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FACTORS OF MULTIPLE FATALITIES IN CAR CRASHES

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Introduction

Road safety is a major concern for all United States of America citizens. According to the National Highway Traffic Safety Administration, 30,000 deaths are caused by automobile accidents annually. Oftentimes fatalities occur due to a number of factors such as driver carelessness, speed of operation, impairment due to alcohol or drugs, and road environment. Some studies suggest that car crashes are solely due to driver factors, while other studies suggest car crashes are due to a combination of roadway and driver factors. However, other factors not mentioned in previous studies may be contributing to automobile accident fatalities. The objective of this project was to identify the significant factors that lead to multiple fatalities in the event of a car crash.

Data

The FARS database the team was provided contained all fatal traffic crashes within the United States from 1999 to 2013. The 2012 database, for example, contained a total of 18 different files (see *Figure 1* in the appendix for the file names and relations between the files). The ACCIDENT data file contained the characteristic and environment conditions at the time of the crash, with one record per accident. The VEHICLE data file contained information regarding each vehicle involved in the crash. The PERSON data file contained information describing each individual involved in the crash. The rest of the files included CEVENT, VEVENT, VSOE, FACTOR, VIOLATN, VISION, MANEUVER, DISTRACT, DRIMPAIR, NMIMPAIR, NMCRAASH, NMPRIOR, SAFETYEQ, PARKWORK, and DAMAGE. These files included additional characteristics of the crash and contained multiple records per vehicle or person.

The team focused on the years 2012 and 2013 because they were the most recent records, and the databases and variables were consistent for those 2 years. Over time, numerous databases were created, and several variables changed either in formats or in values. For example, the variable *IMPACT1* had categories added and deleted over time and changed meanings several times. Tables 1 and 2 (in the appendix) compare the different categories between the years 1999 and 2012. The year 2012 was used as the training data and year 2013 was used as the testing data. Therefore, one should be able to see whether a big change occurs in the relationship after year 2012. Since no change occurred between the years, the current year data can be used to predict the next year's fatalities or to make new recommendations. If significant changes over the years had occurred, a time series-based model could have been adopted to investigate the seasonality, trends, and change points.

A quick insight into the data revealed that the frequency of accidents by state shown in Figure 2 (in the appendix) does not change significantly between the years. For example, the states Georgia and California both contained the highest number of accidents. The team randomly selected states to check the frequency counts in details. The states included Georgia, North Carolina, California, and Wyoming (as shown in Figures 3 through 6 in the appendix).

Problem

The project goal was to examine the number of deaths in a single accident and the contributing factors strongly related to accidents with multiple fatalities. The team's recommendations will aim at reducing the number of accidents that potentially lead to multiple fatalities.

Only the first event in the sequence of events in a multiple events accident was used, for once the accident sequence started, little action could be taken to prevent the subsequent sequence of events

(based on the available data). This, plus a careful inspection of what each database contained and what each variable represented, gave a basis of making the data preparation decisions described next.

Data Cleaning/Validation

In preparation for data analysis, the following actions were taken:

1. The team chose to use 2012 datasets as the training sets and 2013 data for validation purposes. The reasons for this decision were explained in the previous section.
2. The CEVENT and VEVENT databases were streamlined to include only those records pertaining to event number one. The team decided to take only event one due to the fact that little action could be taken to prevent the subsequent sequence of events.
3. The VSOE database was not used because it was a subset of the VEVENT database.
4. An analysis of the databases with multiple responses was completed. For the vehicle level databases, the team found the duplications were due to the multiple descriptions for the same vehicle from different angles. Therefore, the deduplication was done so that only one record per vehicle was available which created additional variables based on the categories. The following vehicle level files were transformed: DAMAGE and DRIMPAIR. Similar duplications were found in the person level files. The deduplication was processed as well in order for only one record to be available per person. The person level files included NMCRASH, NMIMPAIR, NMPRIOR, and SAFETYEQ.
5. Additional databases that included multiple responses were condensed by the number of different categories. For example, the variable *MVIOLATN* from the database VIOLATN identified all violations charged to the driver. Due to the fact that there were several drivers with multiple violations, the team decided to collapse similar categories. The variable *MVIOLATN* was collapsed from 99 categories to 11. As a result, only one record per vehicle for the violation codes occurred. More details are given in the appendix in Tables 3 and 4. Other variables included *MDRDSTRD* in the DISTRACT database. This variable was condensed from 26 categories to 2 based on whether the vehicle had multiple distractions or not (as shown in Tables 5 and 6 in appendix). The variable *MFACTOR* in the FACTOR database was condensed from 21 categories to 2 by summing up the total number of factors per vehicle (as shown in Tables 7 and 8 in the appendix). The variable *MDRMANAV* in the MANEUVER database was condensed from 10 categories to seven (as shown in Tables 9 and 10 in the appendix), and VISION was condensed from 19 categories to 14 (as shown in Tables 11 and 12 in the appendix).
6. For the PARKWORK dataset, only the records associated with event number 1 were kept.
7. By simple descriptive statistical analysis, no influential points such as outliers were found in the data bases. The missing values were replaced with the median for each numeric variable because most of the distributions were skewed. A histogram of the variable *VSPD_LIM* is shown in the appendix as an example (Figure 7).
8. A careful inspection of each variable's description was done. Identification variables, such as VIN number and variables that did not meet the team's goal were dropped. See the completed list in the appendix (table 13).

9. The various databases were merged together into person level, so each record was a person. Note that there could be multiple people in a vehicle and multiple vehicles in an accident. The merged data may have duplicated information for the same accident and same vehicle. The team decided to do so to keep the most detailed information in an accident. The order of merging was as follows:
 - a. CEVENT into ACCIDENT by case number
 - b. VEVENT into VEHICLE by case number and vehicle number
 - c. All vehicle level databases into VEHICLE by case number and vehicle number and finally that resulting database into the PERSON database by case number and vehicle number.
 - d. The final database for analysis contained 76436 records and 239 variables, the same number of records in the person database.

After the final dataset was created, the response variable was analyzed. The goal of this analysis was to determine what factors caused multiple deaths, so the team focused on the target variable *FATALS*. This variable identified the number of fatally injured persons in a crash. The frequency table of the variable *FATALS* is shown in appendix (Table 14). From this variable, a binary categorical variable was created to run a logistic regression model. This variable called *MULTIPLE* was used with 1 equal to multiple deaths and 0 equal to a single death. The frequency table of *MULTIPLE* is shown in appendix (table 15).

Analysis

After merging the datasets, the next step was to determine which variables were statistically related with fatalities in automobile accidents. The team identified these variables in 3 steps:

Step 1 -- Relation between one predictor and the target based on one-way ANOVA or Pearson Correlation

The team first identified the potential significant factors through a one-by-one checking. Only the variables with the p-value less than 0.05 were kept. As a result, 152 predictors were strongly related with the target variable, when no other factors were considered. 84 variables were not significant and were discarded from further consideration.

Among the 152 significant variables, 14 were quantitative and 138 are categorical (full list in Table 16 in the appendix). Many of the categorical variables had too many categories, which would increase the complexity of the models and make the explanation too difficult in the later analysis stage. Therefore, Tukey's post-hoc tests were applied to combine the categories with no significant difference. For example, the variable *WEATHER* (describing the atmospheric conditions that existed at the time of crash) initially had 12 categories but Tukey's grouping suggested condensing these categories to 3 (see Table 17 & 18 in the appendix).

Step 2 -- Variable clustering to reduce the collinearity among the predictors

The above selected variables may have overlapped redundant information. For example, variable *VSPD_LIM* (speed limit just prior to vehicle's critical pre-crash) and variable *INJ_SEV* (severity of injury) are highly correlated. They measure the similar characters in the accident (of a vehicle or of a person). When redundant variables are included in some of the model building procedures, the parameter estimates can become unstable and create a confounded interpretation. Therefore, deciding on the correct relationships between dependent and independent variables becomes difficult if multicollinearity is strong. In fact, given the nature of the datasets for this project,

multicollinearity could be an issue to cause biased results. In order to reduce its effect, predictor variables were grouped into clusters, and representative variables selected from each cluster.

The PROC VARCLUS procedure was used to do variable clustering based on the maximum eigenvalue threshold. The VARCLUS procedure only performs the clustering for numerical variables. Most of our variables were categorical. In order to do the grouping, the team changed the categorical coding into the mean of the target variable (*FATALS*, number of deaths) in that specific category. Note that this transformation will keep the category differences and also save the relation between the categorical factor and the target. This transformation was only used in this stage. In the later modelling stage, the team used the original categorical coding.

As a result, there were 53 clusters (Table 19 of the Appendix). Variables in the same cluster were similar to each other, and variables in different clusters were different from each other. Representative variables from each cluster were then identified. Since the variables selected should have a high correlation with their respective cluster and low correlation with other clusters, $1 - R^2$ ratio was used to select the variables to be used for modelling. The variables with the lowest $1 - R^2$ ratio were picked as the representation of the cluster. In the case of a tie, the tied variables with the lowest ratio were picked. Fifty-eight variables were selected (Table 13 of the Appendix).

Step 3 -- Logistic regression models for multiple deaths

The original target (*FATALS*) contained 9 different level values (or a total of 76436 counts), 88% of which was single deaths. A logistic regression for multi-category response may not perform well. Therefore, the team tried to focus on multiple deaths versus a single death. A categorical variable called *MULTIPLE* was created containing values of 1 (multiple deaths) and 0 (single death) for the purpose of completing a binary classification. A separate sampling technique was used in order to sample the value of 0s and keep all of the values of 1s to get a balanced (50/50 split) target. As a result, the variable *MULTIPLE* consisted of a 50/50 split. This is in accordance with the idea that the amount of information in a dataset with a categorical outcome is determined not by the total number of cases in the dataset itself but by the number of cases in the rarest outcome category. (For binary target datasets, this is usually the primary outcome.) (Harrell 2006). The 2013 testing data also had 50/50 splitting.

Table 24 in the Appendix shows the frequency for variable *MULTIPLE* after sampling. The two completed models are explained below.

Model A: A logistic regression analysis using 58 variables from the clustering analysis was conducted. Stepwise selection was used to determine the most important factors from the primary dataset. An alpha value of 0.15 was used for variable entry into and removal from the model.

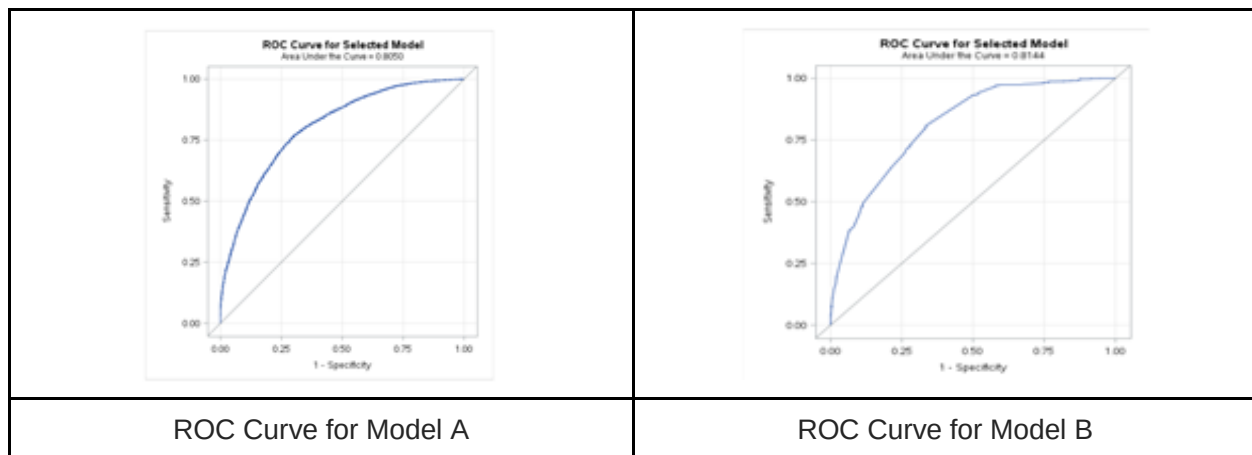
Table 20 (in the Appendix) shows the summary of the stepwise selection for model A. Table 21 (in the Appendix) shows the odds ratio estimates from the resulting model. An example from the results showed that the *CF1* categorical variable was included in the model and had a high odds ratio for some events. For example, the odds of multiple deaths was 12 times higher if items from a vehicle came loose and struck a bystander than if that didn't happen. A second example is the *PRIOR_3* variable, a categorical variable manually created from the dataset indicating whether the vehicle was crossing a roadway. The model predicted that the odds of multiple fatalities occurring were 3.5 times higher if the vehicle is crossing a roadway than if it is not.

The Receiver Operating Characteristic (ROC) curve was used to assess the accuracy of predictions as shown in Figure 4A. This model produced a high ROC curve with a c-value of 0.805, showing a good performance on the year 2012 data.

Model B: A logistic regression analysis and stepwise selection procedure was conducted using the same technique for model A but with all of the 152 variables in the dataset. Therefore, the selected variables may have a multicollinearity issue. This model was built to see if we ignored multicollinearity, whether a stronger model will be possible because the existence of multicollinearity does not affect the prediction of the target variable. So if the goal of a model user is to make accurate predictions about the likely occurrence of a fatal crash that results in multiple deaths, this model may be preferred. Table 22 shows the summary of the stepwise selection. Table 23 show the odds ratio estimates. An example of the model results for variable *DOA* is that based on the odds ratio estimate, the odds of multiple deaths are 2.3 times higher if someone died at the crash scene compared to no deaths at the crash scene. This variable is in a variable cluster containing three other variables. They are *PCRASH4* (vehicle skidding, etc.), *PCRASH5* (vehicle departed lane or roadway etc.) and *EJECTION* (people ejected from vehicle). These variables did not end up in this model but they are likely to affect the severity of the accident so they may have diluted the reported effects of the *DOA* variable because of collinearity.

The ROC curve (Figure 9) was used to assess the accuracy of predictions. This model did produce a high ROC curve with a c-value of 0.8144.

Figure 9: ROC curves for Model A and B



Models A and B resulted in significantly different variables. Variables from model B were examined to check if any of them were in the same cluster and therefore likely to be co-linear.

For example, while the variable *ROUTE* representing accident route (classified into Interstate, US Highway, County Road, Local Street, and others) was not included in model B, this variable was significant in Model A. Model A tells us that the odds of multiple fatalities for an accident on an interstate highway is less than 1 on state routes but the odds of multiple fatalities for an accident on other US routes that are not Interstate highways is greater than that 1 State routes. We might interpret this to rank highway types in terms of their likelihood for multiple fatality accidents from Interstates being the safest, to other US routes being the most dangerous with other State routes being between them.

From Model B, it can be seen that the odds of multiple deaths were 1.5 times higher if an equipment was used to remove a person from the crash vehicle versus no equipment extraction (Variable *EXTRICAT*). Another variable from the same cluster is also in this model, namely *INJ_SEV* introducing the possibility of collinearity so the actual effect of *EXTRICAT* may differ than what Model B predicts. Variable *EXTRICAT* does not appear in Model A but *INJ_SEV*, from the same cluster, appears in Model A, evidence that they measure similar effects.

Generalization

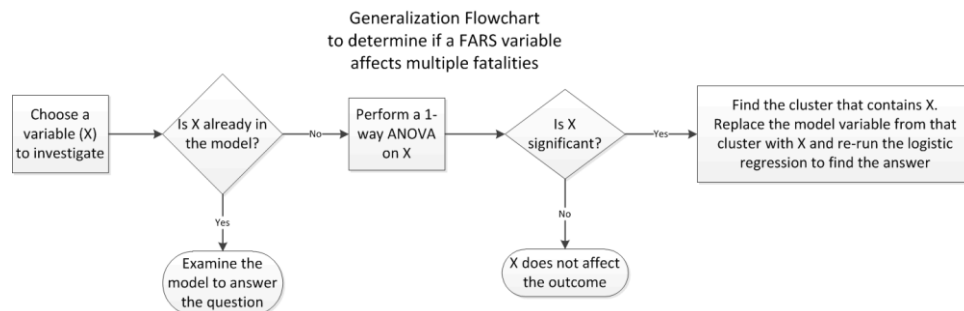
The models were tested on 2013 data (Figure 10). The ROC curve for the 2013 validation dataset produced a ROC curve value of 0.7796 for Model A and 0.8022 for Model B. Compared to the c-values based on the training data, the values did not drop much, showing that our approach is correct: It is appropriate to use the current year data to predict the next situation.

Also, Model B generated a higher c-value than Model A in both the training data and the validation data. Therefore, Model A is recommended for determining the correct effects of each factor on multiple deaths. Model B is recommended if better prediction of the target is the main goal. If multicollinearity is a concern, Model A is suggested. Otherwise, the team suggests the use of Model B.

In case the user is interested in the effect of a factor that was not picked as the cluster representative, an easy modification of Model A can be made. One can change the cluster

representative into the factor that one is interested in and run Model A again to see the effect (whether it is significant, and if so, whether the effect is positive or negative). Figure 8 below shows the flow chart of how to find effects of factors on multiple deaths in general.

Figure 8: Flow Chart to Find the Effects of a Variable



An example of how to investigate whether a variable of interest is significant and can be predicted using the flowchart in figure 8 is demonstrated by using the variable *DAY*. Assume that the variable *DAY* (day of the month 1-31) is of interest and we want to know whether multiple fatalities are more likely on certain days of the month. A one-way ANOVA analysis indicates that *FATALS* is predicted by *DAY* and is significant at the .001 level, yet this variable is not included any of the models above. The variable is in cluster number 37. The variable in that cluster which was used in Model A in this study was *EJ_PATH*. Model A should be re-run with *EJ_PATH*, replaced with *DAY*, and the results examined.

Suggestions for Future Studies

The predictor model was built based on accidents reported during the year 2012 and validated for the 2013 data.

- Future work could be done for multiple years both to strengthen the model and to see if the key variables change with time.
- A time series analysis of important trends over time that could show if important characteristics are increasing or decreasing with time, if there is any seasonality to the data, or if there are any unusual outlier time periods.
- Many different cause and effect relationships could also be investigated.
- This analysis would have been better if the accident data could have been put on a normalized basis, perhaps per capita by state or per driving miles per state. While state populations are available, contest rules prohibited using them since the data was not in FARS databases. The Government should consider adding demographic data into the FARS databases so that analyses could be made even better.

A key assumption was that the data in the FARS dataset was accurate. It is likely that there were errors in it. There were many conditions listed as 'unknown' which did not help much. Error rates in the data should be examined. It might be possible to do a Measurement Systems Analysis to help to know the level of confidence to put in many of the measurements in the data values. The data available for the project was not adequate to perform this kind of analysis.

Conclusion

Since accidents are undesirable and unplanned, they can be prevented given the circumstances leading to the accident are recognized, and acted upon, prior to its occurrence. Model A and model B suggested that a number of factors contribute to the risk of multiple fatalities, including *PERMVIT*, *INJ_SEV*, *PERNOTMVIT*, *DOA*, *PERSONS*, *NUMOCCS*, *FIRE_EXP*, *COUNTY*, *CITY*, *VE_TOTAL*, *DEFORMED*, *VSPD_LIM*, *HOURL*, *DRUNK_DR*, etc. Model A would be ideal for a better understanding of effects of factors on multiple deaths while model B would be ideal for prediction purposes.

Since the ROC curves for the 2012 and 2013 data were very similar, investigators can use previous year's data to predict the following year's data. This project also provided a general procedure for the users if any factor becomes of interest to them. This study is a step towards sensible analysis of the worst kind of motor vehicle fatalities and that all stakeholders in the transportation industry can be better informed and take sensible actions to help reduce them.

Appendix

TABLE OF CONTENTS	PAGE
<i>Tables</i>	
Table 1: IMPACT1 in year 1999	2
Table 2: IMPACT1 in year 2012	3
Table 3: Before <i>MVIOLATN</i> is collapsed from <i>VIOLATN</i> database	4
Table 4: After <i>MVIOLATN</i> is collapsed into <i>VIOLATN</i> from the <i>VIOLATN</i> database	6
Table 5: Before <i>MDRDSTRD</i> categories are condensed from <i>DISTRACT</i> database	7
Table 6: After <i>MDRDSTRD</i> condensed in variable <i>DISTRACT</i>	8
Table 7: Before <i>MFACTOR</i> it was condensed from <i>FACTOR</i> database	9
Table 8: After <i>MFACTOR</i> was condensed into variable <i>FACTOR</i> from <i>FACTOR</i> database	10
Table 9: Before <i>MDRMANAV</i> is condensed from <i>MANEUVER</i> database	11
Table 10: After <i>MDRMANAV</i> is condensed into <i>MANAV</i> from <i>MANEUVER</i> database	12
Table 11: Before <i>MVISOBSC</i> is condensed from <i>VISION</i> database	13
Table 12: After <i>MVISOBSC</i> from <i>VISION</i> database is condensed into <i>VIS</i>	14
Table 13: List of variables dropped	15
Table 14: Table on variable <i>FATALS</i>	17
Table 15: Table on <i>MULTIPLE</i>	18
Table 16: List of categorical and Numeric Variables used in one-way ANOVA	19
Table 17: Tukey's Table of <i>WEATHER</i> variable with all the 12 categories	23
Table 18: <i>WEATHER</i> Variable after Grouping	24
Table 19: Cluster grouping of the 152 Variables used in VARCLUS procedure	25
Table 20: Summary of Stepwise Selection for Model A	30
Table 21: Odds Ratio Estimate for Model A	31
Table 22: Summary of Stepwise Selection for Model B	34
Table 23: Odds Ratio Estimates for Model B	35
Table 24: <i>MULTIPLE</i> frequency after sampling	39
 <i>Figures</i>	
Figure 1: FARS Data Base	40
Figure 2: Frequency of Accidents in the USA for years 2012 & 2013	41
Figure 3: Map of Georgia for years 2012 & 2013	42
Figure 4: Map of North Carolina for years 2012 & 2013	43
Figure 5: Map of California for years 2012 & 2013	44
Figure 6: Map of Wyoming for years 2012 & 2013	45
Figure 7: Histogram of variable <i>VSPD_LIM</i>	46
Figure 8: Flow Chart to Find the Effects of a Variable	47
Figure 9: ROC curves side by side comparison	48

<i>Figure 10:</i>	ROC Curve for 2013 Validation Data	49
<i>SAS Code</i>		
Summary of Coding		
Step 1:	Filter First Event from datasets.	50
Step 2:	ANOVA to check significant variables	50
Step 3:	Clustering	51

Table 1: IMPACT1 in year 1999

IMPACT1	Frequency	Percent
0	3471	6.11
1	2980	5.24
2	1411	2.48
3	3221	5.67
4	502	0.88
5	539	0.95
6	2516	4.43
7	732	1.29
8	573	1.01
9	3976	7
10	1533	2.7
11	4238	7.46
12	28585	50.31
13	280	0.49
14	952	1.68
99	1311	2.31

Table 2: IMPACT1 in year 2012

IMPACT1	Frequency	Percent
0	3426	7.45
1	1649	3.59
2	610	1.33
3	1919	4.18
4	266	0.58
5	336	0.73
6	2614	5.69
7	452	0.98
8	352	0.77
9	2321	5.05
10	689	1.5
11	2018	4.39
12	24388	53.06
13	124	0.27
14	1093	2.38
18	87	0.19
61	672	1.46
62	369	0.8
63	187	0.41
81	564	1.23
82	340	0.74
83	141	0.31
98	658	1.43
99	685	1.49

TABLE 3: Before *MVIOLATN* is collapsed from VIOLATN database

MVIOLATN	Frequency	Percent
0	40413	82.71
1	1260	2.58
2	326	0.67
3	233	0.48
4	429	0.88
5	30	0.06
6	2	0
7	354	0.72
8	65	0.13
9	152	0.31
11	1140	2.33
12	123	0.25
13	13	0.03
14	7	0.01
15	41	0.08
16	9	0.02
18	12	0.02
19	51	0.1
21	4	0.01
22	139	0.28
23	163	0.33
24	4	0.01
25	1	0
26	2	0
29	84	0.17
31	63	0.13
32	4	0.01
33	4	0.01
34	2	0
35	24	0.05
36	1	0
37	120	0.25
38	18	0.04
39	45	0.09
41	10	0.02
42	20	0.04
43	7	0.01
45	5	0.01
46	542	1.11
48	10	0.02

49	68	0.14
51	21	0.04
52	110	0.23
53	36	0.07
54	1	0
55	2	0
56	1	0
58	48	0.1
59	20	0.04
61	36	0.07
62	16	0.03
66	1	0
69	218	0.45
71	192	0.39
72	349	0.71
73	18	0.04
74	89	0.18
75	68	0.14
76	201	0.41
79	80	0.16
81	13	0.03
82	19	0.04
83	213	0.44
84	8	0.02
86	5	0.01
89	64	0.13
91	5	0.01
92	13	0.03
93	9	0.02
95	252	0.52
97	19	0.04
98	50	0.1
99	687	1.41

Table 4: After *MVIOLATN* is collapsed into *VIOLATN* from the VIOLATN database

VIOLATN		
MV	Frequency	Percent
EQUIPMENT	303	0.63
IMPAIRMENT	1328	2.76
LANE	271	0.56
LICENSE	836	1.74
NONE	40413	84.14
OTHER	1027	2.14
RECKLESS	2288	4.76
SPEED	393	0.82
TRAFFIC	281	0.59
TURNING	656	1.37
WRONG	236	0.49

Table 5: Before *MDRDSTRD* categories are condensed from DISTRACT database

MDRDSTRD	Frequency	Percent
0	33152	72.08
1	366	0.8
3	148	0.32
4	15	0.03
5	113	0.25
6	106	0.23
7	54	0.12
9	28	0.06
10	68	0.15
12	205	0.45
13	39	0.08
14	16	0.03
15	180	0.39
16	252	0.55
17	255	0.55
18	15	0.03
19	76	0.17
92	446	0.97
93	1186	2.58
96	4063	8.83
97	11	0.02
98	242	0.53
99	4959	10.78

Table 6: After *MDRDSTRD* condensed in variable *DISTRACT*

DISTRACT	Frequency	Percent
0	76331	99.86
30	105	0.14

Table 7: Before *MFACTOR* it was condensed from *FACTOR* database

MFACTOR	Frequency	Percent
0	43025	93.45
1	672	1.46
2	135	0.29
3	30	0.07
4	12	0.03
5	23	0.05
6	2	0
7	52	0.11
8	14	0.03
9	32	0.07
11	17	0.04

Table 8: After *MFACTOR* was condensed into variable *FACTOR* from FACTOR database

FACTOR	Frequency	Percent
0	65181	93.14
1	4705	6.72
2	85	0.12
3	8	0.01
4	2	0
5	1	0

Table 9: Before *MDRMANAV* is condensed from MANEUVER database

MDRMANAV	Frequency	Percent
0	39023	84.88
1	78	0.17
2	24	0.05
3	124	0.27
4	2565	5.58
5	504	1.1
92	277	0.6
95	252	0.55
98	1954	4.25
99	1176	2.56

Table 10: After *MDRMANAV* is condensed into *MANAV* from MANEUVER database

MANAV	Frequency	Percent
0	59753	85.38
2	46	0.07
3	236	0.34
30	5267	7.53
95	108	0.15
98	2914	4.16
99	1658	2.37

Table 11: Before *MVISOBSC* is condensed from VISION database

MVISOBSC	Frequency	Percent
0	43110	93.72
1	400	0.87
2	208	0.45
3	154	0.33
4	17	0.04
5	68	0.15
6	216	0.47
7	52	0.11
8	3	0.01
9	2	0
10	4	0.01
11	5	0.01
13	12	0.03
14	13	0.03
95	252	0.55

Table 12: After *MVISOBSC* from VISION database is condensed into *VIS*

VIS	Frequency	Percent
0	66264	94.69
1	589	0.84
2	275	0.39
3	226	0.32
4	23	0.03
5	80	0.11
6	327	0.47

Table 13: List of variables dropped

VE_FORMS
PEDS
NHS
TWAY_ID
TWAY_ID2
MILEPT
RAIL
MAK_MOD
VIN
VIN_1
VIN_2
VIN_3
VIN_4
VIN_5
VIN_6
VIN_7
VIN_8
VIN_9
VIN_10
VIN_11
VIN_12
VINTYPE
VINMAKE
VINA_MOD
VIN_BT
VINMODYR
VIN_LNGT
VIN_WGT
VINTYPE
VINMAKE
VINA_MOD
VIN_BT
VINMODYR
VIN_LNGT
VIN_WGT
WHLBS_LG
WHLBS_SH
SER_TR
MCYCL_DS
CARBUR
CYLINDER
MCYCL_CY
MCYCL_WT
TIRE_SIZE
TON_RAT
TRK_WT
TRKWTVAR
VIN_REST
WHLDRWHL
MCARR_I1
MCARR_I2

MCARR_ID
HAZ_ID
HAZ_CNO
FIRST_MO
FIRST_YR
LAST_MO
LAST_YR
NAME
DRUG_DET
DSTATUS
DRUGTST1
DRUGTST2
DRUGTST3
DRUGRES1
DRUGRES2
DRUGRES3
HOSPITAL
DEATH_DA
DEATH_MO
DEATH_HR
DEATH_MN
DEATH_TM
P_SF1
P_SF2
P_SF3
CERT_NO
HISPANIC
RACE
PVIN
PVIN_1
PVIN_2
PVIN_3
PVIN_4
PVIN_5
PVIN_6
PVIN_7
PVIN_8
PVIN_9
PVIN_10
PVIN_11
PVIN_12

Table 14: Table on variable *FATALS*

FATALS	Frequency	Percent
1	67289	88.03
2	7065	9.24
3	1220	1.6
4	531	0.69
5	153	0.2
6	26	0.03
7	65	0.09
9	64	0.08
15	23	0.03

Table 15: Table on *MULTIPLE*

MULTIPLE	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	67289	88.03	67289	88.03
1	9147	11.97	76436	100

Table 16: List of categorical and Numeric Variables used in one-way ANOVA

No	Variable	Type
1	CRSH_0	Categorical
2	DR_DRINK	Categorical
3	DR_PRES	Categorical
4	DR_ZIP	Categorical
5	FIRE_EXP	Categorical
6	HAZ_INV	Categorical
7	HIT_RUN	Categorical
8	IMPAIR_0	Categorical
9	J_KNIFE	Categorical
10	MANAV	Categorical
11	P_CRASH1	Categorical
12	REST_MIS	Categorical
13	ROLLOVER	Categorical
14	SAFE_1	Categorical
15	SPEEDREL	Categorical
16	UNITTYPE	Categorical
17	VALIGN	Categorical
18	VNUM_LAN	Categorical
19	VPROFILE	Categorical
20	VTRAFWAY	Categorical
21	DAMAGEN	Categorical
22	DAM_1	Categorical
23	DAM_2	Categorical
24	DAM_3	Categorical
25	DAM_4	Categorical
26	DAM_5	Categorical
27	DAM_6	Categorical
28	DAM_13	Categorical
29	DAM_14	Categorical
30	DR_SF4	Categorical
34	PERMVIT	Categorical
35	PERSONS	Categorical
36	CEVENT_SOE	Categorical
37	P_CRASH2	Categorical
38	RELJCT2	Categorical
39	VEVENT_SOE	Categorical
40	L_STATE	Categorical

41	NUMOCCS	Categorical
42	REG_STAT	Categorical
43	DISPLACEN	Categorical
44	GVWR	Categorical
45	V_CONFIG	Categorical
46	DEFORMED	Categorical
47	HARM_EV	Categorical
48	PERNOTMVIT	Categorical
49	REST_USE	Categorical
50	TOWED	Categorical
51	VIS	Categorical
52	WEATHER	Categorical
53	WEATHER1	Categorical
54	CRSH_1	Categorical
55	CRSH_2	Categorical
56	CRSH_12	Categorical
57	CRSH_19	Categorical
58	IMPAIR_9	Categorical
59	PRIOR_3	Categorical
60	EXTRICAT	Categorical
61	INJ_SEV	Categorical
62	WORK_INJ	Categorical
63	MODEL	Categorical
64	REL_ROAD	Categorical
65	ROAD_FNC	Categorical
66	ROUTE	Categorical
67	VIOLATN_LANE	Categorical
69	DRINKING	Categorical
70	DRUGS	Categorical
71	CRSH_99	Categorical
72	PRIOR_99	Categorical
73	SAFE_9	Categorical
74	CRSH_5	Categorical
75	PRIOR_11	Categorical
76	CF1	Categorical
77	CF2	Categorical
78	CRSH_4	Categorical
79	IMPAIR_8	Categorical
80	PRIOR_8	Categorical

81	DOA	Categorical
82	EJECTION	Categorical
83	PCRASH4	Categorical
84	PCRASH5	Categorical
85	CRSH_98	Categorical
86	PRIOR_98	Categorical
87	CRSH_9	Categorical
88	PRIOR_6	Categorical
89	PRIOR_5	Categorical
90	SAFE_2	Categorical
91	DAM_7	Categorical
92	DAM_8	Categorical
93	DAM_9	Categorical
94	DAM_10	Categorical
95	DAM_11	Categorical
96	DAM_30	Categorical
100	DRUNK_DR	Categorical
101	VE_TOTAL	Categorical
102	DAM_12	Categorical
103	IMPACT1	Categorical
104	TRAV_SP	Categorical
106	L_TYPE	Categorical
107	VIOLATN_RECKLESS	Categorical
108	CRSH_21	Categorical
109	PRIOR_14	Categorical
112	STATE	Categorical
113	IMPAIR_98	Categorical
114	SAFE_8	Categorical
115	CARGO_BT	Categorical
116	SEAT_POS	Categorical
117	CITY	Categorical
118	COUNTY	Categorical
119	PRIOR_2	Categorical
120	DRIMP_NONE	Categorical
121	L_COMPL	Categorical
122	VIOLATN_NONE	Categorical
123	OWNER	Categorical
124	IMPAIR_99	Categorical
127	DAY	Categorical

128	DR_SF1	Categorical
129	EJ_PATH	Categorical
130	SAFE_3	Categorical
131	WRK_ZONE	Categorical
132	BODY_TYP	Categorical
133	BUS_USE	Categorical
134	MONTH	Categorical
135	VSURCOND	Categorical
136	DAY_WEEK	Categorical
137	HOLIDA	Categorical
138	PRIOR_4	Categorical
139	IMPAIR_96	Categorical
140	ALC_STATUS	Categorical
141	SEX	Categorical
142	CRSH_6	Categorical
143	CRSH_3	Categorical
144	DISTRACT	Categorical
145	VIOLATN_TRAFFIC	Categorical
146	FUELCODEN	Categorical
147	VEH_SC1	Categorical
148	SP_JUR	Categorical
149	TYP_INT	Categorical
150	PREV_OTH	Categorical
31	ARR_HOUR	Numeric
32	HOUR	Numeric
33	NOT_HOUR	Numeric
68	VSPD_LIM	Numeric
97	ARR_MIN	Numeric
98	MINUTE	Numeric
99	NOT_MIN	Numeric
105	AGE	Numeric
110	HOSP_HR	Numeric
111	HOSP_MN	Numeric
125	LAG_HRS	Numeric
126	LAG_MINS	Numeric
151	DR_HGT	Numeric
152	DR_WGT	Numeric

Table 17: Tukey's Table of *WEATHER* variable with all the 12 categories

Tukey Grouping		Mean	N	Weather
	A	1.45161	31	7
	A			
B	A	1.36957	92	11
B	A			
B	A	1.3669	1022	5
B				
B	C	1.193	11975	10
B	C			
B	C	1.18321	131	6
B	C			
B	C	1.18067	952	4
B	C			
B	C	1.17251	5165	2
B	C			
B	C	1.16276	56360	1
B	C			
B	C	1.15116	172	3
	C			
	C	1.11151	278	99
	C			
	C	1.06742	178	98
	C			
	C	1	80	8

Table 18: *WEATHER* Variable after Grouping

Significant Var WEATHER		
TUKEY GROUPING		
7,11,5		A
10,6,4,2,1,3		B
99,98,8		C

Table 19: Cluster grouping of the 152 Variables used in VARCLUS procedure

Cluster	Variable	Own	Next	1-R**2	Label				
		Cluster	Cluster						
Cluster 2	PREV_OTH	0.0003	0.0002	0.9999	Previous other harmful MV convictions				
	NOT_MIN	0.6253	0.159	0.4455	Notification Time EMS (MIN)				
	TYP_INT	0.5256	0.0077	0.4781	Type of Intersection				
	DR_DRINK	0.9816	0.4938	0.0363	Driver Drinking				
	DAM_4	0.8289	0.4177	0.2939					
Cluster 3	NOT_HOUR	0.8084	0.2968	0.2725	Notification Time EMS (HOUR)				
Cluster 4	PERMVIT	0.9803	0.4038	0.0331	Number of Persons in Motor Vehicles In-Transport				
	VEVENT_SO E	0.9015	0.028	0.1014	Sequence of Events				
Cluster 6	BODY_TYP	0.7225	0.1127	0.3127	Body Type				
	DISPLACEN	0.7386	0.0388	0.272					
	DEFORMED	0.7984	0.2394	0.265	Extent of Damage				
	WEATHER	0.908	0.0349	0.0953	Atmospheric Conditions				
	PRIOR_3	0.7323	0.4723	0.5073					
Cluster 11	INJ_SEV	0.8497	0.1705	0.1812	Injury Severity				
	VSPD_LIM	0.5912	0.0158	0.4154	Speed Limit				
	ROUTE	0.6503	0.0171	0.3558	Route Signing				
Cluster 13	DRINKING	0.849	0.0337	0.1563	Police Reported Alcohol Involvement				
	DRUGS	0.849	0.0137	0.1531	Police Reported Drug Involvement				
	PRIOR_99	0.6846	0.0194	0.3216					
Cluster 15	CRSH_5	0.7544	0.0052	0.2469					
Cluster 16	CF1	0.7758	0.0038	0.225	Related Factors (1)				
Cluster 17	CRSH_4	0.7583	0.1062	0.2704					
	PCRASH5	0.5685	0.1753	0.5232	Pre- Impact Location				
	PRIOR_98	0.6818	0.0096	0.3213					
Cluster 20	CRSH_9	0.6681	0.0192	0.3384					
	SAFE_2	0.6283	0.0209	0.3796					
	DAM_8	0.8588	0.5192	0.2937					
Cluster 23	SP_JUR	0.5256	0.0016	0.4752	Special Jurisdiction				
Cluster 24	MINUTE	1	0.0167	0	Crash Time (MINUTE)				
	DRUNK_DR	0.797	0.0621	0.2164	Drunk Drivers				

Cluster 26	HOUR	1	0.0754	0	Crash Time (HOUR)			
	DAM_12	0.764	0.1431	0.2754				
Cluster 28	AGE	0.4957	0.0506	0.5311	Age			
Cluster 29	CRSH_21	0.6198	0.0327	0.393				
Cluster 30	IMPAIR_98	0.6379	0.1242	0.4135				
Cluster 31	SEAT_POS	0.6698	0.0912	0.3633	Seating Position			
	L_STATE	0.7756	0.1976	0.2797	Driver License State			
Cluster 33	PRIOR_2	1	0.0097	0				
Cluster 34	OWNER	1	0.0637	0	Registered Vehicle Owner			
	DRIMP_NON E	0.5255	0.133	0.5473				
Cluster 36	IMPAIR_99	1	0.1777	0				
Cluster 37	LAG_HRS	0.6061	0.0328	0.4072	Crash to Death Time (Hours)			
Cluster 38	CITY	1	0.0309	0	City			
	EJ_PATH	0.5135	0.0203	0.4965	Ejection Path			
Cluster 40	WRK_ZONE	0.5488	0.0044	0.4532	Work Zone			
	VSURCOND	0.532	0.0365	0.4857	Roadway surface Condition			
	HOSP_HR	0.7856	0.3905	0.3518	EMS time at Hospital (HOUR)			
	HOSP_MN	0.7804	0.2005	0.2746	EMS time at Hospital (MIN)			
Cluster 43	DAY_WEEK	0.5394	0.0138	0.467	Crash Date (Day of Week)			
Cluster 45	PRIOR_4	1	0.0066	0				
Cluster 46	IMPAIR_96	1	0.005	0				
	ALC_STATU S	0.5169	0.0103	0.4881	Alcohol Test-Status			
Cluster 48	CRSH_6	1	0.019	0				
Cluster 49	CRSH_3	1	0.0405	0				
Cluster 50	DISTRACT	0.5015	0.0002	0.4986				
Cluster 51	FUELCODE N	1	0.0001	0				
Cluster 52	VEH_SC1	1	0.0091	0	Vehicle Related factors (1)			
Cluster 53	DR_SF4	1	0.0005	0	Driver Related Factors (4 choices)			
Cluster 1	ROLLOVER	0.5347	0.2812	0.6473	Rollover Type			
	FIRE_EXP	0.3191	0.1537	0.8046	Fire Occurrence			
	REST_MIS	0.9594	0.5143	0.0837				

	UNITTYPE	0.9816	0.4938	0.0363	Unit Type				
	HIT_RUN	0.7666	0.4502	0.4245	Hit and Run				
	J_KNIFE	0.9685	0.4863	0.0614	Jackknife				
	HAZ_INV	0.9816	0.4938	0.0363					
	DR_PRES	0.966	0.4849	0.066	Driver Presence				
	DR_ZIP	0.2487	0.1098	0.844	Driver ZIP Code				
	SPEEDREL	0.7501	0.3866	0.4074	Speed Related				
	VTRAFWAY	0.9751	0.4853	0.0484	Trafficway Description				
	VNUM_LAN	0.7241	0.3437	0.4204	Total Lanes in Roadway				
	VALIGN	0.972	0.4828	0.0541	Roadway Alignment				
	VPROFILE	0.7561	0.3607	0.3816	Roadway Grade				
	P_CRASH1	0.8342	0.4022	0.2773	Pre-Event movement				
	MANAV	0.4698	0.2137	0.6743					
	CRSH_0	0.2723	0.1063	0.8143					
	IMPAIR_0	0.474	0.1912	0.6503					
	SAFE_1	0.7051	0.4069	0.4973					
	DAM_1	0.627	0.309	0.5398					
	DAM_2	0.7597	0.3796	0.3874					
	DAM_3	0.6884	0.3022	0.4465					
	DAM_5	0.8026	0.4081	0.3335					
	DAM_6	0.5522	0.3637	0.7038					
	DAM_13	0.5427	0.3767	0.7336					
	DAM_14	0.6391	0.4398	0.6442					
	damagen	0.6922	0.4867	0.5997					
	ARR_HOUR	0.81	0.3168	0.2781	Arrival Time EMS (HOUR)				
	ARR_MIN	0.6191	0.1598	0.4533	Arrival Time EMS (MIN)				
	PERSONS	0.9803	0.4135	0.0336	Number of MV occupant				
Cluster 5	P_CRASH2	0.3403	0.0275	0.6783	Critical Event - Precrash (Event)				
	RELJCT2	0.1679	0.0084	0.8391	Relation to Junction - Specific Location				
	CEVENT_SEQUENCE	0.8921	0.0318	0.1115	Sequence of Events				
	BUS_USE	0.7225	0.1788	0.3379	Bus Use				
Cluster 7	GVWR	0.7521	0.143	0.2892	Gross vehicle weight rating				
	V_CONFIG	0.291	0.0066	0.7137	Vehicle Configuration				
Cluster 8	HARM_EV	0.5846	0.1961	0.5167	First Harmful Event				

	REST_USE	0.1197	0.1328	1.0152	Restraint System/Helmet Use		
	TOWED	0.7931	0.2252	0.267	Vehicle Removal		
	PERNOTMVI T	0.6074	0.2431	0.5187			
Cluster 9	WEATHER1	0.9054	0.0323	0.0977	Atmospheric Conditions		
	VIS	0.3211	0.0666	0.7274			
Cluster 10	CRSH_12	0.407	0.1186	0.6728			
	CRSH_2	0.4526	0.2115	0.6942			
	CRSH_1	0.2766	0.1072	0.8103			
	CRSH_19	0.2368	0.1277	0.875			
	IMPAIR_9	0.2717	0.1086	0.817			
	EXTRICAT	0.1932	0.0504	0.8496	Extrication		
	WORK_INJ	0.814	0.1577	0.2208	Fatal Injury at work		
Cluster 12	ROAD_FNC	0.6139	0.0179	0.3931	Roadway Function Class		
	MODEL	0.0002	0.0001	1	Vehicle Model		
	REL_ROAD	0.1411	0.0261	0.8818	Relation To Trafficway		
	VIOLATN_LA NE	0.0029	0.0069	1.004			
Cluster 14	CRSH_99	0.6765	0.035	0.3353			
	SAFE_9	0.1765	0.0099	0.8317			
	PRIOR_11	0.7544	0.0068	0.2473			
	CF2	0.7758	0.0105	0.2265	Related Factors (2)		
	IMPAIR_8	0.0771	0.0072	0.9296			
	PRIOR_8	0.7542	0.1081	0.2756			
Cluster 18	EJECTION	0.4014	0.0501	0.6302	Ejecti on		
	DOA	0.2834	0.3538	1.1089	Died at scene/en route		
	PCRASH4	0.4188	0.0481	0.6106	Pre- Impact Stability		
Cluster 19	CRSH_98	0.6818	0.0183	0.3241			
	PRIOR_6	0.6681	0.0273	0.3412			
Cluster 21	PRIOR_5	0.6283	0.1218	0.4232			
Cluster 22	DAM_11	0.6736	0.3499	0.502			
	DAM_7	0.8084	0.5245	0.403			
	DAM_9	0.7614	0.3798	0.3847			
	DAM_10	0.8272	0.449	0.3136			
	DAM_30	0.0216	0.0311	1.0098			
Cluster 25	VE_TOTAL	0.797	0.0766	0.2198	Number of vehicle forms submitted		
Cluster 27	IMPACT1	0.766	0.2017	0.2931	Area of Impact- Initial Contact Point		
	TRAV_SP	0.0064	0.0055	0.9991	Travel Speed		

	L_TYPE	0.4446	0.0415	0.5795	Non-CDL license Type				
	VIOLATN_R ECKLESS	0.2235	0.0479	0.8155					
	PRIOR_14	0.6198	0.039	0.3956					
	SAFE_8	0.6379	0.1754	0.4392					
	CARGO_BT	0.6698	0.1153	0.3732	Cargo Body Type				
Cluster 32	NUMOCCS	0.5007	0.7887	2.363	Number of Occupants				
	REG_STAT	0.6362	0.1148	0.411	Vehicle Registration State				
Cluster 35	L_COMPL	0.6131	0.3075	0.5587	License Compliance with class of vehicle				
	VIOLATN_N ONE	0.5862	0.3458	0.6324					
	LAG_MINS	0.6061	0.0452	0.4125	Crash to Death Minutes (Minutes)				
Cluster 39	DAY	0.0607	0.0093	0.9481	Crash Date (DAY)				
	DR_SF1	0.5205	0.1024	0.5342	Driver Related Factors (4 choices)				
	SAFE_3	0.5488	0.0127	0.457					
Cluster 41	MONTH	0.532	0.0377	0.4863	Crash Date (MONTH)				
Cluster 42	STATE	0.2172	0.0221	0.8005	State Number				
	HOLIDA	0.5394	0.0445	0.4821					
Cluster 44	COUNTY	1	0.0549	0	Count y				
Cluster 47	SEX	0.5169	0.0167	0.4913	Sex				
	VIOLATN_T RAFFIC	0.5015	0.0025	0.4998					

Table 20: Summary of Stepwise Selection for Model A

Summary of Stepwise Selection								
Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq	Variable Label
	Entered	Removed						
1	PERMVIT		9	1	2990.1317		<.0001	Number of Persons in Motor Vehicles In-Transport
2	INJ_SEV		1	2	1287.1013		<.0001	Injury Severity
3	CITY		1	3	209.0768		<.0001	City
4	DEFORMED		2	4	166.9710		<.0001	Extent of Damage
5	VSPD_LIM		16	5	216.1523		<.0001	Speed Limit
6	HOUR		1	6	111.1223		<.0001	Crash Time (HOUR)
7	DRIMP_NONE		1	7	61.6409		<.0001	
8	DRINKING		2	8	65.1708		<.0001	Police Reported Alcohol Use
9	PRIOR_3		1	9	58.3525		<.0001	
10	DISPLACEN		1	10	41.8751		<.0001	
11	DRUNK_DR		2	11	40.4049		<.0001	Drunk Drivers
12	DAY_WEEK		2	12	32.7051		<.0001	Crash Date (Day of Week)
13	DAM_8		1	13	27.3820		<.0001	
14	CF1		19	14	65.3254		<.0001	Related Factors (1)
15	ROUTE		2	15	27.6672		<.0001	Route Signing
16	DR_DRINK		1	16	17.6369		<.0001	Driver Drinking
17	PCRASH5		1	17	15.1368		<.0001	Pre- Impact Location
18	HOSP_MN		1	18	12.5065		0.0004	EMS time at Hospital (MIN)
19	LAG_HRS		1	19	11.3204		0.0008	Crash to Death Time (Hours)
20	DAM_12		1	20	10.2514		0.0014	
21	IMPAIR_99		1	21	10.0619		0.0015	
22	OWNER		1	22	7.7191		0.0055	Registered Vehicle Owner
23	PRIOR_98		1	23	7.0661		0.0079	
24		PRIOR_98	1	22		0.0036	0.9524	

Table 21: Odds Ratio Estimate for Model A

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
DR_DRINK 1 vs 99	0.453	0.350	0.588
PERMVIT 9 vs 50	11.191	9.956	12.579
PERMVIT 17 vs 50	>999.999	<0.001	>999.999
PERMVIT 18 vs 50	36.463	10.931	121.638
PERMVIT 21 vs 50	6.072	5.551	6.642
PERMVIT 23 vs 50	>999.999	<0.001	>999.999
PERMVIT 24 vs 50	76.929	41.921	141.170
PERMVIT 26 vs 50	>999.999	<0.001	>999.999
PERMVIT 33 vs 50	3.653	<0.001	>999.999
PERMVIT 47 vs 50	>999.999	<0.001	>999.999
DEFORMED 2 vs 6	0.567	0.486	0.661
DEFORMED 4 vs 6	0.636	0.563	0.719
PRIOR_3 0 vs 1	3.496	2.524	4.844
INJ_SEV 2 vs 6	0.320	0.294	0.348
ROUTE 1 vs 3	0.869	0.766	0.986
ROUTE 2 vs 3	1.205	1.103	1.315
VSPD_LIM 0 vs 80	0.194	0.076	0.500
VSPD_LIM 5 vs 80	<0.001	<0.001	>999.999
VSPD_LIM 10 vs 80	0.186	0.034	1.013
VSPD_LIM 15 vs 80	0.179	0.049	0.648
VSPD_LIM 20 vs 80	0.232	0.069	0.778
VSPD_LIM 25 vs 80	0.223	0.096	0.518
VSPD_LIM 30 vs 80	0.252	0.109	0.582
VSPD_LIM 35 vs 80	0.189	0.083	0.433
VSPD_LIM 40 vs 80	0.250	0.109	0.575

VSPD_LIM 45 vs 80	0.285	0.125	0.650
VSPD_LIM 50 vs 80	0.283	0.123	0.651
VSPD_LIM 55 vs 80	0.329	0.145	0.747
VSPD_LIM 60 vs 80	0.405	0.176	0.933
VSPD_LIM 65 vs 80	0.386	0.170	0.878
VSPD_LIM 70 vs 80	0.426	0.188	0.966
VSPD_LIM 75 vs 80	0.543	0.235	1.255
DRINKING 0 vs 8	0.782	0.725	0.843
DRINKING 1 vs 8	0.612	0.537	0.698
CF1 0 vs 99	2.834	0.559	14.366
CF1 1 vs 99	2.630	0.217	31.847
CF1 2 vs 99	3.924	0.533	28.873
CF1 3 vs 99	2.816	0.444	17.848
CF1 4 vs 99	3.181	0.493	20.526
CF1 5 vs 99	<0.001	<0.001	>999.999
CF1 6 vs 99	1.374	0.150	12.551
CF1 7 vs 99	>999.999	<0.001	>999.999
CF1 13 vs 99	<0.001	<0.001	>999.999
CF1 14 vs 99	3.235	0.630	16.595
CF1 15 vs 99	11.984	1.845	77.848
CF1 16 vs 99	<0.001	<0.001	>999.999
CF1 17 vs 99	<0.001	<0.001	>999.999
CF1 18 vs 99	3.753	0.555	25.393
CF1 19 vs 99	4.219	0.809	22.002
CF1 20 vs 99	5.740	1.100	29.961
CF1 22 vs 99	3.424	0.639	18.336
CF1 23 vs 99	5.147	0.973	27.232
CF1 24 vs 99	<0.001	<0.001	>999.999

PCRASH5	5 vs 7	0.851	0.785	0.923
DAM_8	0 vs 1	0.822	0.755	0.896
DRUNK_DR	1 vs 4	0.432	0.326	0.571
DRUNK_DR	3 vs 4	>999.999	<0.001	>999.999
DAM_12	0 vs 1	0.879	0.814	0.950
DRIMP_NONE	0 vs 1	1.324	1.216	1.440
OWNER	4 vs 6	1.109	1.031	1.192
IMPAIR_99	0 vs 1	2.002	1.299	3.085
DAY_WEEK	1 vs 7	0.889	0.794	0.996
DAY_WEEK	2 vs 7	0.780	0.713	0.853
HOUR		0.980	0.975	0.985
DISPLACEN		1.001	1.001	1.001
HOSP_MN		0.997	0.995	0.999
CITY		1.000	0.999	1.000
LAG_HRS		0.999	0.998	0.999

Table 22: Summary of Stepwise Selection for Model B

Summary of Stepwise Selection								
Step	Effect		DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq	Variable Label
	Entered	Removed						
1	PERMVIT		9	1	2990.1317		<.0001	Number of Persons in Motor Vehicles In-Transport
2	INJ_SEV		1	2	1287.1013		<.0001	Injury Severity
3	PERSONS		2	3	627.5972		<.0001	Number of MV occupant
4	PERNOTMVIT		2	4	453.5760		<.0001	Number of Persons Not in Motor Vehicles In-Transport
5	DOA		2	5	435.2631		<.0001	Died at scene/en route
6	FIRE_EXP		2	6	304.8571		<.0001	Fire Occurrence
7	CITY		2	7	162.1558		<.0001	City
8	COUNTY		3	8	163.2669		<.0001	County
9	HARM_EV		3	9	105.9981		<.0001	First Harmful Event
10	VSPD_LIM		16	10	142.9096		<.0001	Speed Limit
11	DRIMP_NONE		1	11	62.7570		<.0001	
12	STATE		50	12	178.4668		<.0001	State Number
13	EXTRICAT		1	13	54.0121		<.0001	Extrication
14	TRAV_SP		2	14	51.8671		<.0001	Travel Speed
15	DAMAGE		2	15	49.6337		<.0001	
16	VE_TOTAL		3	16	51.8259		<.0001	Number of vehicle forms submitted
17		VE_TOTAL	3	15		0.0257	0.9989	Number of vehicle forms submitted

Table 23: Odds Ratio Estimates for Model B

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
VSPD_LIM 0 vs 80	0.268	0.106	0.678
VSPD_LIM 5 vs 80	<0.001	<0.001	>999.999
VSPD_LIM 10 vs 80	0.314	0.057	1.743
VSPD_LIM 15 vs 80	0.217	0.058	0.805
VSPD_LIM 20 vs 80	0.338	0.099	1.149
VSPD_LIM 25 vs 80	0.360	0.158	0.820
VSPD_LIM 30 vs 80	0.393	0.174	0.887
VSPD_LIM 35 vs 80	0.272	0.121	0.608
VSPD_LIM 40 vs 80	0.331	0.147	0.743
VSPD_LIM 45 vs 80	0.415	0.187	0.925
VSPD_LIM 50 vs 80	0.387	0.172	0.873
VSPD_LIM 55 vs 80	0.449	0.202	0.996
VSPD_LIM 60 vs 80	0.577	0.256	1.301
VSPD_LIM 65 vs 80	0.542	0.243	1.210
VSPD_LIM 70 vs 80	0.555	0.249	1.236
VSPD_LIM 75 vs 80	0.668	0.293	1.523
STATE 1 vs 56	1.664	0.927	2.985
STATE 2 vs 56	3.785	1.408	10.177
STATE 4 vs 56	1.613	0.907	2.870
STATE 5 vs 56	2.076	1.145	3.766
STATE 6 vs 56	1.751	1.009	3.040
STATE 8 vs 56	2.627	1.430	4.828
STATE 9 vs 56	1.060	0.518	2.168
STATE 10 vs 56	6.449	2.365	17.584
STATE 11 vs 56	4.098	0.790	21.257

STATE	12 vs 56	1.846	1.058	3.221
STATE	13 vs 56	1.393	0.784	2.474
STATE	15 vs 56	2.113	0.969	4.607
STATE	16 vs 56	1.595	0.774	3.287
STATE	17 vs 56	1.345	0.752	2.405
STATE	18 vs 56	1.371	0.757	2.482
STATE	19 vs 56	2.891	1.539	5.428
STATE	20 vs 56	1.808	0.966	3.383
STATE	21 vs 56	1.460	0.802	2.657
STATE	22 vs 56	2.311	1.277	4.179
STATE	23 vs 56	1.282	0.568	2.896
STATE	24 vs 56	3.533	1.904	6.552
STATE	25 vs 56	1.444	0.743	2.805
STATE	26 vs 56	1.668	0.933	2.980
STATE	27 vs 56	3.676	1.940	6.965
STATE	28 vs 56	3.140	1.727	5.710
STATE	29 vs 56	2.442	1.360	4.387
STATE	30 vs 56	1.218	0.618	2.400
STATE	31 vs 56	1.912	0.946	3.867
STATE	32 vs 56	1.549	0.792	3.031
STATE	33 vs 56	0.737	0.269	2.020
STATE	34 vs 56	2.078	1.137	3.799
STATE	35 vs 56	1.184	0.635	2.206
STATE	36 vs 56	1.706	0.951	3.060
STATE	37 vs 56	1.589	0.894	2.824
STATE	38 vs 56	2.130	1.027	4.418
STATE	39 vs 56	1.749	0.986	3.103
STATE	40 vs 56	2.056	1.141	3.704

STATE	41 vs 56	1.412	0.731	2.730
STATE	42 vs 56	2.114	1.191	3.750
STATE	44 vs 56	0.673	0.215	2.113
STATE	45 vs 56	1.804	0.998	3.259
STATE	46 vs 56	1.641	0.787	3.422
STATE	47 vs 56	1.910	1.071	3.406
STATE	48 vs 56	2.424	1.398	4.204
STATE	49 vs 56	1.601	0.793	3.235
STATE	50 vs 56	2.536	0.960	6.704
STATE	51 vs 56	2.463	1.364	4.447
STATE	53 vs 56	1.888	1.005	3.545
STATE	54 vs 56	0.918	0.457	1.842
STATE	55 vs 56	1.885	1.039	3.418
CITY	1128 vs 9997	67.983	25.596	180.559
CITY	5183 vs 9997	4.187	<0.001	>999.999
HARM_EV	2 vs 19	1.750	1.524	2.008
HARM_EV	10 vs 19	7.162	3.509	14.616
HARM_EV	17 vs 19	1.443	1.153	1.805
FIRE_EXP	0 vs 99	1.736	0.768	3.924
FIRE_EXP	1 vs 99	3.764	1.631	8.686
COUNTY	153 vs 443	0.135	0.095	0.190
COUNTY	175 vs 443	1.200	0.691	2.084
COUNTY	373 vs 443	0.753	0.616	0.921
INJ_SEV	2 vs 6	0.519	0.474	0.569
EXTRICAT	1 vs 99	1.540	1.373	1.727
DOA	7 vs 99	2.338	2.120	2.578
DOA	8 vs 99	1.835	1.164	2.894
TRAV_SP	28 vs 106	0.062	0.019	0.200

TRAV_SP	30 vs 106	0.457	0.308	0.678
PERNOTMVIT	1 vs 8	0.007	0.002	0.026
PERNOTMVIT	4 vs 8	0.149	0.041	0.544
PERMVIT	9 vs 50	7.652	6.717	8.717
PERMVIT	17 vs 50	>999.999	<0.001	>999.999
PERMVIT	18 vs 50	42.393	12.446	144.393
PERMVIT	21 vs 50	4.271	3.861	4.726
PERMVIT	23 vs 50	>999.999	<0.001	>999.999
PERMVIT	24 vs 50	101.574	54.747	188.453
PERMVIT	26 vs 50	>999.999	<0.001	>999.999
PERMVIT	33 vs 50	>999.999	<0.001	>999.999
PERMVIT	47 vs 50	>999.999	<0.001	>999.999
PERSONS	8 vs 50	7.772	6.456	9.356
PERSONS	9 vs 50	13.438	10.338	17.467
DRIMP_NONE	0 vs 1	1.388	1.275	1.511
DAMAGE	DAMAGE vs TOTAL	0.795	0.706	0.896
DAMAGE	MISSING vs TOTAL	7.699	3.471	17.078

Table 24 : MULTIPLE frequency after sampling

MULTIPLE	Frequency	Percent	Cumulative Freq.	Cumulative %
0	9147	50.0	9147	50.0
1	9147	50.0	18294	100.0

Figure 1: FARS Data Base

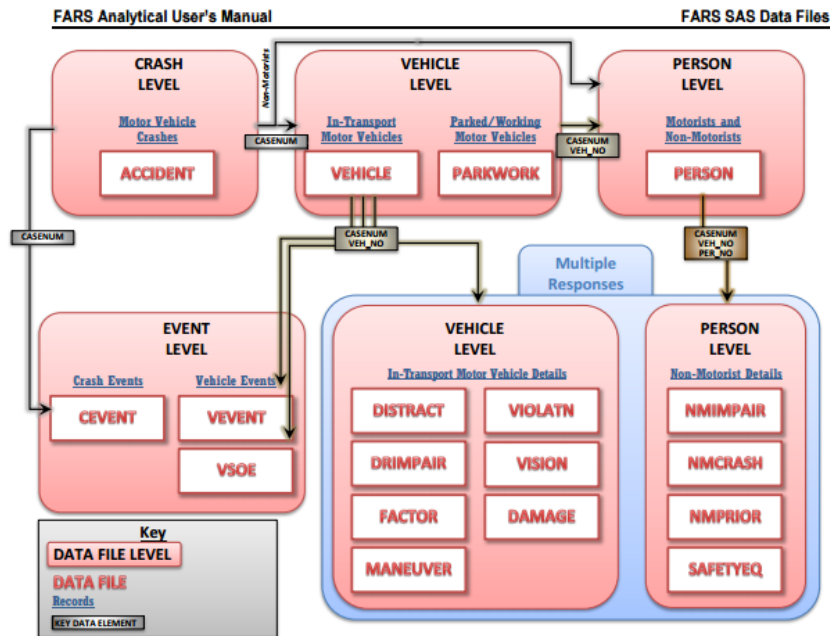


Figure 2: USA map

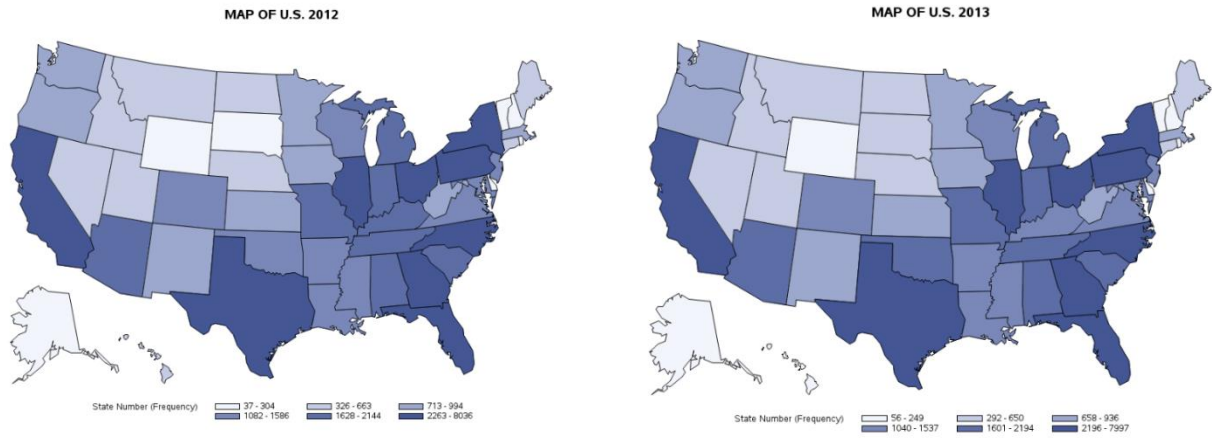


Figure 3: Map of Georgia for years 2012 & 2013

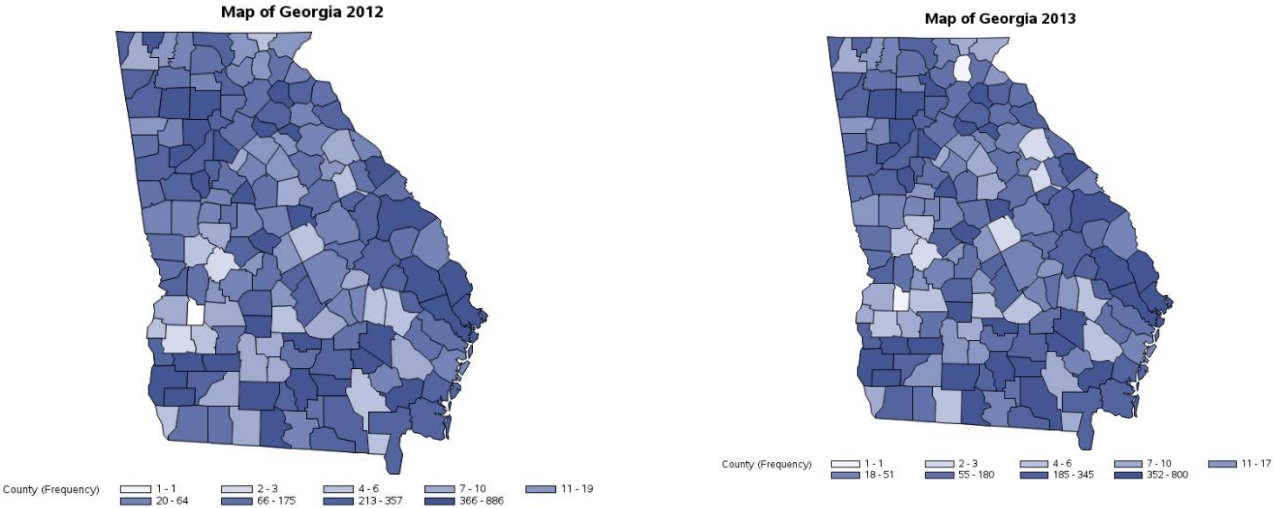


Figure 4: Map of North Carolina for years 2012 & 2013

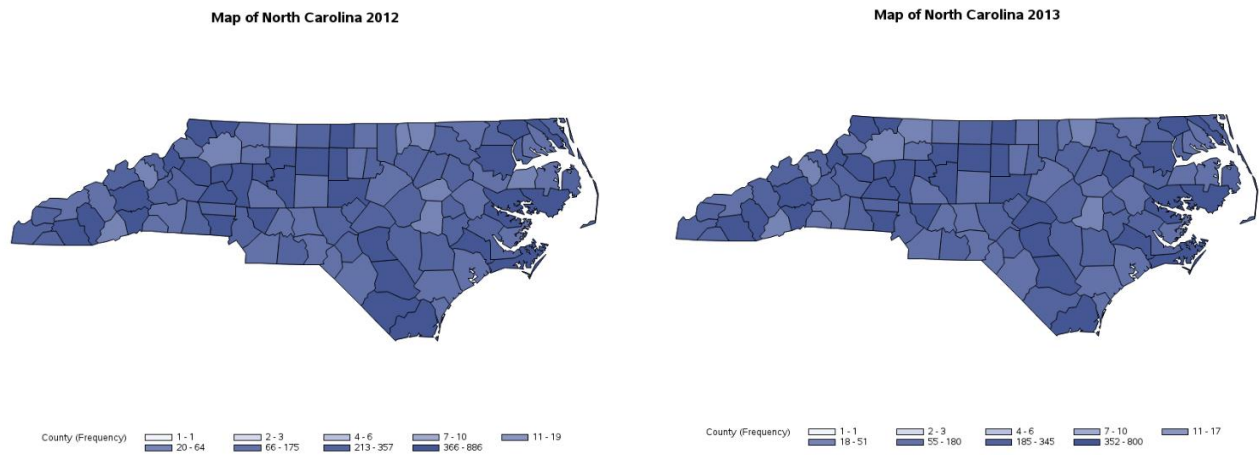


Figure 5: Map of California for years 2012 & 2013

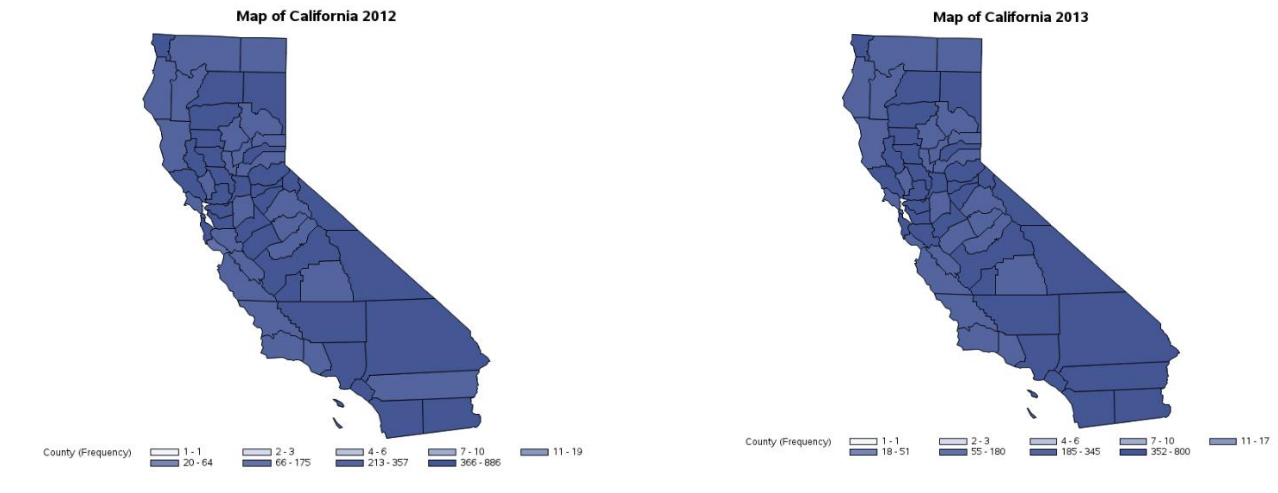


Figure 6: Map of Wyoming for years 2012 & 2013

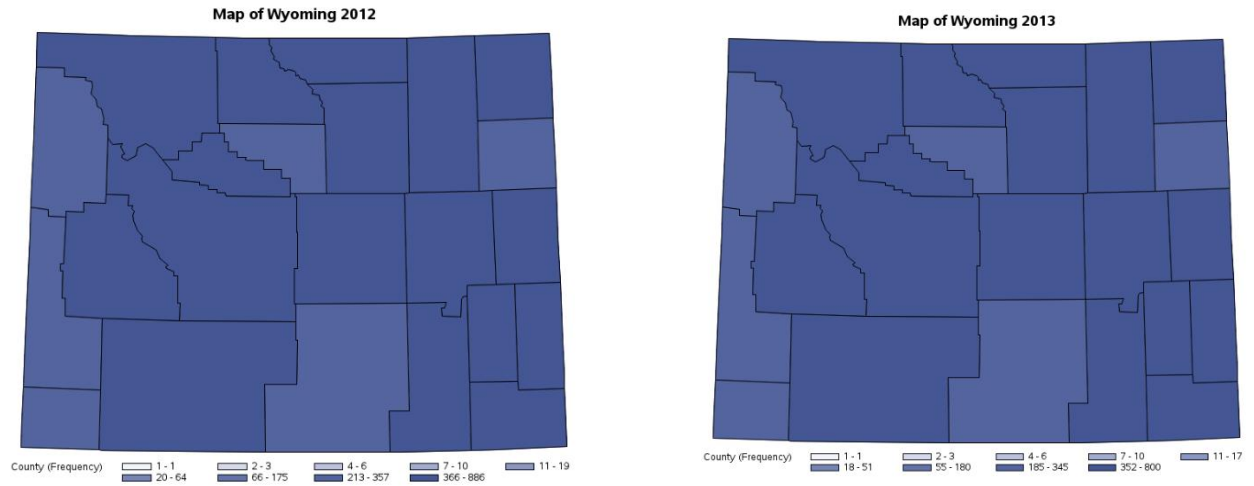


Figure 7: Histogram of variable *VSPD_LIM*

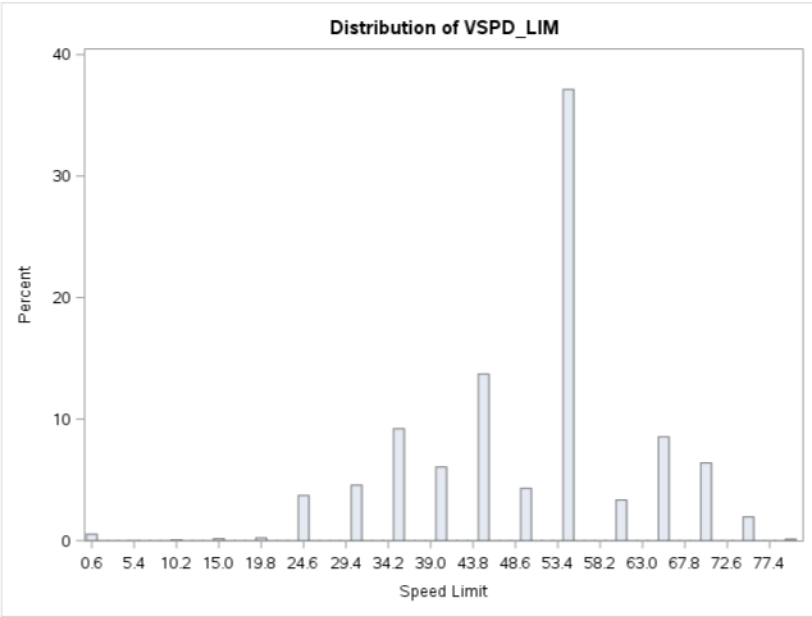


Figure 8: Flow Chart to Find the Effects of a Variable

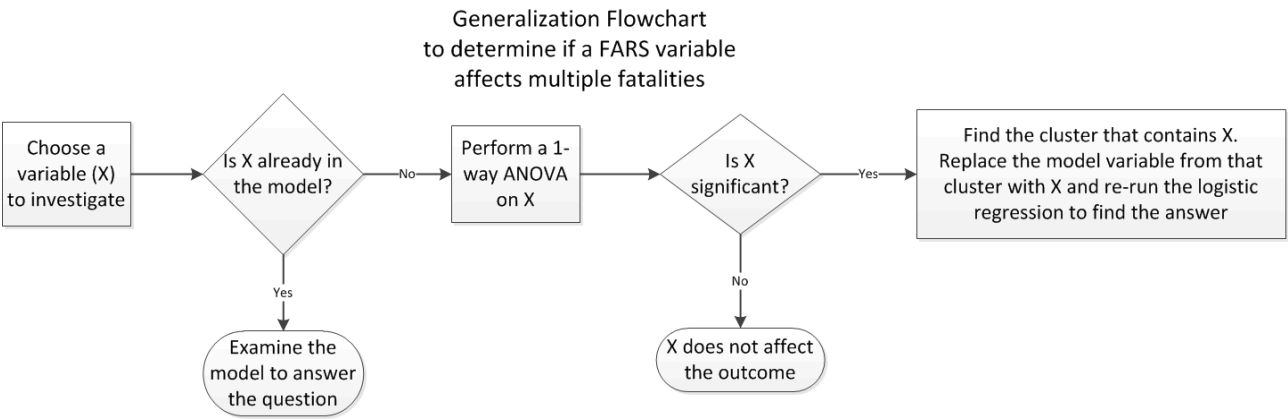


Figure 9: ROC curves side by side comparison

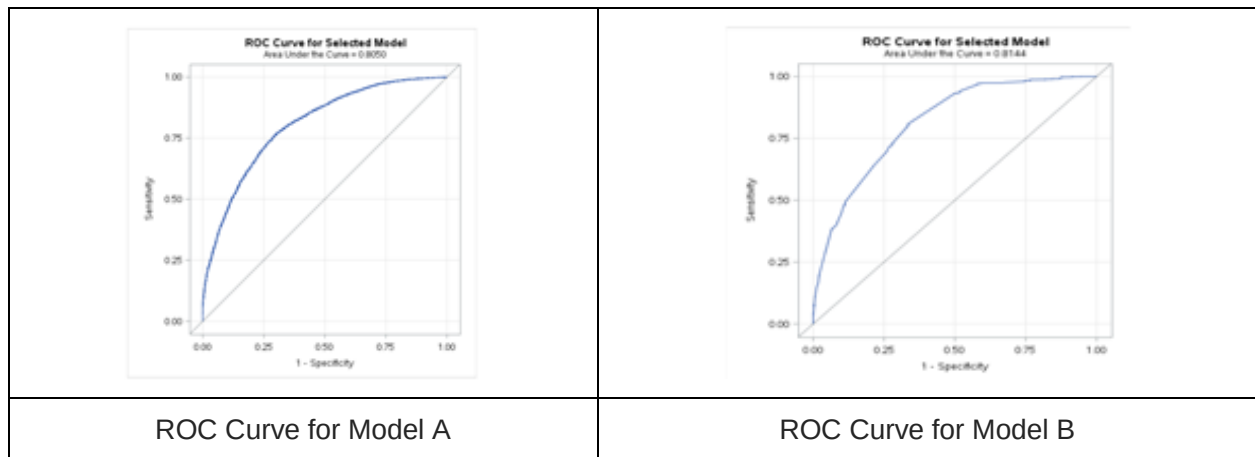
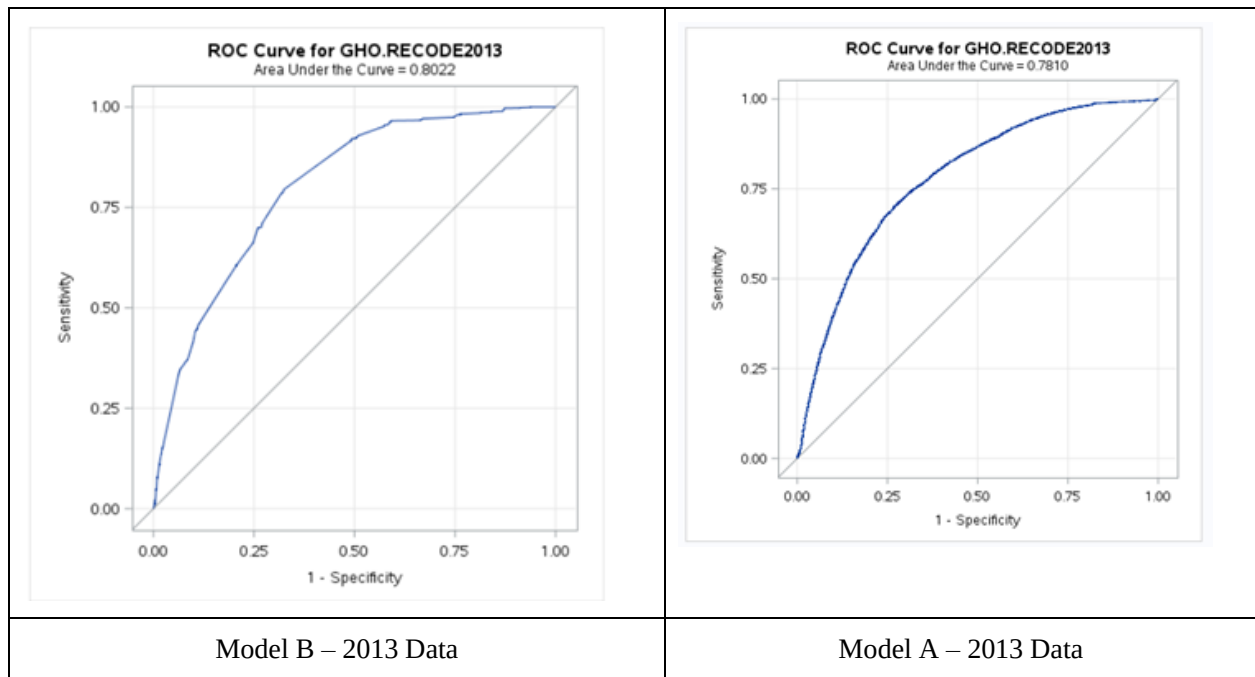


Figure 10: ROC Curve for 2013 Validation Data



SAS Code Summary

Stage 1: Merge data and data exploration. Filter first event from datasets: CEVENT & VEVENT. Transform or condensed the data that have multiple records per vehicle include: DAMAGE, DISTRACT, DRIMPAIR, MANEUVER, VIOLATN, and VISION. For the dataset called FACTOR, the count of the number of different categories was summed. Transformed the data that have multiple records per person include: NMCRASH, NMIMPAIR, NMPRIOR, and SAFETYEQ. Then merged all the datasets together. Some of the variables of PARKWORK dataset were renamed before merged. After all the datasets were merged and validated the group decided to go ahead and drop some variables that we did not want to include in the model.

Stage 2: ANOVA was run to see which variables were significant. More variables were dropped due to them not being significant and some categories were collapsed for the variables that were kept.

Stage 3: Modeling. Clustering was done on the rest of the variables to reduce the amount of variables selection for the model. Next, the data was sampled using a stratified sample method which only sampled the zero's in the variable MULTIPLE. A logistic regression analysis using the variables from the clustering analysis was conducted and stepwise selection to determine a model from our primary dataset; this was model A. For Model B, a logistic regression analysis and stepwise selection procedure was done using the same technique done for model A but with all of the variables in the dataset.

Map code example

Stage 1: data exploration

```
/* WHOLE US 2012*/
TITLE1 'MAP OF U.S. 2012';
PROC GMAP DATA=FARS2012.PERSON MAP=MAPS.US;
    ID STATE;
    CHORO STATE/ STATISTIC=frequency;
RUN;
QUIT;
```

```
/* Transformation example */
PROC TRANSPOSE DATA=drimpair1_COUNT OUT=drim_TRANS;
    BY ST_CASE VEH_NO ;
    ID drimp;
    VAR COUNT;
RUN;
```

Stage 2:

```
/* PROC ANOVA example */
```

```
%LET FIELD = DAY;
PROC FREQ DATA=FAR;
TABLE &FIELD. ;
RUN;
```

```
PROC GLM DATA=gho.fars2012_new;
CLASS &FIELD. ;
MODEL fatals= &FIELD. ;
MEANS &FIELD. / LINES TUKEY;
RUN;
```

Stage 3: modeling

```
/* sample data before model*/  
proc surveyselect data=GHO.RECODE  
  method=srs n=9147  
  seed=1953 out=GHO.SampleRECODE;  
  strata MULTIPLE;  
run;
```

PROC LOGISTIC example for Model A

```
libname GHO spde '/contest/team09' hdfs host=default;  
/* LOGISTIC REGRESSION*/  
  PROC LOGISTIC DATA=GHO.SAMPLERECODE outest=betas;  
    CLASS  
    DR_SF4  
    DR_DRINK  
    DAM_4  
    PERMVIT  
    VEVENT_SOE  
    L_STATE  
    DEFORMED  
    WEATHER  
    PRIOR_3  
    INJ_SEV  
    ROUTE  
    VSPD_LIM  
    DRINKING  
    DRUGS  
    PRIOR_99  
    CRSH_5  
    CF1  
    CRSH_4  
    PCRASH5  
    PRIOR_98  
    CRSH_9  
    SAFE_2  
    DAM_8  
    DRUNK_DR  
    DAM_12  
    CRSH_21  
    IMPAIR_98  
    SEAT_POS  
    PRIOR_2  
    DRIMP_NONE  
    OWNER  
    IMPAIR_99  
    EJ_PATH  
    WRK_ZONE  
    BODY_TYP  
    VSURCOND  
    DAY_WEEK  
    PRIOR_4  
    IMPAIR_96  
    ALC_STATUS
```

CRSH_6
CRSH_3
DISTRACT
VEH_SC1
SP_JUR
TYP_INT
PREV_OTH
FUELCODE
;

MODEL MULTIPLE(EVENT='1') =

DR_SF4
DR_DRINK
DAM_4
PERMVIT
VEVENT_SOE
L_STATE
DEFORMED
WEATHER
PRIOR_3
INJ_SEV
ROUTE
VSPD_LIM
DRINKING
DRUGS
PRIOR_99
CRSH_5
CF1
CRSH_4
PCRASH5
PRIOR_98
CRSH_9
SAFE_2
DAM_8
DRUNK_DR
DAM_12
CRSH_21
IMPAIR_98
SEAT_POS
PRIOR_2
DRIMP_NONE
OWNER
IMPAIR_99
EJ_PATH
WRK_ZONE
BODY_TYP
VSURCOND
DAY_WEEK
PRIOR_4
IMPAIR_96
ALC_STATUS
CRSH_6
CRSH_3

DISTRACT
VEH_SC1
SP_JUR
TYP_INT
PREV_OTH
HOUR
MINUTE
NOT_HOUR
DISPLACEN
NOT_MIN
AGE
HOSP_HR
HOSP_MN
CITY
LAG_HRS
FUELCODE

```
/selection=stepwise sle=0.15 sls=0.15 outroc=ROCData ctable ;  
  output out=pred p=phat lower=lcl upper=ucl  
predprob=(individual crossvalidate) ;  
score data=gho.samlerecode2013 out=vpred outroc=vroc;  
roc; roccontrast;  
run;
```