SSRG International Journal of Computer Science and Engineering
ISSN: 2348 – 8387 /doi:10.14445/23488387/IJCSE-V7I10P103

Volume 7 Issue 10, 13-17, October 2020

Prediction of Roadway Crashes Using Logistic Regression in SAS

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Abstract

Roadway crashes occur instantly with less time to respond. Predicting these crashes or identifying the major factors affecting these crashes can help to reduce these from occurring. As machine learning techniques help make these predictions and identify the impact factors, they can be applied to the roadway crash data set. The data set is obtained for the State of Virginia from the Department of Transportation. The logistic regression method was applied by grouping the dataset into fatal and non-fatal crashes. The model was built in SAS studio software and had an accuracy of 76%. The major factors were identified as Road, not lighted, Ramps, and Intersections on Divided roadways.

Keywords — *Fatal roadway crashes, Machine Learning, Logistic Regression, State of Virginia*

I. INTRODUCTION

A road crash is one of the significant reasons for loss of life. A crash could occur due to various reasons and can be preventable in many cases. Safe and defensive driving is always advisable. As per the statistics obtained from the Department of Motor Vehicles in Virginia, almost 8.5 million vehicles are registered, and more than 120 thousand crashes occur every year. There is a very high volume of traffic movement in the state, and the number of fatal crashes varies from 600 to 1000 every year. There could be many factors involved in a fatal crash, and almost 35% is alcohol-related. Immense measures are taken to reduce these fatal crashes. In a few cases, the Road characteristics can also contribute to these types of crashes to some extent. Using a machine learning technique named logistic regression, the major causes of a fatal road crash can be analyzed. Also, a model can be built to identify possible fatal crashes. The logistic regression method is suitable for analyzing binary outcomes. SAS studio software comes up with different options to conduct machine learning studies. This study is performed in the SAS studio by consuming the roadway crash data from the Virginia Department of Transportation.

II. LITERATURE SURVEY

Roadway crashes were predicted through various traditional and machine learning methods. Kononen, Flannagan & Wang (2011) have predicted serious injuries caused by motor vehicle crashes using the logistic regression method. The model was developed using variables available post-crash, and a different screening algorithm was developed to model injuries for each mode of the crash. Feng et al. (2014) have developed a multivariable linear regression model to reflect the various factors on traffic accidents and improve the accuracy of predicting accidents in China. Dong et al. (2019) have performed studies to understand the risk factors for road crashes and their impact on the crashes. A two-step method involving the support vector regression model and state-space models were used.

III. DATA PREPARATION

A. Data Source

The Department of Motor Vehicles gathers all reported crashes in the State of Virginia, and this data is available to the public from the Virginia Department of Transportation. The crash data required for the analysis is obtained from the State of Virginia (VDOT, 2018) for the period 2013 to 2017. The overall crash dataset is huge, and hence, the research is limited to only Fatal crashes. Fatal crashes are represented with KABCO code as K. The other levels are non-fatal crashes and classified based on the injury's intensity. The data is imported in the form of a rich text file from the website and later converted to a spreadsheet for analysis.

B. Data preprocessing

The crash dataset contains many observations and details regarding the crash incident. A high-level cleanup is done to remove unwanted reported data. The details apart from the crash cause like Latitude, Longitude, and Route name are removed. These could add bias to the prediction. Most of the predictor variables required for the analysis are categorical ones, as they represent the road characteristics in which the crash has occurred.

As the regression analysis is performed at the state level, any references to a specific county, jurisdiction was also removed from it. The attributes were renamed for easier understanding of data and to get a better display in the results. Fatal crashes are represented as 1, and non-fatal crashes are represented as 0 in the dataset. This would help to understand the reasons behind a fatal crash when compared to a non-fatal crash.

IV. REGRESSION ANALYSIS

A. Logistic Regression

Logistic regression performs classification in the provided data and groups them into a discrete set of classes. It can be a binary or multilinear function. This is used as a machine learning technique to classify the dataset or predict events based on probability. The cost function associated with logistic regression, also called a sigmoid function, is complex. The logistic regression method limits the cost function between 0 and 1.

$$0 \leq h_\theta(x) \leq 1$$

The formula for the sigmoid function is defined as

$$f(x) = \frac{1}{1+e^{-(x)}}$$

The hypothesis of the logistic regression is expected to give values between 0 and 1

$$Z = \beta_0 + \beta_1 X$$

$$h\Theta(x) = \text{sigmoid}(Z)$$

$$h\theta(X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X)}}$$

B. Data description

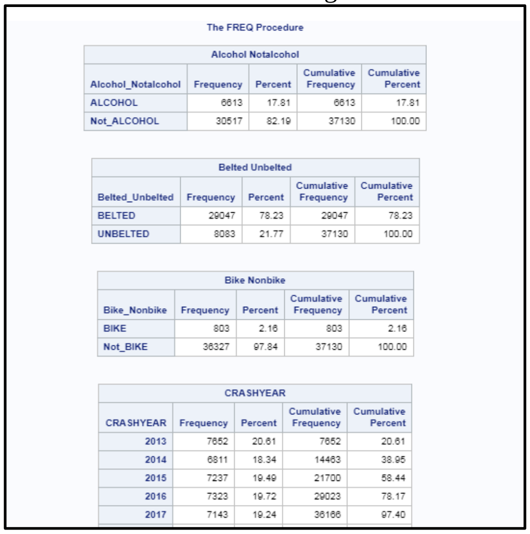
SAS Studio is used to analyze the crash data. As the count of predictor variables is more, the regression analysis would be a complex process. Since SAS is a powerful analytical tool, it is chosen for this analysis. A similar analysis can be performed in Python or R as well. The spreadsheet data is loaded into a SAS work file using PROC IMPORT, as shown in figure 1.

CODE LOG RESULTS

```
FILENAME REFFILE '/folders/myfolders/Crash/Summary_Trend_data- K - Limited Fields - Cleanup_v1.xlsx';

PROC IMPORT DATAFILE=REFFILE DBMS=XLSX OUT=WORK.IMPORT;
    GETNAMES=YES;
RUN;

PROC CONTENTS DATA=WORK.IMPORT;
RUN;
```

Fig 1: Loading the excel spreadsheet into SAS

PROC FREQ is used to analyze the dataset. From the results, the various categorical values present in the dataset can be observed in figure 2.



The FREQ Procedure

Alcohol Notalcohol				
Alcohol_Notalcohol	Frequency	Percent	Cumulative Frequency	Cumulative Percent
ALCOHOL	6613	17.81	6613	17.81
Not_ALCOHOL	30517	82.19	37130	100.00

Belted Unbelted				
Belted_Unbelted	Frequency	Percent	Cumulative Frequency	Cumulative Percent
BELTED	29047	78.23	29047	78.23
UNBELTED	8083	21.77	37130	100.00

Bike Nonbike				
Bike_Nonbike	Frequency	Percent	Cumulative Frequency	Cumulative Percent
BIKE	803	2.16	803	2.16
Not_BIKE	36327	97.84	37130	100.00

CRASHYEAR				
CRASHYEAR	Frequency	Percent	Cumulative Frequency	Cumulative Percent
2013	7652	20.61	7652	20.61
2014	6811	18.34	14463	38.95
2015	7237	19.49	21700	58.44
2016	7323	19.72	29023	78.17
2017	7143	19.24	36166	97.40

Fig 2: A part of PROC FREQ output

The crashes are observed over the year using the SGPLOT, as shown in figure 3. The percentage of fatal crashes is at a peak in 2017.

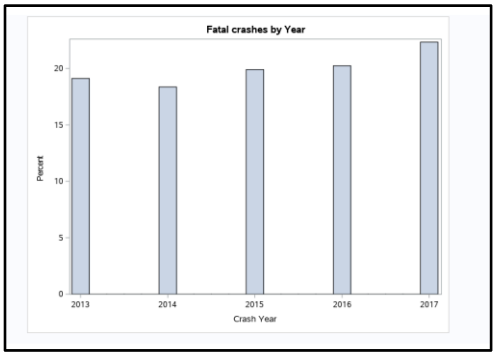


Fig 3: Percentage of Fatal crashes by year

The weather condition during fatal crashes is observed over the years, as shown in figure 4.

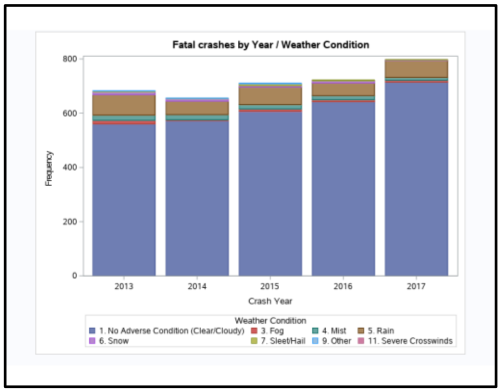


Fig 4: Fatal crashes by year sliced by weather conditions

It seems most of the crashes have occurred during No adverse condition.

C. Regression model

Usually, principal component analysis is performed to identify the component with the most variance in Numeric variables. Since most of them involved in this analysis are Categorical, the Multiple Correspondence analysis is performed here (NCBI, 2009). The SAS program, PROC CORRESP is used to identify the variables with most variance based on the chi-square value and cumulative percent as in figures 5, 6, and 7

```
ODS GRAPHICS ON;
PROC CORRESP DATA=WORK.IMPORT PLOTS=ALL;
    TABLES Alcohol_Usage_Ind Animal_ind Area_Type Belt_Usage_Ind Bike_Ind
        Distraction_ind Facility_Type Functional_Class Guardrail_Ind Intersection_Ind
        K_People Light_Condition Median_Type Motorcycle_ind Pedestrian_ind Road_Type
        Roadway_Alignment Roadway_Surface_Cond School_Zone Speed_Ind Time_Window
        Truck_Ind Weather_Condition Work_Zone_Ind Young_Age_Ind;
RUN;
```

Fig 5: Command to perform the Multiple Correspondence Analysis

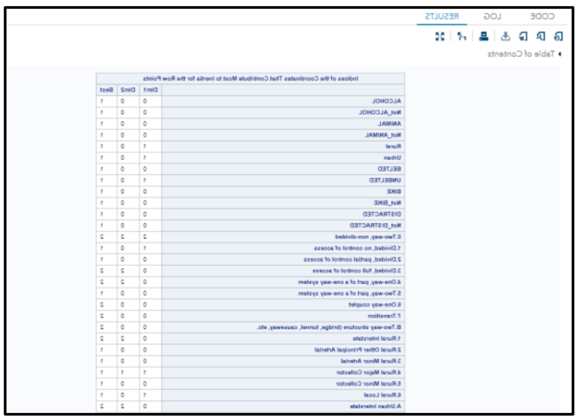


Fig 6: Displaying the best contributors to the inertia

The CORRESP Procedure

Inertia and Chi-Square Decomposition

Singular Value	Principal Inertia	Chi-Square	Percent	Cumulative Percent
0.12243	0.01499	282210	9.12	9.12
0.09760	0.00953	179331	5.80	14.91
0.09032	0.00816	153571	4.96	19.88
0.07597	0.00577	108663	3.51	23.39
0.07248	0.00525	98905	3.20	26.59
0.06584	0.00433	81612	2.64	29.22
0.06171	0.00381	71684	2.32	31.54
0.05608	0.00315	59217	1.91	33.45
0.05546	0.00308	57907	1.87	35.32
0.05342	0.00285	53730	1.74	37.06
0.05219	0.00272	51281	1.66	38.72
0.04853	0.00235	44332	1.43	40.15
0.04758	0.00226	42625	1.38	41.53
0.04691	0.00220	41423	1.34	42.87
0.04605	0.00212	39923	1.29	44.16
0.04490	0.00202	37959	1.23	45.38
0.04472	0.00200	37657	1.22	46.60
0.04386	0.00192	36220	1.17	47.77
0.04328	0.00187	35269	1.14	48.91
0.04313	0.00186	35027	1.13	50.04
0.04242	0.00180	33881	1.09	51.14
0.04239	0.00180	33826	1.09	52.23
0.04204	0.00177	33278	1.08	53.30
0.04159	0.00173	32566	1.05	54.36
0.04143	0.00172	32309	1.04	55.40
0.04137	0.00171	32214	1.04	56.44
0.04130	0.00171	32118	1.04	57.48
0.04114	0.00169	31871	1.03	58.51
0.04106	0.00169	31742	1.03	59.54
0.04096	0.00168	31586	1.02	60.56
0.04077	0.00166	31288	1.01	61.57
0.04069	0.00166	31165	1.01	62.57
0.04061	0.00165	31053	1.00	63.58
0.04045	0.00164	30811	1.00	64.57
0.04034	0.00163	30631	0.99	65.56
0.04024	0.00162	30489	0.99	66.55
0.04013	0.00161	30314	0.98	67.53

Fig 7: Showing the cumulative percent of the Chi-Square value

The input data is split into the Train and Validation data set using the PROC STRATA is shown in figure 8.

```
PROC SORT DATA=WORK.IMPORT OUT=WORK.DEVELOP_SORT;
     BY CRASH;
RUN;

PROC SURVEYSELECT NOPRINT DATA=WORK.DEVELOP_SORT SAMPRATE=.6667
        STRATUMSEED=RESTORE OUT=WORK.DEVELOP_SAMPLE SEED=44444 OUTALL;
    STRATA CRASH;
RUN;

DATA WORK.TRAIN(DROP=SELECTED SELECTIONPROB SAMPLINGWEIGHT)
        WORK.VALID(DROP=SELECTED SELECTIONPROB SAMPLINGWEIGHT);
    SET WORK.DEVELOP_SAMPLE;

    IF SELECTED THEN
        OUTPUT WORK.TRAIN;
    ELSE
        OUTPUT WORK.VALID;
RUN;
```

```
NOTE: There were 37130 observations read from the data set WORK.DEVELOP_SAMPLE.
NOTE: The data set WORK.TRAIN has 24755 observations and 30 variables.
NOTE: The data set WORK.VALID has 12375 observations and 30 variables.
NOTE: DATA statement used (Total process time):
      real time           0.03 seconds
      cpu time            0.04 seconds
```

Fig 8: Command to split the dataset into Train and Validate and log statements

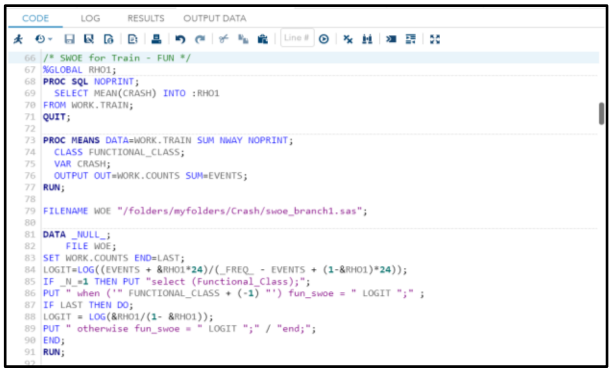
As the regression model contains categorical variables, the logistic regression model was chosen. Using PROC LOGISTIC, the model was initially built with the identified Categorical variables from the Multiple Correspondence Analysis. The NULL Hypothesis is these variables do not have an impact on the occurrence of Fatal Crashes.

When calculating the logistic model, the quasi separation of data is observed, as shown in figure 10.

```
CODE   LOG   RESULTS
Errors, Warnings, Notes
Errors
Warnings (2)
Notes (16)
NOTE: PROC LOGISTIC is modeling the probability that Crash='1'.
NOTE: Convergence criterion (GCONV=1E-8) satisfied in Step 0.
NOTE: Convergence criterion (GCONV=1E-8) satisfied in Step 1.
NOTE: Convergence criterion (GCONV=1E-8) satisfied in Step 2.
NOTE: Convergence criterion (GCONV=1E-8) satisfied in Step 3.
NOTE: Convergence criterion (GCONV=1E-8) satisfied in Step 4.
NOTE: Convergence criterion (GCONV=1E-8) satisfied in Step 5.
NOTE: Convergence criterion (GCONV=1E-8) satisfied in Step 6.
NOTE: Convergence criterion (GCONV=1E-8) satisfied in Step 7.
NOTE: Convergence criterion (GCONV=1E-8) satisfied in Step 8.
NOTE: Convergence criterion (GCONV=1E-8) satisfied in Step 9.
NOTE: Convergence criterion (GCONV=1E-8) satisfied in Step 10.
NOTE: Convergence criterion (GCONV=1E-8) satisfied in Step 11.
NOTE: Convergence criterion (GCONV=1E-8) satisfied in Step 12.
WARNING: There is possibly a quasicomplete separation of data points in step 13. The maximum likelihood estimate may n
WARNING: The LOGISTIC procedure continues in spite of the above warning. Results shown are based on the last maximum l
         iteration. Validity of the model fit is questionable.
NOTE: There were 24755 observations read from the data set WORK.TRAIN_SWOE.
NOTE: PROCEDURE LOGISTIC used (Total process time):
      real time           30:30.72
      cpu time            29:45.54

         OPTIONS NONOTES NOSTIMER NOSOURCE NOSYNTAXCHECK;
```

Fig 9: Logs showing quasi complete separation issue

To overcome it, initially, the clustering of data is performed based on business knowledge. But, a similar issue was faced. Hence, the smooth weight of the evidence approach was performed.

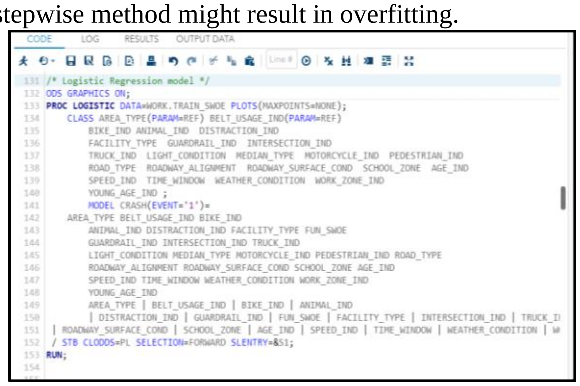


```
/* SWOE for Train - FUN */
%GLOBAL RHO1;
PROC SQL NOPRINT;
  SELECT MEAN(CRASH) INTO :RHO1
FROM WORK.TRAIN;
QUIT;

PROC MEANS DATA=WORK.TRAIN SUM NWAY NOPRINT;
  CLASS FUNCTIONAL_CLASS;
  VAR CRASH;
  OUTPUT OUT=WORK.COUNTS SUM=EVENTS;
RUN;

FILENAME WOE "/folders/myfolders/Crash/swoe_branch1.sas";

DATA _NULL_;
    FILE WOE;
SET WORK.COUNTS END=LAST;
LOGIT=LOG((EVENTS + &RHO1*24)/(_FREQ_ - EVENTS + (1-&RHO1)*24));
IF _N_=1 THEN PUT "select (Functional_Class);";
PUT " when ('" FUNCTIONAL_CLASS + (-1) "') fun_swoe = " LOGIT ";" ;
IF LAST THEN DO;
LOGIT = LOG(&RHO1/(1- &RHO1));
PUT " otherwise fun_swoe = " LOGIT ";" / "end;";
END;
RUN;
```

Fig 10: Showing the commands to perform Smooth Weight of Evidence

With this smoothed data, the logistic model was rebuilt, and it does remove the quasi separation issue (Paul D. Allison, 2008).

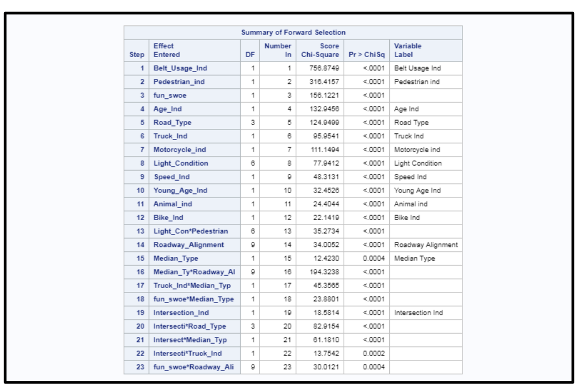
The PROC LOGISTIC command used to build the model is shown below (Fig 13). It includes the categorical variables qualifying to 95% of the variance from the Multiple Correspondence Analysis. The standardized estimates are calculated along with the model. The forward selection method is used here as there are more categorical variables, and using the stepwise method might result in overfitting.



```
/* Logistic Regression model */
ODS GRAPHICS ON;
PROC LOGISTIC DATA=WORK.TRAIN_SWOE PLOTS(MAXPOINTS=NONE);
    CLASS AREA_TYPE(PARAM=REF) BELT_USAGE_IND(PARAM=REF)
        BIKE_IND ANIMAL_IND  DISTRACTION_IND
        FACILITY_TYPE  GUARDRAIL_IND  INTERSECTION_IND
        TRUCK_IND  LIGHT_CONDITION  MEDIAN_TYPE  MOTORCYCLE_IND  PEDESTRIAN_IND
        ROAD_TYPE  ROADWAY_ALIGNMENT  ROADWAY_SURFACE_COND  SCHOOL_ZONE  AGE_IND
        SPEED_IND  TIME_WINDOW  WEATHER_CONDITION  WORK_ZONE_IND
        YOUNG_AGE_IND ;
        MODEL CRASH(EVENT='1')=
    AREA_TYPE BELT_USAGE_IND BIKE_IND
        ANIMAL_IND DISTRACTION_IND FACILITY_TYPE FUN_SWOE
        GUARDRAIL_IND INTERSECTION_IND TRUCK_IND
        LIGHT_CONDITION MEDIAN_TYPE MOTORCYCLE_IND PEDESTRIAN_IND ROAD_TYPE
        ROADWAY_ALIGNMENT ROADWAY_SURFACE_COND SCHOOL_ZONE AGE_IND
        SPEED_IND TIME_WINDOW WEATHER_CONDITION WORK_ZONE_IND
        YOUNG_AGE_IND
        AREA_TYPE | BELT_USAGE_IND | BIKE_IND | ANIMAL_IND
        | DISTRACTION_IND | GUARDRAIL_IND | FUN_SWOE | FACILITY_TYPE | INTERSECTION_IND | TRUCK_I
 | ROADWAY_SURFACE_COND | SCHOOL_ZONE | AGE_IND | SPEED_IND | TIME_WINDOW | WEATHER_CONDITION | W
 / STB CLODDS=PL SELECTION=FORWARD SLENTRY=&S1;
RUN;
```

Fig 11: Command to build a Logistic Regression model

The final predictors and interactions determined by the logistic regression model are shown below in figure 12.



Summary of Forward Selection

Step	Effect Entered	DF	Number In	Score Chi-Square	Pr > ChiSq	Variable Label
1	Belt_Usage_Ind	1	1	756.8749	<.0001	Belt Usage Ind
2	Pedestrian_ind	1	2	316.4157	<.0001	Pedestrian ind
3	fun_swoe	1	3	156.1221	<.0001	
4	Age_Ind	1	4	132.9456	<.0001	Age Ind
5	Road_Type	3	5	124.9499	<.0001	Road Type
6	Truck_Ind	1	6	95.9541	<.0001	Truck Ind
7	Motorcycle_ind	1	7	111.1494	<.0001	Motorcycle ind
8	Light_Condition	6	8	77.9412	<.0001	Light Condition
9	Speed_Ind	1	9	48.3131	<.0001	Speed Ind
10	Young_Age_Ind	1	10	32.4526	<.0001	Young Age Ind
11	Animal_ind	1	11	24.4044	<.0001	Animal ind
12	Bike_Ind	1	12	22.1419	<.0001	Bike Ind
13	Light_Con*Pedestrian	6	13	35.2734	<.0001	
14	Roadway_Alignment	9	14	34.0052	<.0001	Roadway Alignment
15	Median_Type	1	15	12.4230	0.0004	Median Type
16	Median_Ty*Roadway_Al	9	16	194.3238	<.0001	
17	Truck_Ind*Median_Typ	1	17	45.3565	<.0001	
18	fun_swoe*Median_Type	1	18	23.8801	<.0001	
19	Intersection_Ind	1	19	18.5814	<.0001	Intersection Ind
20	Intersecti*Road_Type	3	20	82.9154	<.0001	
21	Intersect*Median_Typ	1	21	61.1810	<.0001	
22	Intersecti*Truck_Ind	1	22	13.7542	0.0002	
23	fun_swoe*Roadway_Ali	9	23	30.0121	0.0004	

Fig 12: Summary of the Forward Selection approach

Based on the standardized estimates output value, the top 5 categorical values are shown in Table 1.

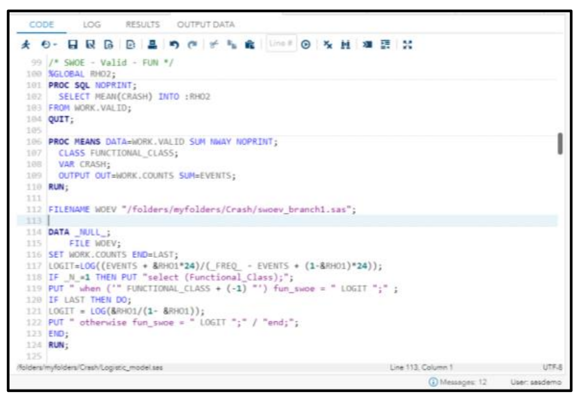
TABLE 1: Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Wald Chi-Square	Pr > Chi Sq	Std Est
Intercept	1	-0.1162	0	0.99	
Darkness - Road Not Lighted	1	2.2489	0.002	0.98	0.515
On/Off Ramp	1	6.9227	0.005	0.94	0.370
Grade - Straight	1	1.7833	0.003	0.95	0.324
Intersection - Divided Roadway	1	0.5458	55.26	<.0001	0.278

The top factors for fatal crashes are listed below:

a) Darkness - Road Not Lighted
b) On/Off Ramp on a Divided Roadway
c) Grade - Straight
d) The intersection at a Divided Roadway

The smooth weight of evidence is done on the validation dataset, too, and the model is scored with it.



```
/* SWOE - Valid - FUN */
%GLOBAL RHO2;
PROC SQL NOPRINT;
  SELECT MEAN(CRASH) INTO :RHO2
FROM WORK.VALID;
QUIT;

PROC MEANS DATA=WORK.VALID SUM NWAY NOPRINT;
  CLASS FUNCTIONAL_CLASS;
  VAR CRASH;
  OUTPUT OUT=WORK.COUNTS SUM=EVENTS;
RUN;

FILENAME WOEV "/folders/myfolders/Crash/swoev_branch1.sas";

DATA _NULL_;
    FILE WOEV;
SET WORK.COUNTS END=LAST;
LOGIT=LOG((EVENTS + &RHO1*24)/(_FREQ_ - EVENTS + (1-&RHO1)*24));
IF _N_=1 THEN PUT "select (Functional_Class);";
PUT " when ('" FUNCTIONAL_CLASS + (-1) "') fun_swoe = " LOGIT ";" ;
IF LAST THEN DO;
LOGIT = LOG(&RHO1/(1- &RHO1));
PUT " otherwise fun_swoe = " LOGIT ";" / "end;";
END;
RUN;
```

Fig 13: Smooth weight of evidence performed on the VALID dataset

The logistic regression model built with the TRAIN dataset is scored with the VALID dataset.

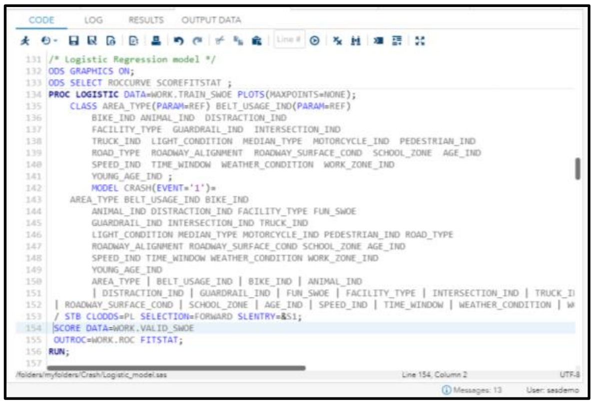


Fig 14: Logistic regression model with evaluating the VALID dataset

A ROC curve is built for the same (Fig 18), and the model turned out to be 76% accurate.

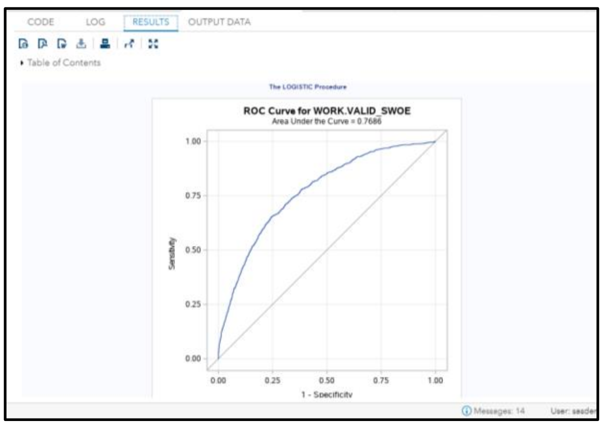


Fig 15: ROC Curve for the VALID dataset

D. Conclusion

From the regression analysis, it could be inferred that the major root causes for a fatal crash are the darkness in road condition and ramps/intersections on a divided roadway by improving the light conditions on the routes and improvising the ramps/intersections on a divided roadway could reduce the fatal crashes. For further research, one option is to perform the analysis in detail for each county, and improvisation can be made. Another option is to utilize the traffic data, identify the busy routes, and reduce crashes. This could help in saving a lot of travel time.

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