94%
10						541	4723	11.45%
11						23	295	7.80%
12						6	79	7.59%
13						15	117	12.82%
14						75	541	13.86%
15						14	119	11.76%
16						34	1329	2.56%
17						91	899	10.12%
18						275	2302	11.95%
19						241	2098	11.49%
20						36	386	9.33%
21						40	284	14.08%
22						30	269	11.15%
30						381	7576	5.03%
99	382.357	1418.852	0	64500	499.849	583	14020	4.16%
						44099	*400000*	11.02%
		With Injury_Type	Without Injury_type	Considering as an Indicator				
Tree Evaluator_Absolute		54.7015	55.0159	**Y**				
Optimal_Tree Depth		2						
Max_Tree Depth		24						

Table 3

	Save					Population		
Injury_Type(13)	Mean	Std	Min	Max	ERR	SI_Done	Total	Percentage
1	802.954	2544.6	0	29000	1355.145	1061	36826	2.88%
3	2077.654	4089.497	0	20000	2821.898	136	3134	4.34%
4	923.126	2647.884	0	25000	1478.106	1170	33019	3.54%
5	2054.337	3714.105	0	100000	2557.582	11298	249283	4.53%
10	669.551	2588.603	0	20000	1183.831	196	4723	4.15%
12	0	0	0	0	0	4	79	5.06%
13	5600	7838.367	0	20000	6720	5	117	4.27%
15	12857.14	25892.241	0	75000	18367.35	7	119	5.88%
16	666.667	3265.986	0	20000	1274.074	45	1329	3.39%
18	996.253	3367.884	0	36500	1680.881	221	2302	9.60%
20	0	0	0	0	0	11	386	2.85%
99	1921.895	3593.821	0	20000	2603.499	306	14020	2.18%
2						141	3405	4.14%
6						797	22785	3.50%
7						280	6598	4.24%
8						353	8766	4.03%
9						45	1147	3.92%
11						7	295	2.37%
14						30	541	5.55%
17						34	899	3.78%
19						243	2098	11.58%
21						20	284	7.04%
22						13	269	4.83%
30	1621.494	5131.193	0	125000	2529.773	245	7576	3.23%
						16668	*400000*	4.17%
		With Injury_Type	Without Injury_type	Considering as an Indicator				
Tree Evaluator_Absolute		102.3299	105.1064	**Y**				
Optimal_Tree Depth		13						
Max_Tree Depth		24						

Table 4

	Save					Population		
MP1_Type(26)	Mean	Std	Min	Max	ERR	IME_Req	Total	Percentage
N/A	358.812	1127.875	0	17000	570.734	2073	87630	2.37%
PO	379.414	1299.146	0	38000	589.951	9349	46751	20.00%
CO	350.128	987.217	0	18000	515.598	15366	65555	23.44%
PT	301.494	988.623	0	17500	483.896	3009	12067	24.94%
MI						764	4212	18.14%
MO						11167	72222	15.46%
MD						6351	37454	16.96%
CH	343.643	1537.258	0	100000	544.51	18797	74109	25.36%
						66876	*400000*	16.72%
		With MP1_Type	Without MP1_Type	Considering as an Indicator				
Tree Evaluator_Absolute		93.553	93.5752	**Y**				
Optimal_Tree Depth		5						
Max_Tree Depth		8						

Table 5

	Save					Population		
MP1_Type(26)	Mean	Std	Min	Max	ERR	MA_Req	Total	Percentage
N/A	132.418	763.424	0	24000	196.792	6902	87630	7.88%
MO	519.719	2001.89	0	50000	692.11	7537	46751	16.12%
MD	402.561	1383.545	0	42500	517.611	4562	65555	6.96%
PO	483.502	1299.492	0	30000	563.638	6154	12067	51.00%
MI	497.37	1931.702	0	28159	706.835	546	4212	12.96%
CO	328.463	1133.668	0	36518	425.729	7535	72222	10.43%
PT	452.002	1176.24	0	30870	507.492	2010	37454	5.37%
CH	326.401	1343.097	0	64500	420.902	8853	74109	11.95%
						44099	*400000*	11.02%
		With MP1_Type	Without MP1_Type	Considering as an Indicator				
Tree Evaluator_Absolute		53.5276	55.0159	**Y**				
Optimal_Tree Depth		8						
Max_Tree Depth		8						

Table 6

	Save					Population		
MP1_Type(26)	Mean	Std	Min	Max	ERR	SI_Done	Total	Percentage
N/A	2551.823	4103.758	0	30000	3041.499	1387	87630	1.58%
PO	1778.504	3951.583	0	70000	2455.147	1903	12067	15.77%
CO	2129.509	3389.197	0	50000	2488.124	2843	72222	3.94%
CH	1794.732	3315.591	0	47250	2358.634	4688	74109	6.33%
MO						2895	46751	6.19%
MD						1963	65555	2.99%
MI						162	4212	3.85%
PT	1488.019	4334.548	0	125000	2252.835	827	37454	2.21%
						16668	*400000*	4.17%
		With MP1_Type	Without MP1_Type	Considering as an Indicator				
Tree Evaluator_Absolute		103.8852	105.1064	**Y**				
Optimal_Tree Depth		5						
Max_Tree Depth		8						

Table 7

	Save					Population		
MP2_Type(34)	Mean	Std	Min	Max	ERR	IME_Req	Total	Percentage
N/A						29646	244954	12.10%
PO						3435	14074	24.41%
CO						2231	8408	26.53%
PT						1703	5333	31.93%
MI						865	3588	24.11%
MO	354.464	1334.102	0	100000	546.487	13930	63455	21.95%
MD	320.941	1603.456	0	77500	521.686	11484	48462	23.70%
CH	351.73	1354.446	0	38000	552.41	3582	11726	30.55%
						66876	*400000*	16.72%
		With MP2_Type	Without MP2_Type	Considering as an Indicator				
Tree Evaluator_Absolute		93.5198	93.5752	**Y**				
Optimal_Tree Depth		2						
Max_Tree Depth		8						

Table 8

	Save					Population		
MP2_Type(34)	Mean	Std	Min	Max	ERR	MA_Req	Total	Percentage
N/A	266.272	939.873	0	28159	363.93	24233	244954	9.89%
MO	518.098	1734.502	0	42500	652.56	7093	14074	50.40%
MD	458.721	1865.305	0	51531	566.652	6840	8408	81.35%
PO	561.318	2057.387	0	64500	691.165	1892	5333	35.48%
MI	466.138	1562.84	0	25000	624.652	523	3588	14.58%
CO	454.794	1445.345	0	25000	572.384	975	63455	1.54%
PT	378.547	737.649	0	6340	429.119	916	48462	1.89%
CH	508.086	1850.491	0	47834	650.294	1627	11726	13.88%
						44099	*400000*	11.02%
		With MP2_Type	Without MP2_Type	Considering as an Indicator				
Tree Evaluator_Absolute		54.3172	55.0159	**Y**				
Optimal_Tree Depth		8						
Max_Tree Depth		8						

Table 9

	Save					Population		
MP2_Type(34)	Mean	Std	Min	Max	ERR	SI_Done	Total	Percentage
N/A	2425.372	3763.2	0	47500	2777.447	8178	244954	3.34%
MO	1234.202	3832.611	0	100000	1921.886	3427	14074	24.35%
MD	1071.068	3366.322	0	75000	1738.958	2735	8408	32.53%
PO	1307.747	6099.943	0	125000	2076.938	668	5333	12.53%
MI	1698.188	4912.354	0	40000	2632.989	176	3588	4.91%
CO	1816.882	4148.572	0	40000	2558.172	382	63455	0.60%
PT	1106.36	3358.413	0	40000	1748.841	367	48462	0.76%
CH	1123.814	2709.471	0	22534	1738.362	735	11726	6.27%
						16668	*400000*	4.17%
		With MP2_Type	Without MP2_Type	Considering as an Indicator				
Tree Evaluator_Absolute		99.9907	105.1064	**Y**				
Optimal_Tree Depth		8						
Max_Tree Depth		8						

Table 10

Step	Variable	Coefficient
1	Constant	352.96
2	IME_Req=N	-351.78
3	Tot_Paid ($1000)	1.79
4	MP1_BILL ($1000)	1.68
5	MP1_TYPE=CH	-20.17
6	Inj_Type=14	120.93
7	SI_Done=N	-20.60
8	Inj_Type=99	17.82
9	REP_LAGT	2.12
10	Inj_Type=18	44.83
11	MP1_TYPE=N/A	8.84
12	Inj_Type=19	40.21
13	Inj_Type=11	-105.91
14	MP1_TYPE=PT	-16.44
15	Inj_Type=16	-44.92
16	Inj_Type=07	-18.02

Table 11

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