Analyzing Firefighter Casualties using FEMA Data

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Abstract:

In this study, we aimed to learn more about how firefighter deaths occur and can possibly be prevented in the future. Utilizing a relatively clean dataset provided by the Federal Emergency Management Agency (FEMA), we were able to conduct various exploratory and regression analyses on records of firefighter deaths. Our models constructed were as follows: a Gaussian model predicting a firefighter's age at death, a nominal model predicting the nature of a firefighter's death, a logistic model predicting whether or not a situation was labeled an emergency, and an ordinal model predicting the level of danger a firefighter was engaged in during the incident that led to their death. Following an in-depth discussion of the methods behind each of these models, we explain the statistical results attained. Finally, we interpret interesting coefficients for each model in context and discuss implications for firefighter safety and first responders generally.

Introduction:

First responders face inherent risk through their duties, whether in regular training exercises or emergency situations. While these first responders—and especially firefighters—play an essential role in maintaining safe communities, their own safety while working represents a paramount concern. The following analyses and discussions aim to identify why and how firefighters died on duty. Four models were considered with the following questions of interest: What explains a firefighter's age at death? What explains the nature of a firefighter's death? What factors influence whether a first response situation was deemed an emergency? How can we predict the level of danger (*duty*) a firefighter was involved in at the time of death? Our aim was to develop predictive models which help explain firefighter deaths so that steps can be taken to create safer on-duty working conditions.

Methods and Materials:

The United States Fire Administration (USFA), housed under the Federal Emergency Management Agency (FEMA), operates an annual assessment which identifies specific problems that result in firefighter fatalities. These analyses have two primary outcomes, those being (1) finding solutions that will reduce future fatalities and (2) measuring the effectiveness of programs directed toward firefighter health and safety. Pursuing these goals, the United States Fire Administration publishes a yearly report which reviews the recorded firefighter deaths and the context surrounding each incident. The report also places the single year data into perspective through comparison with recent years' fatalities. The following analysis outlines four predictive models which can advance the Fire Administration's understanding of firefighting risk; moreover, this knowledge can equip local fire departments with methods for keeping their firefighters safe.

The data analyzed comes from USFA and FEMA's firefighter fatality incident data, a dataset documenting each national firefighter fatality from 2000 through 2018. The dataset identifies all on-duty firefighter fatalities that occurred in the United States and in the US territories. FEMA considers the term "firefighter" to include "all members of organized fire departments with assigned fire suppression duties." Regarding inclusion requirements, FEMA's most recent report states:

> An on-duty fatality includes any injury or illness that was sustained while on duty and proves fatal. The term "on duty" refers to being involved in operations at the scene of an emergency, whether it is a fire or nonfire incident; responding to or returning from an incident; performing other officially assigned duties, such as training, maintenance, public education, inspection, investigations, court testimony or fundraising; and being on call, under orders or on standby duty (except at the individual's home or place of business).

The USFA solicits information on firefighter fatalities directly from the fire service, from fire departments and fire service organizations, and from various other sources, including many federal agencies. After being notified about a fatal firefighter incident, USFA verifies the incident, location, jurisdiction, and the fire department or agency involved. After all details are collected, USFA will determine whether the death constitutes an on-duty fatality, and if so, the fatality will be added.

The dataset includes 2,289 observations on 16 variables. The variables include firefighter age, rank, classification, duty, and activity, as well as the incident date, death date, cause of death, nature of death, whether the incident was an emergency, and the property where the individual was responding. The original dataset includes only one continuous variable, age. Most firefighters were between 37 and 57 years old when they died, with the average age at death being 46.78 years (See Figure 1). We created a ‘Date Spread’ variable in order to numerically capture the severity of a firefighter's eventually fatal injury (See Figure 2). We calculated the variable by subtracting the Incident Date variable from the Death Date variable in numerical form in an Excel file, resulting in the spread between when the firefighter died and when the incident occurred. The InterQuartile Range (IQR) for this variable was 0, as the 1st Quartile, Median, and 3rd Quartile all had values of 0. This shows that the majority of firefighters died with no spread between their incident and death dates, or in other words, succumbed to their injuries almost immediately. Of the categorical variables featured in the dataset, our analyses include: cause of death, nature of death, activity, and property type. Cause of death has 13 levels, with the four most common causes being stress/overexertion (984 cases), collapse (400 cases), vehicle collision (262 cases), and being struck by an object (244 cases) (See Figure 3). The prevalence of the September 11, 2001 terrorist attacks appears throughout the data, with one such area being the inflated number of deaths caused by collapse, which in this case refers to the Twin Towers’ collapse. One model also includes nature of death, which has 13 levels with two prominent ones being death from heart attack (906 people) and death from trauma (892 people) (See Figure 4). Another relevant categorical variable, activity, has 23 levels (See Figure 5). The largest amount of firefighters (434 people) died while performing search and rescue operations. This is followed closely by various activities identified as “other” in the dataset (representing 399 deaths) and by 298 firefighters who died while working hose lines. Notably, 190 firefighters died while “not on scene,” an additional 169 died while driving/operating a vehicle, and 131 died while driving/riding a personal vehicle. Finally, the variable for property type has 13 levels (See Figure 6). The most common properties where deaths occurred were residential, at a store/office, on a street/road, or outdoors. Graphical summaries of these variables can be found in the appendix.

Our primary interests concerned what factors influenced when, where, and how firefighters died. Four analyses were conducted: an ordinary least squares regression, a nominal regression, logistic regression, and an ordinal regression. The raw dataset was already nicely cleaned; however, there were missing observations throughout given the large amount of observations and variables on which information was collected. Any deaths with missing observations on one or more variables were excluded from analysis. A deletion method was chosen because the dataset maintained a sizeable amount of observations (n=1893) after removing incomplete entries and because there appeared no missingness dependent on other variables in the data. All models were built up rather than using backwards variable selection. The quantity of categorical variables, and a high number of levels included in each of these variables, necessitated this approach.

Our first model predicts age at death based on the firefighter's cause of death and the activity he/she was performing. The relationships between age and cause of death, as well as age and activity, are displayed in Figures 7 and 8, respectively. Cause of death and activity are categorical variables; therefore, these figures mainly display differences in age at death based on various levels of the explanatory variables. We modeled this relationship using an ordinary least squares regression because the data fulfilled the assumptions for this model (See Figure 9). The model was considered for multicollinearity; however, the resulting variance inflation factors were 1.05 for cause of death and 1.03 for activity, which were deemed appropriate for an OLS model. There were approximately 140 observations which represented either high leverage points or outliers, which make up about 7% of the data. Three alternative robust regression models with unique M-estimators were thus considered, thereby accounting for high leverage points by adjusting weights. Ultimately, we returned to the OLS model because, upon examining the fit of each model's line against our data, OLS best accounted for the distribution of the data. The null and alternative hypotheses for the models under consideration are:

H_0: No association exists between age and the explanatory variables.

H_a: An association exists between age and the explanatory variables.

Our second model examines the relationship between nature of death and date spread, age and cause of death. We selected this model in order to analyze the effect that date spread, age and cause of death may have on nature of death through a nominal model. A nominal model is appropriate for this regression due to the fact that nature of death – which includes heart attack, crushed, trauma, drowning, asphyxiation electrocution, violence, burns, heat exhaustion, and cerebrovascular accident – does not have any natural ordering to it. Since a nominal model bases the analysis off of a reference variable, we selected heart attack as the reference variable because it is the largest category with 906 counts. Additionally, we chose these three variables using the AIC selection criterion. This model with date spread, age and cause of death as predictors of nature of death resulted in the lowest AIC of 2412 whereas other models had AICs as large as 4861.

Our third model predicts whether the situation surrounding a firefighter's death was classified as an emergency or not based on the type of activity a firefighter was performing, the property type served, and the age of the firefighter. We utilized a logistic model as the outcomes for the 'Emergency' variable are binary, which is a key assumption of this type of model. The appropriateness of the model was assessed using the best of all models' Bayesian Information Criterion (BIC) and the pseudo-R^2 value which were 1779.383 and 0.4262672 respectively.

Our fourth model examines the relationship between a firefighter's assigned duty and the age of the firefighter, property type where the fire occurred and the nature of the firefighter's death. We ordered the response variable, Duty, according to the perceived danger each type of task necessitated. In order of most to least dangerous our levels were: 1.) On-Scene Fire, 2.) On-Scene Non-Fire, 3.) Other on-duty, 4.) Returning, 5.) Responding, 6.) After, 7.) Training. The AIC was 4286.47 and the pseudo R^2 was 0.2453.

Finally, we attempted to run a gaussian model that predicted the spread between a firefighter's death and the incident that caused that death, using firefighter's cause of death, the specific nature of death, age at death, and activity as predictor variables. We originally modeled this relationship using an ordinary least squares regression, however, several model assumptions were violated, making this type of regression irresponsible to interpret further. In an attempt to remedy the heteroscedasticity and unequal variance present in the dataset (Figures 11 & 12), we transformed the Age predictor variable. We also attempted to transform the date spread variable, however this oftentimes resulted in NaNs being produced and little progress being made on the linear assumptions violated. Therefore, we chose not to consider the model in our analysis.

Results:

A multiple linear regression was calculated to predict age at death based on the firefighter’s cause of death and the activity he/she was performing. Table 1 summarizes the descriptive statistics and regression results. As seen in Table 1, both *cause of death* and *activity* are significant predictors of age at death, although the levels of these variables vary in significance. Reference categories for *cause of death* and *activity* were chosen based on the highest instance of each, being respectively "Stress/Overexertion" and "Search and Rescue." A significant regression equation was found ($F(36, 1892) = 17.86$, $p < 2.2e-16$), with an adjusted R^2 of 0.2394. The results show that when a firefighter dies from stress/overexertion while completing search and rescue operations, his/her expected age at death equals 45.0183 years, on average.

Our second model analyzed the relationship between nature of death and date spread, age and cause of death through a nominal model. The results of this regression can be found in Figure 10. These regression results provide quantitative data that show if an increase in a variable or a certain category within the variable will lead to a higher or lower odds of a nature of death rather than a heart attack. Examining the date spread variable, we see that 7 out of the 12 nature of death categories–Asphyxiation, Cerebrovascular Accident, Crushed, Drowning, Heat Exhaustion, and Violence–have a negative coefficient, representing that they have an odds of less than 1, whereas 5 of the 12 nature of categories–Burns, Electrocution, Other, and Trauma–have an odds greater than 1. The most notable result shows that holding age and cause of death constant, for every increase in date spread, the odds that the nature of death is from being crushed rather than a heart attack is multiplied by exp(-0.01499) which is 0.86. Looking at the age variable, the results show that all nature of death categories have a negative coefficient, representing that as age increases and holding all else constant, the odds of death by any nature other than heart attack is multiplied by a range less than 1. Looking at assault as cause of death, the most notable result shows that holding date spread and age constant, the odds of an assaulted firefighter dying from violence rather than a heart attack is exp(27.39), 785825032788 times the odds for the other causes of death. Looking at caught or trapped as cause of death, we see that both asphyxiation and burns have an extremely high coefficient for cause of death with coefficients of 29 and 30, respectively. For collapse as cause of death, we see that asphyxiation, burns and crushed have extremely high coefficients for cause of death with coefficients of 30.391, 28.944, and 29.507, respectively. Similarly, for fall as cause of death, we see that asphyxiation, burns and trauma have high coefficients of 27.91, 28.11, and 15, respectively. For out of air as cause of death, we see that burns and drowning have the highest coefficients with 17 and 11, respectively. For cause of death due to being struck by an object, we see that asphyxiation, crushed and violence have the highest coefficients of 29.99l, 29.215, and 23.9289, respectively.

A logistic regression was fitted in order to predict whether or not a situation was declared an emergency using Age, Property type, and Activity as predictor variables. Figure 13 summarizes the regression results and model coefficients. It should be noted that the reference levels for the categorical explanatory variables, Property type and Activity, were chosen based on the most frequently occurring category, which were "Store/Office" and "Search and Rescue" respectively. The coefficients in the model itself were in large part significant, the p-values for Property type variable and Activity variable being 0.010378 and 0.08502 respectively, with the significance of individual categories varying widely at a prescribed alpha of 0.05. Interestingly, the Age variable did not end up being significant in the overall model, with a corresponding p-value of 0.205684, which is well above our prescribed alpha of 0.05. The overall model had a residual deviance statistic of 1499.5, improving on a null deviance of 2613.6, and a BIC value of 1779.383. In calculating McFadden's pseudo R^2, we obtained a value of 0.4262672, which shows that roughly 43% of the variance in our dataset can be explained by our model.

An ordinal model was fitted to predict the odds of a firefighter being engaged in a specific danger level over another based on their age, property type where the incident occurred, and the nature of the firefighter's death. Figure 14 summarizes the regression results and model coefficients. The Nature of death variable utilized "Heart Attack" as the reference category, as it had the highest count of observations from the dataset. For this model, we generated a pseudo R^2 value of 0.2453759, and a corresponding residual deviance statistic of 4224.47 and AIC of 4286.47.

Discussion and Conclusions:

Our first model predicts age at death based on two variables, cause of death and activity. While this model had some explanatory power, it does not completely account for the variability in age at death. As the model stands, about 24% of the variability in age at death can be explained by the model on cause of death and activity. Some practical considerations produced this model. Firstly, the model ultimately selected was restrained by how well it could be understood and interpreted. For example, including the firefighter's rank in the model increased the adjusted R-squared value by two. This means a model including cause of death, activity, *and* rank would explain around 50% of the variability in age at death. However, rank has about 100 levels, which would make this model extremely difficult to interpret or glean much information from. Additionally, many of the ranks seem to vary or overlap because fire departments across the United States do not report ranks consistently.

A few interesting observations can be made about the model on age. Examining the regression output, one sees that the reference level "Stress/Overexertion" has a higher age at death than every other category except for those whose causes of death were unknown. We can make some inferences from this observation. Firstly, older firefighters often die from stress and overexertion. This makes sense; for example, as firefighters get older, they become stressed or overexerted more easily since their bodies have been beaten down and may be less adept. We may also have a confounding variable at play here: experience. While the dataset does not report on years of experience firefighting, one might assume that older firefighters have more experience and younger firefighters have less (although this might not always be true). However, this idea is supported by the data. For example, there are some causes of death which are associated with lower ages at death and which also seem to be linked with lack of experience. These include the causes "Caught or Trapped," "Contact with," "Lost," "Struck By," and "Vehicle Collision," all of which imply deaths from accidents or from lack of experience. As an example, for firefighters who are killed doing the same activity, those whose cause of death was "lost" are expected to be 14.1673 years younger than whose cause of death was "stress/overexertion," on average ($t = -4.167$, $p = 3.23e\text{-}05$). This shows USFA and FEMA that additional or continued training may be necessary for younger firefighters, especially for situations where they may die from any of the above causes that may be prevented (like being lost).

The variable *activity* reveals less obvious conclusions; however, it does contribute somewhat to explaining age at death. The results from activity help focus the areas that might require more training. A clear example is salvage and overhaul. For firefighters who die from the same cause, those who are performing salvage and overhaul are expected to be 11.4304 years younger than those performing search and rescue, on average ($t = -2.290$, $p = 0.022$). This result indicates that younger firefighters may need more training with salvage and overhaul and how to stay safe while performing these tasks. Activity also shows that older firefighters may need more training in specific areas. Again for firefighters who die from the same cause, those who die performing scene safety are expected to be 14.2115 years older than those who die performing search and rescue, on average ($t = 6.213$, $p = 6.39e-10$). While these results are helpful, they do not consider how being older likely means having a higher rank and therefore only undertaking a specific subset of tasks. This is where having rank included in the model would be helpful, but again, for the sake of clarity in results this was not practical. For example, the average age of someone doing scene safety (overseeing others or leading decision-making on the scene) is linked with age. Those who are older and have more experience on a scene are more likely to be supervising. Therefore, in the context of our earlier analysis on scene safety, this tells us that maybe older firefighters are not less adept at scene safety but rather that those performing scene safety are older just by the nature of them being better fit for this activity. This gap in information thus represents a drawback of the multiple regression model discussed here.

Our second model analyzed the relationship between nature of death and date spread, age and cause of death through a nominal model. The first variable, date spread, showed that Asphyxiation, Cerebrovascular Accident, Crushed, Drowning, Heat Exhaustion and Violence – have a negative coefficient, representing that they have an odds of less than 1. Essentially, this conveys that holding all else constant, for every one day increase in date spread, the odds that a firefighter dies from asphyxiation, cerebrovascular accident, crushed, drowning, heat exhaustion and violence is less than the odds of dying from a heart attack. This makes sense because these cause of death variables all point to immediate death; one that is crushed or drowns will die immediately, thus resulting in a date spread of 0. When we looked at the age variable, the results show that all nature of death categories have a negative coefficient, representing that as age increases and holding all else constant, the odds of death by any nature other than heart attack is multiplied by a range less than 1. This points to the idea that as a firefighter grows older, the odds that they die from a heart attack rather than another cause of death is greater. It can be inferred that an older firefighter has more experience, thus will not die from technical errors such as drowning or asphyxiation. Rather, it is more likely that they die from an unavoidable death of a heart attack which is more common among elders as well. For assault as cause of death, it is logical that violence has the greatest odds in relation to the odds of a heart attack as violence typical involves assaulting a person. For caught or trapped as cause of death, it is also logical that the nature of death with the highest odds in relation to the odds of a heart attack is asphyxiation and burns. If a firefighter becomes trapped at the scene of a fire, the surrounding fire would likely cause suffocation and severe burns since they cannot escape. For collapse as cause of death, in addition to asphyxiation and burns, crushed as nature of death has the highest odds in relation to the odds of a heart attack. Naturally, if a building collapses onto someone, the cause of death is due to being crushed. Additionally, for out of air as cause of death, burns and drowning have the highest odds as nature of death in relation to odds of heart attack death. This points to the fact that fire, which results in burns, depletes the oxygen in the air. Similarly, drowning would deplete the oxygen that a firefighter needs to survive. Lastly, for cause of death due to being struck by an object, we see that asphyxiation, crushed and violence have the highest coefficients of 29.99l, 29.215, and 23.9289.

Our third model reveals much in terms of which situations are labeled as emergencies and which ones are not. Such a model might be relevant to firefighters as it would allow stations to examine whether or not certain situations might need to be classified as Emergency situations based on the types of Activity, Property type, and Age of the firefighter dispatched in order to save more lives. As a refreshed, the overall model had a pseudo R^2 value of 0.4951172, meaning that roughly half of the variability within our dataset was explained by this model.

The Activity variable had many different categories encompassed in it, many of which whose interpretation were rather intuitive. For example, the Activity variables corresponding to support, pump operations, and not on scene had the highest negative values for each of their coefficients, being -0.853, -0.6383, and -0.4808 respectively. Interpreted in context, holding Age and Property type constant, each of these coefficients multiplied the log odds of a situation being classified as an Emergency by a negative number as compared to the Activity of Search and Rescue. This makes intuitive sense, as these low-risk activities would be less likely to be classified as Emergencies. Further, more dangerous categories such as Advance Hose Lines/Fire Attack, Extrication and Forcible Entry all had positive coefficient values. This makes intuitive sense, as interpreted in context, each of these coefficients multiplies the log odds of a situation being classified as an Emergency by a positive number compared to the Activity of Search and Rescue. Interestingly, these activities could be interpreted as being more dangerous and "Emergency-worthy" than Search and Rescue, which seemed like the most dangerous type of activity to our group upon first glance.

The Age variable was also interesting to consider as a predictor. The coefficient was positive (0.005875), indicating that as a firefighter's age increases, the log likelihood that a situation be classified as an Emergency increases by the coefficient value. This makes intuitive sense, as older, and thus more likely to be higher ranked and more experienced, are often dispatched to Emergency situations. However, this contrasted to our initial intuition, as it might make more sense for younger firefighters, although relatively inexperienced, to be dispatched to emergency situations since they are generally more physically able than older firefighters. However, as we could not the rank variable–which indicates the relative rank of a deceased firefighter–due to the sheer number of categories, this remains a mystery. This would be an interesting variable to possibly include as an interaction term in future iterations of this model.

Finally, our fourth model helped in predicting the level of danger a firefighter was engaged with using the nature of a firefighter's death, age of the firefighter, and the property type being served. The overall model accounted for roughly 24% of the variability in the dataset, according to the calculated McFadden's pseudo R^2 value. Although we ordered the danger levels according to our own intuitions, this may not reflect the true level of danger posed by each one of these activities. According to Figure 17, On-Scene Fire seems to be the most dangerous, as it has the highest count of deceased firefighters, although Duty types such as "Training" also contain many deaths, 205, which is almost well above the number of deceased firefighters performing On-Scene Non-Fire duties (180). We did not order the Duty variable according to these counts, however, as we wanted to capture the absolute danger inherently posed by each of these types of duties rather than the relative danger in the dataset that each of the possible variables. In other words, although the Training Duty category had a higher overall count of firefighter deaths than On-Scene Non-Fire, we still ordered Training below On-Scene Non-Fire in terms of perceived danger because we believe Training is inherently less dangerous than a firefighter reporting On-Scene to an incident. While we recognize this decision may have resulted in the production of an inaccurate model, we believe ordering the levels in accordance with intrinsic danger rather than conforming to the dataset would benefit further researchers of this same subject, provided they can obtain additional data.

In terms of model predictors of interest, age, overall property type and overall nature of death were all significant according to a prescribed alpha of 0.05, with the latter two variables having varying degrees of significance across all categories. The Age variable had a positive coefficient of 0.01853 (negated due to order of variables), which in context implies that for every 1 unit increase in age of a firefighter, the log likelihood that the firefighter was engaged in a more dangerous type of duty increases by 0.01853 on average all other variables held constant. This makes intuitive sense, as older firefighters are more likely to be more experienced and thus more likely to engage in more dangerous activities. As for the nature of death variable, three positive coefficients of interest corresponded to Asphyxiation (3.063644), Burns (4.900792) and Crushed (3.178524). Interpreted in context, this means that for these categories, the odds of a firefighter being engaged in a more dangerous type of activity increases by the coefficient value compared to the reference category of 'Heart Attack.' This makes intuitive sense, as these types of deaths are more likely to be the result of engaging in more dangerous activities. Additionally, such an insight conforms to the fact that most firefighters dispatched during September 11, 2001 were engaged in either On-Scene Non-Fire or On-Scene Non-Fire duties (more dangerous activities), and thus more likely to result in firefighters having more violent deaths. Property type was not as interesting for us to evaluate implications from, as none of us have an intuitive sense as to which property types are more dangerous for firefighters to work in. The majority of the property types had positive coefficients, meaning that they were more likely to cause less dangerous situations compared to the baseline category of store/office fires.

Bibliography:

U.S. Fire Administration. (2019), "Firefighter fatalities in the United States," *Federal Emergency Management Agency* [online]. Available at *https://apps.usfa.fema.gov/firefighter-fatalities/*.

Appendix:

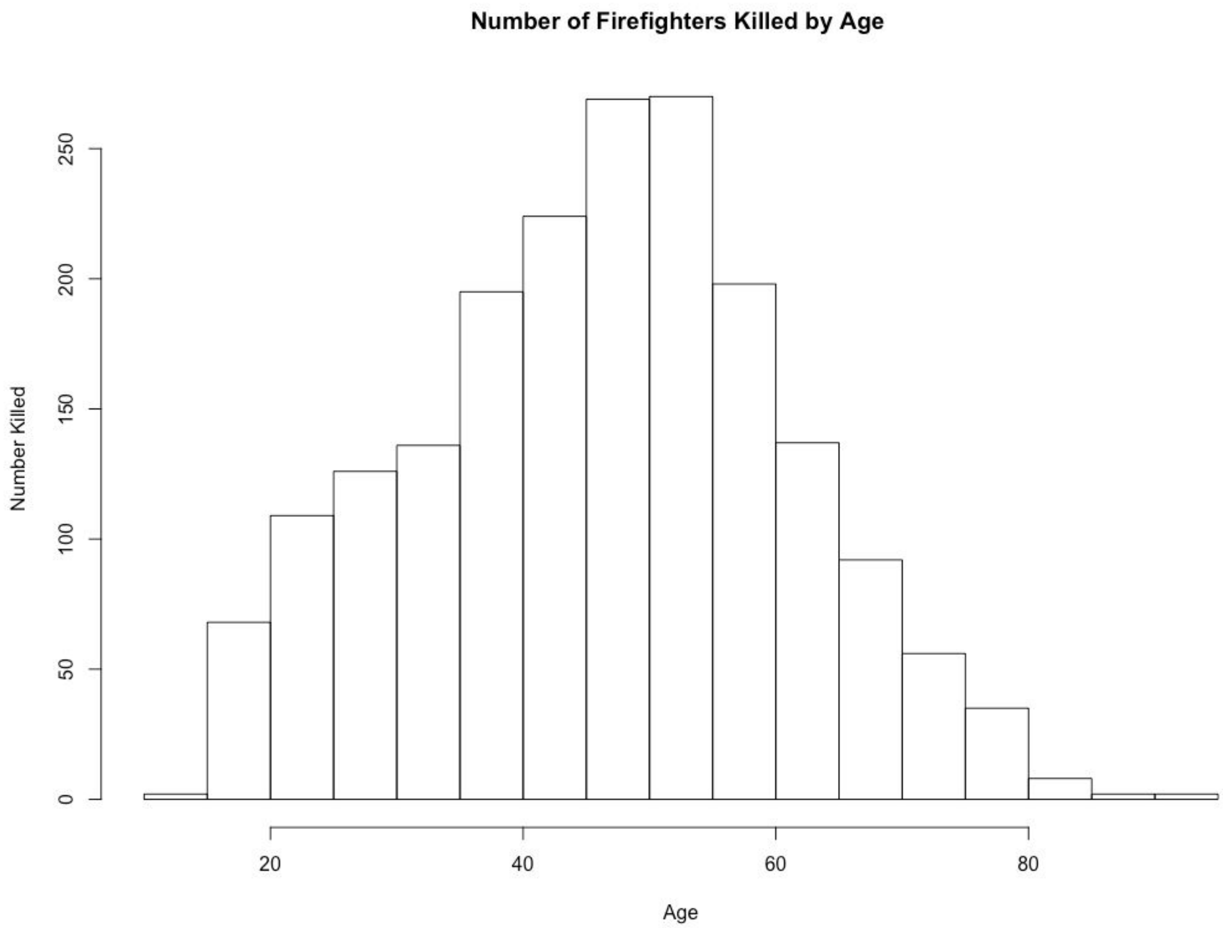
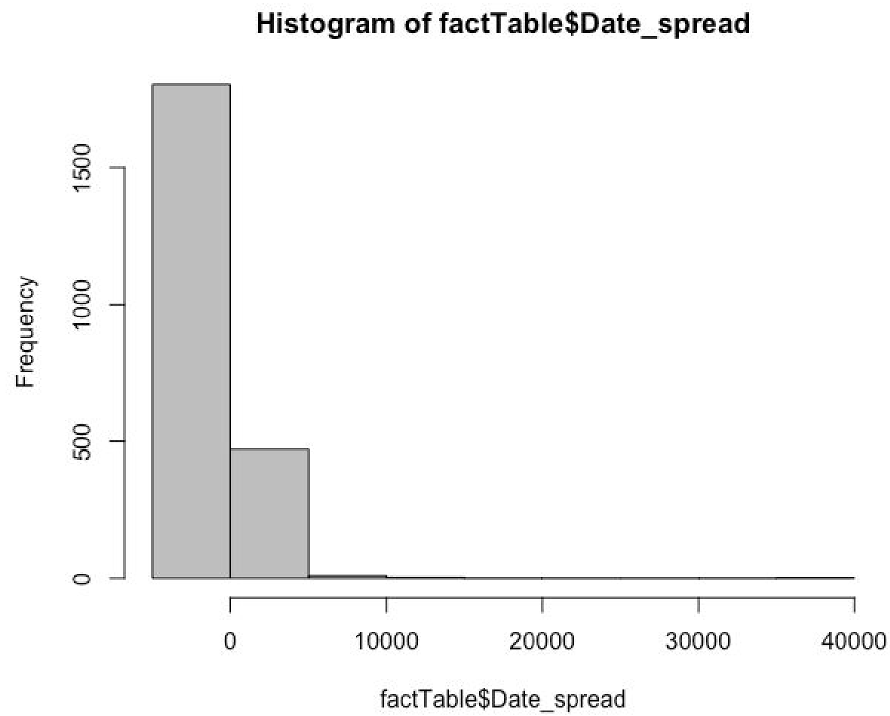


Figure 1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Frequency
0
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1000
1500
0
10000
20000
30000
40000
factTable$Date_spread

Figure 2

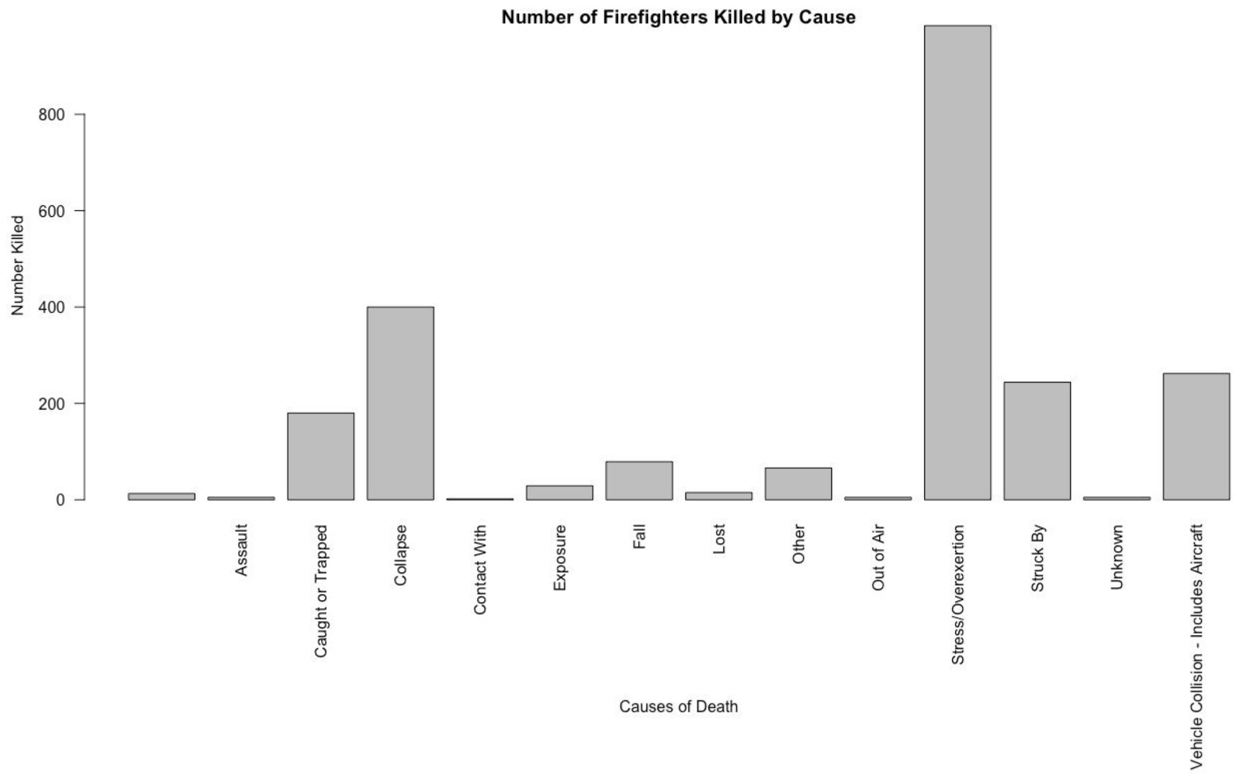

Number of Firefighters Killed by Cause
Number Killed
0
200
400
600
800
Assault
Caught or Trapped
Collapse
Contact With
Exposure
Fall
Lost
Other
Out of Air
Stress/Overexertion
Struck By
Unknown
Vehicle Collision - Includes Aircraft
Causes of Death

Figure 3

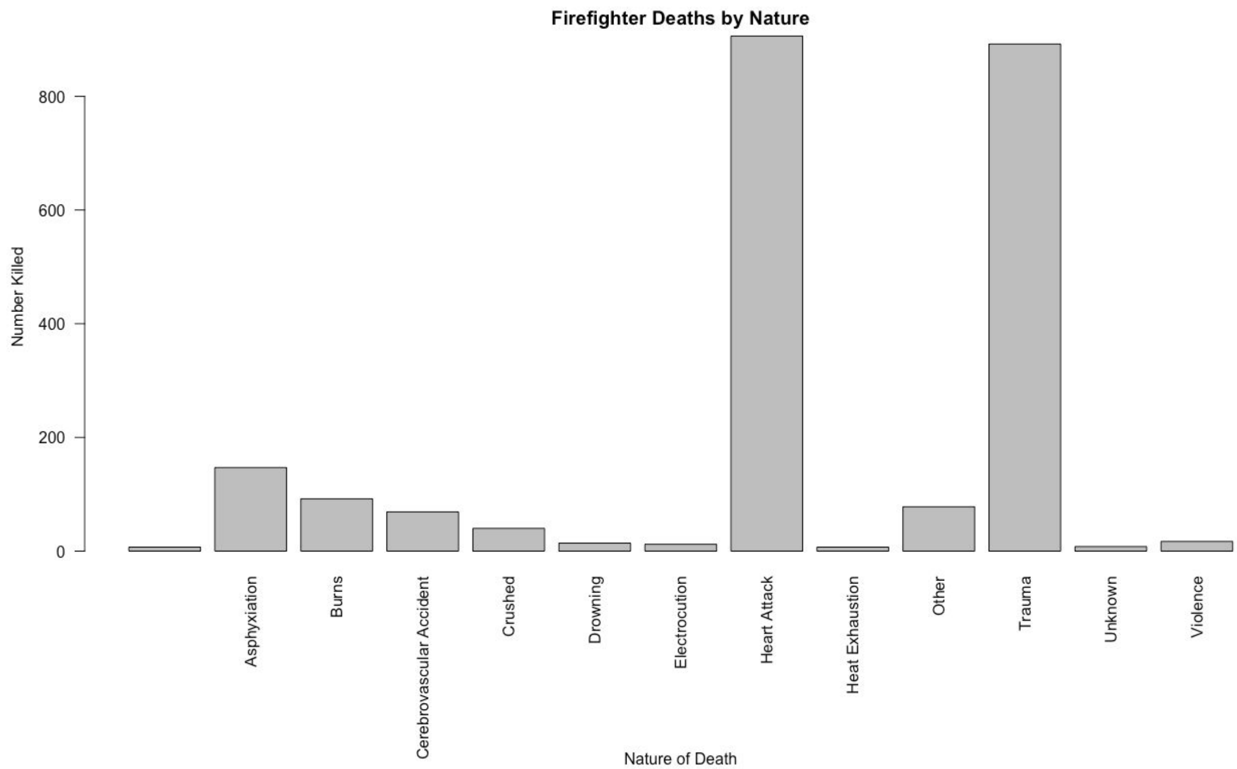

Firefighter Deaths by Nature
Number Killed
0
200
400
600
800
Asphyxiation
Burns
Cerebrovascular Accident
Crushed
Drowning
Electrocution
Heart Attack
Heat Exhaustion
Other
Trauma
Unknown
Violence
Nature of Death

Figure 4

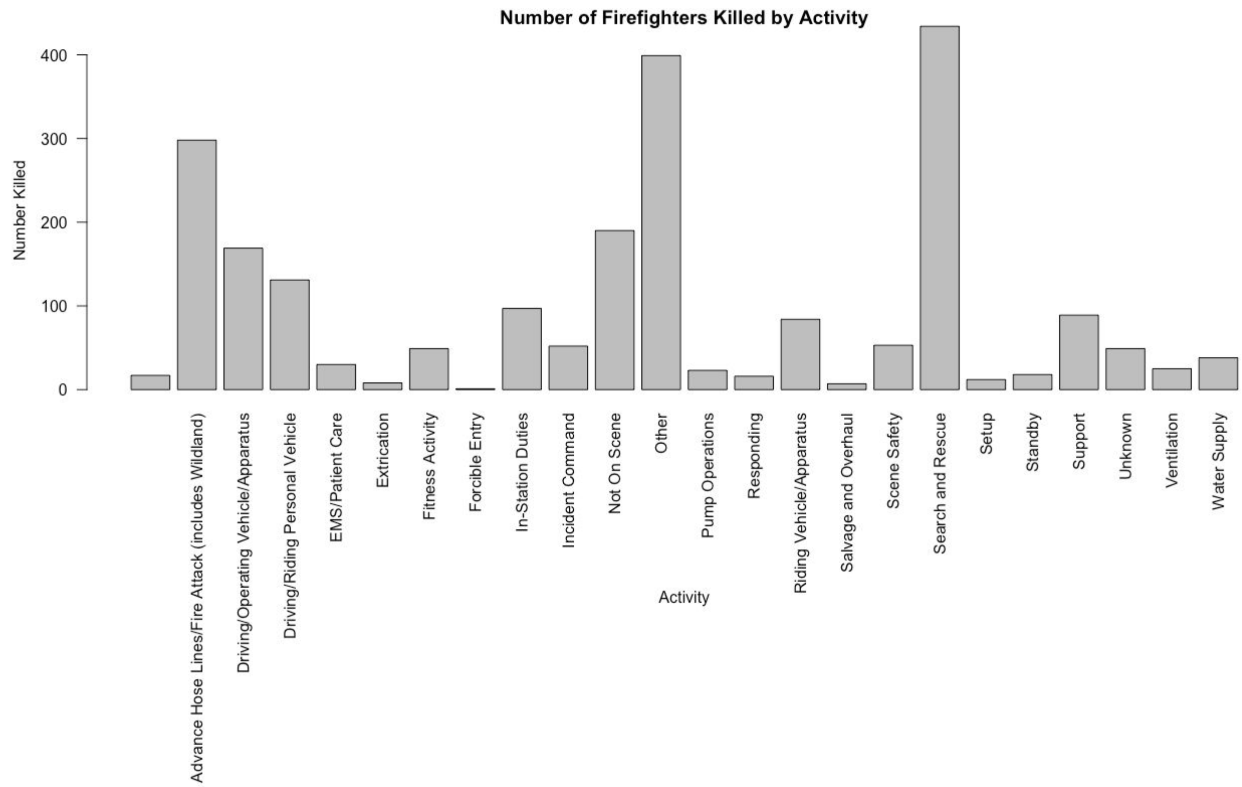

Number of Firefighters Killed by Activity
Number Killed
400
300
200
100
0
Advance Hose Lines/Fire Attack (includes Wildland)
Driving/Operating Vehicle/Apparatus
Driving/Riding Personal Vehicle
EMS/Patient Care
Extrication
Fitness Activity
Forcible Entry
In-Station Duties
Incident Command
Not On Scene
Other
Pump Operations
Responding
Riding Vehicle/Apparatus
Salvage and Overhaul
Scene Safety
Search and Rescue
Setup
Standby
Support
Unknown
Ventilation
Water Supply
Activity

Figure 5

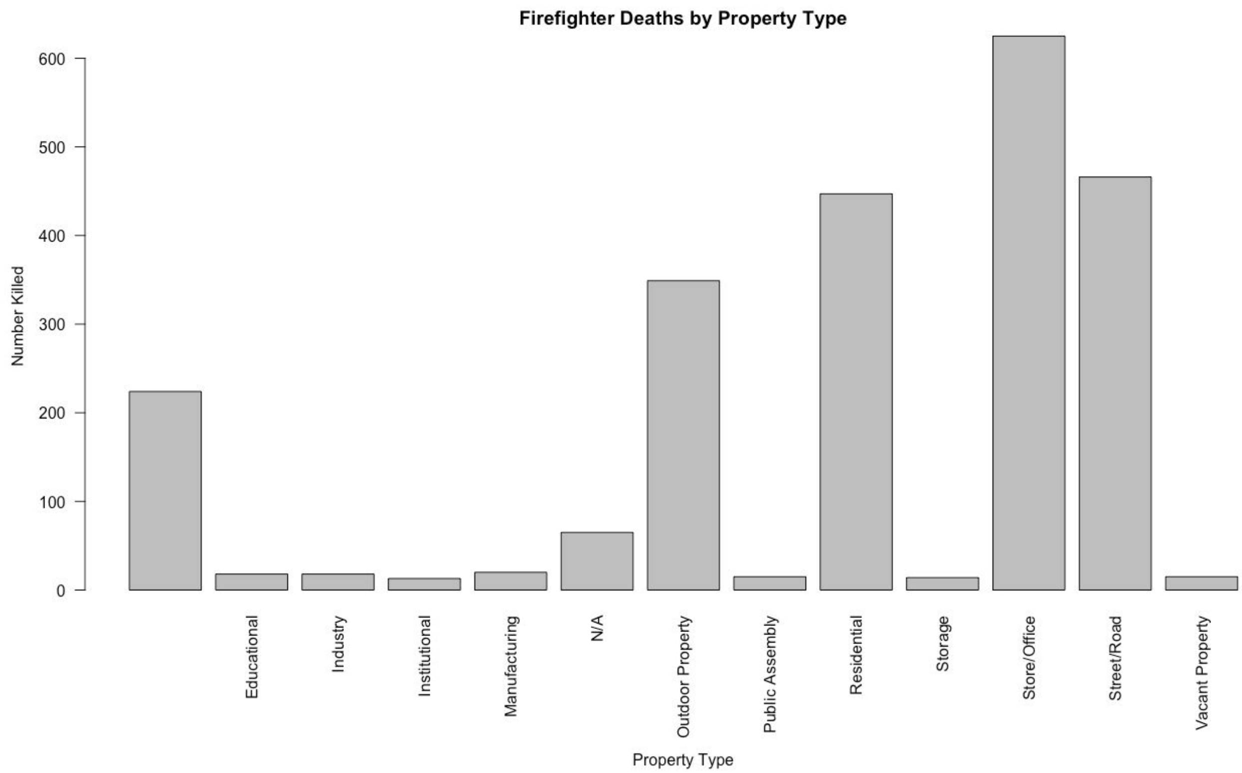

Firefighter Deaths by Property Type
Number Killed
0
100
200
300
400
500
600
Educational
Industry
Institutional
Manufacturing
N/A
Outdoor Property
Public Assembly
Residential
Storage
Store/Office
Street/Road
Vacant Property
Property Type

Figure 6

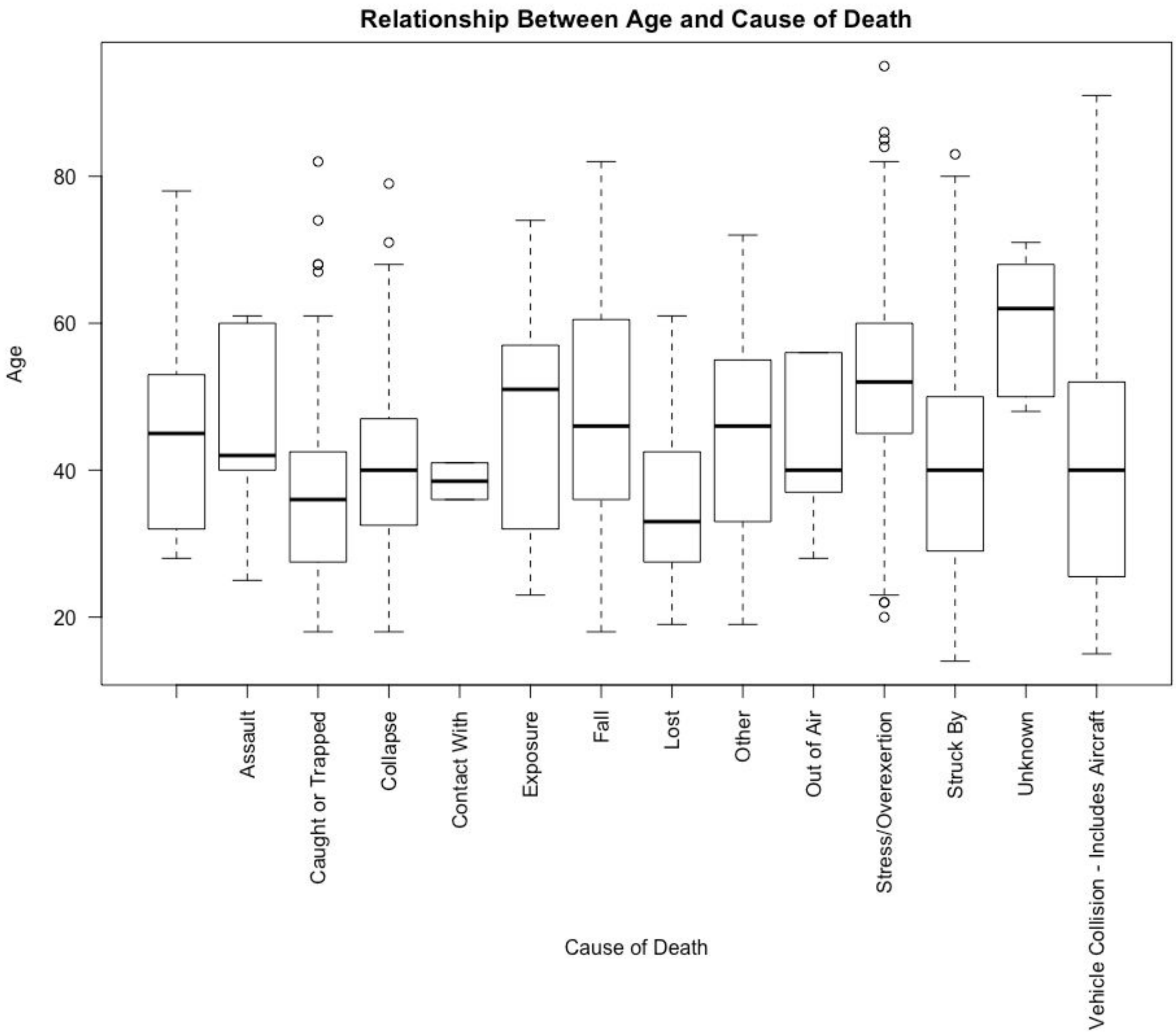
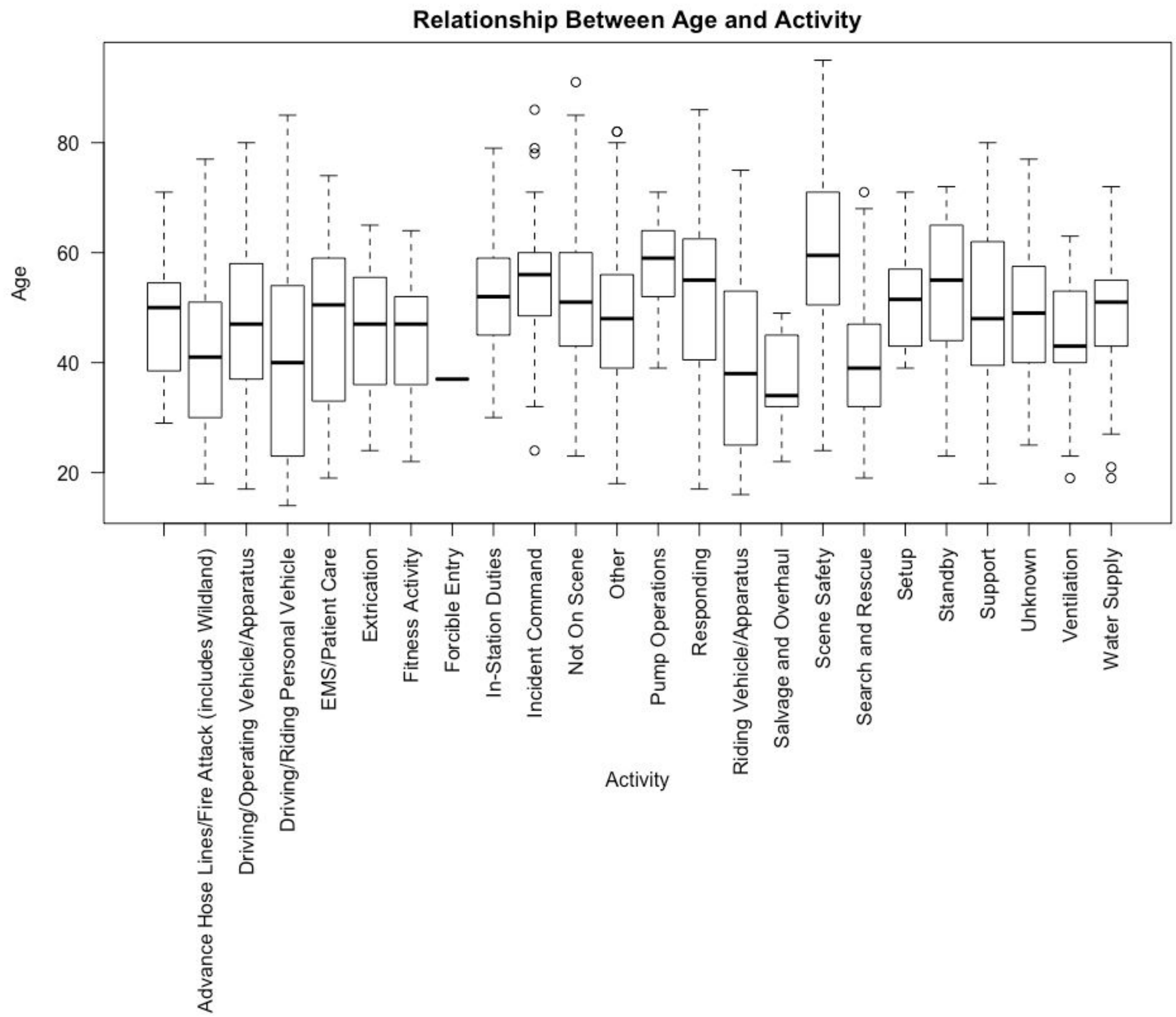

Relationship Between Age and Cause of Death
Age
80
60
40
20
Assault
Caught or Trapped
Collapse
Contact With
Exposure
Fall
Lost
Other
Out of Air
Stress/Overexertion
Struck By
Unknown
Vehicle Collision - Includes Aircraft
Cause of Death

Figure 7



Relationship Between Age and Activity
Age
80
60
40
20
Activity
Advance Hose Lines/Fire Attack (includes Wildland)
Driving/Operating Vehicle/Apparatus
Driving/Riding Personal Vehicle
EMS/Patient Care
Extrication
Fitness Activity
Forcible Entry
In-Station Duties
Incident Command
Not On Scene
Other
Pump Operations
Responding
Riding Vehicle/Apparatus
Salvage and Overhaul
Scene Safety
Search and Rescue
Setup
Standby
Support
Unknown
Ventilation
Water Supply

Figure 8

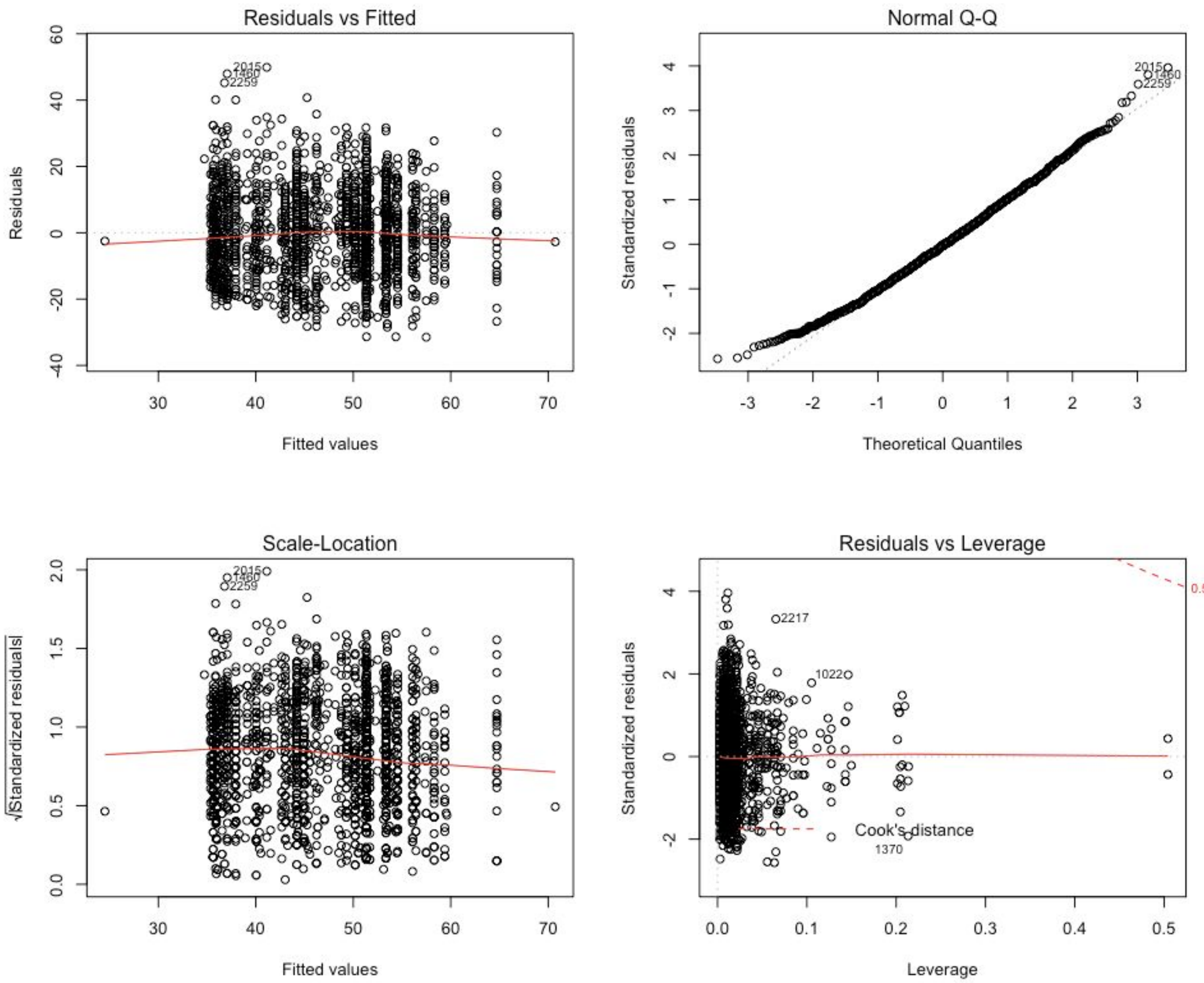

Residuals vs Fitted
Residuals
Fitted values
2015
1460
2259
Normal Q-Q
Standard residuals
Theoretical Quantiles
Scale-Location
√|Standardized residuals|
Residuals vs Leverage
Leverage
Cook's distance
2217
1022
1370
0.5

Figure 9

Coefficient	Estimate	Standard Error	t-value	p-value	Signifi-cance
Cause: Stress/Overexcertion	-8.09228	3.78704	-2.137	0.032739	*
Cause: Assault	-7.09355	5.75779	-1.232	0.218105	
Cause: Caught or Trapped	-14.56725	1.22756	-11.867	< 2e-16	***
Cause: Collapse	-10.14952	1.79571	-5.652	1.83E-08	***
Cause: Contact With	-16.21696	8.99363	-1.803	0.071522	.
Cause: Exposure	-5.19232	2.46016	-2.111	0.034940	*
Cause: Fall	-5.12182	1.51231	-3.387	0.000722	***
Cause: Lost	-14.16732	3.40012	-4.167	3.23E-05	***
Cause: Other	-7.13346	1.64492	-4.337	1.52E-05	***
Cause: Out of Air	-7.38539	5.71436	-1.292	0.196367	
Cause: Struck By	-13.41609	0.96825	-13.856	< 2e-16	***
Cause: Unknown	6.00331	5.69682	1.054	0.292109	
Cause: Vehicle Collision	-12.22883	0.08713	-11.249	< 2e-16	***
Activity: Search and Rescue	2.59910	3.64685	0.713	0.476120	
Activity: Advance Hose Lines/Fire Attack	-0.32018	1.49113	-0.215	0.830009	
Activity: Driving/Operating Vehicle/Apparatus	5.91544	1.82060	3.249	0.001178	**
Activity: Driving/Riding Personal Vehicle	-1.22199	1.89817	-0.644	0.519803	
Activity: EMS/Patient Care	3.19083	2.76459	1.154	0.248572	
Activity: Extrication	-3.46339	4.73299	-0.732	0.464409	
Activity: Fitness Activity	-5.58493	2.33665	-2.390	0.016939	*
Activity: Forcible Entry	-0.09538	12.76673	-0.007	0.994040	
Activity: In-Station Duties	4.04174	1.94225	2.081	0.037572	*
Activity: Incident Command	7.78391	2.27049	3.428	0.000620	***
Activity: Not On Scene	2.83893	1.73279	1.638	0.101514	

Table 1 (continued on next page)

Coefficient	Estimate	Standard Error	t-value	p-value	Signifi-cance
Activity: Other	0.84490	1.56581	0.540	0.589540	
Activity: Pump Operations	8.87858	3.07128	2.891	0.003886	**
Activity: Responding	6.97535	3.50241	1.992	0.046560	*
Activity: Riding Vehicle/Apparatus	-1.74288	2.05507	-0.848	0.396496	
Activity: Salvage and Overhaul	-11.43043	4.99039	-2.290	0.022102	*
Activity: Scene Safety	14.21158	2.28749	6.213	6.39E-10	***
Activity: Setup	3.96839	3.92372	1.011	0.311962	
Activity: Standby	3.85916	3.32405	1.161	0.245796	
Activity: Support	5.57205	1.97026	2.828	0.004732	**
Activity: Unknown	2.97744	2.33637	1.274	0.202682	
Activity: Ventilation	0.16062	2.87330	0.056	0.955426	
Activity: Water Supply	1.18210	2.53868	0.466	0.641530	
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					

Table 1 (continued)

```
> summary(ff.nom3)
Call:
multinom(formula = factTable$Nature_of_death ~ factTable$Date_spread +
    factTable$Age + factTable$Cause_of_death)

Coefficients:
                          (Intercept) factTable$Date_spread factTable$Age factTable$Cause_of_deathAssault
                          -0.21890537           0.001373422  -0.004338707                     -1.14366547
Asphyxiation             -15.64986197          -0.006509738  -0.034207825                     -4.67169527
Burns                    -16.80864064           0.001561467  -0.030916402                     -1.19510332
Cerebrovascular Accident  -0.92562384          -0.002320645  -0.002845048                     -0.98690287
Crushed                  -15.80541931          -0.014998950  -0.009229318                     -1.01317624
Drowning                  -9.75795706          -0.003250264  -0.050438869                     -0.01790001
Electrocution             -0.07928497           0.001187266  -0.035367884                     -0.73915710
Heat Exhaustion          -10.53061944          -0.005712251  -0.127173988                      0.39587368
Other                     -1.52004132           0.001591729  -0.016085841                     -2.53685431
Trauma                    -0.38250652           0.001066557  -0.025444847                     -8.45047489
Unknown                  -14.55376857          -0.003246335  -0.059145066                      1.37101121
Violence                  -9.43862586          -0.002261463  -0.028741034                     27.39244395
                         factTable$Cause_of_deathCaught or Trapped factTable$Cause_of_deathCollapse
                                                        -9.7578395                       10.2963221
Asphyxiation                                            29.5358662                       30.3917812
Burns                                                   30.5146484                       28.9441993
Cerebrovascular Accident                                -3.3843362                       -4.1243773
Crushed                                                 25.0464787                       29.5073210
Drowning                                                22.0852100                        3.1018079
Electrocution                                           -0.8116504                       -4.9452215
Heat Exhaustion                                          6.0690927                        2.5513632
Other                                                   10.2496699                       12.4912657
Trauma                                                  10.6079875                       13.6154871
Unknown                                                 -0.2666974                        1.5011127
Violence                                                 8.2516410                        0.3544905


                         factTable$Cause_of_deathContact With factTable$Cause_of_deathExposure factTable$Cause_of_deathFall
                                                  -1.62015685                       -19.597374                   -7.5035272
Asphyxiation                                      -5.23593768                        18.492676                   27.9189283
Burns                                             -1.45022083                        18.843010                   28.1159241
Cerebrovascular Accident                          -0.97949047                       -13.884257                   10.2316639
Crushed                                           -1.43089025                        -9.040887                    0.9660776
Drowning                                          -0.62561396                        -4.207799                    5.0153594
Electrocution                                     28.15771762                         2.470333                   10.9041032
Heat Exhaustion                                    0.08597121                        14.822874                    5.5199096
Other                                             -3.02277649                         3.499172                   12.1233015
Trauma                                            -5.66793788                       -44.545220                   15.0016028
Unknown                                           -1.04636125                        -3.018120                    4.9076104
Violence                                          -0.55941246                        -8.209490                    3.7084123
                         factTable$Cause_of_deathLost factTable$Cause_of_deathOther factTable$Cause_of_deathOut of Air
                                           -6.1007651                   -19.2997955                         -24.309656
Asphyxiation                               30.7210700                    17.2449028                          17.168737
Burns                                      -1.7559154                    -8.5513011                         -10.132503
Cerebrovascular Accident                   -3.1214260                    -0.3147233                         -24.754062
Crushed                                    27.2901730                    -8.5640677                         -12.526455
Drowning                                    0.1365292                    -6.6258301                          11.258070
Electrocution                              -3.7371862                     1.6810956                         -23.397440
Heat Exhaustion                             0.1585561                   -12.2838638                         -10.334424
Other                                      -4.9656846                     4.5375668                         -16.552136
Trauma                                    -18.0932010                     2.2508553                         -18.961778
Unknown                                     2.3439529                    16.4351033                          -8.613508
Violence                                   -0.5859682                    -7.0933938                          -9.420487
                         factTable$Cause_of_deathStress/Overexertion factTable$Cause_of_deathStruck By
                                                          -6.3040702                         -9.432011
Asphyxiation                                              10.7424257                         28.992783
Burns                                                      3.7447415                         12.376334
Cerebrovascular Accident                                  -1.5283852                         11.854287
Crushed                                                   -0.6954476                         29.215491
Drowning                                                  -1.7202646                         12.783977
Electrocution                                            -10.8530508                          1.018657
Heat Exhaustion                                           11.2271945                          6.872396
Other                                                     -1.8326056                        -17.550689
Trauma                                                    -5.2025613                         17.606324
Unknown                                                   11.6927909                          2.676533
Violence                                                  -1.7088190                         23.928975
```

	factTable$Cause_of_deathUnknown	factTable$Cause_of_deathVehicle Collision - Includes Aircraft
	-24.006324	-2.6644029
Asphyxiation	-13.307736	29.0656486
Burns	-8.398942	28.2683780
Cerebrovascular Accident	-24.507015	-0.2904515
Crushed	-11.760457	27.6892095
Drowning	-7.082229	23.2324234
Electrocution	-20.354364	3.9436677
Heat Exhaustion	-1.681075	5.3812586
Other	-16.211676	12.9809649
Trauma	-19.738283	17.3054214
Unknown	18.511630	7.5168181
Violence	-7.464228	13.2298836

Figure 10 (continued from previous page)

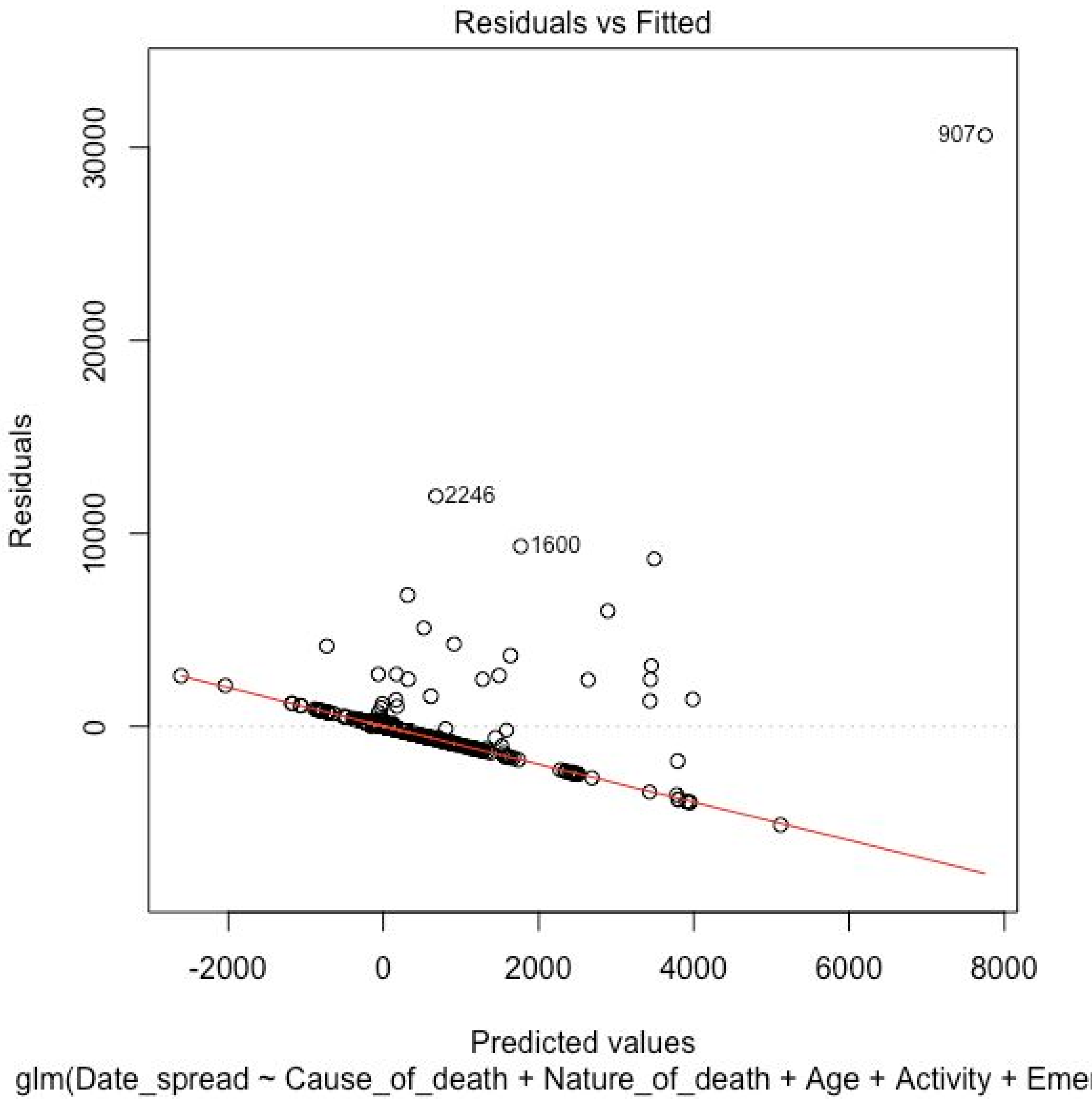

Residuals vs Fitted
Residuals
30000
20000
10000
0
907
2246
1600
-2000
0
2000
4000
6000
8000
Predicted values
glm(Date_spread ~ Cause_of_death + Nature_of_death + Age + Activity + Emer

Figure 11

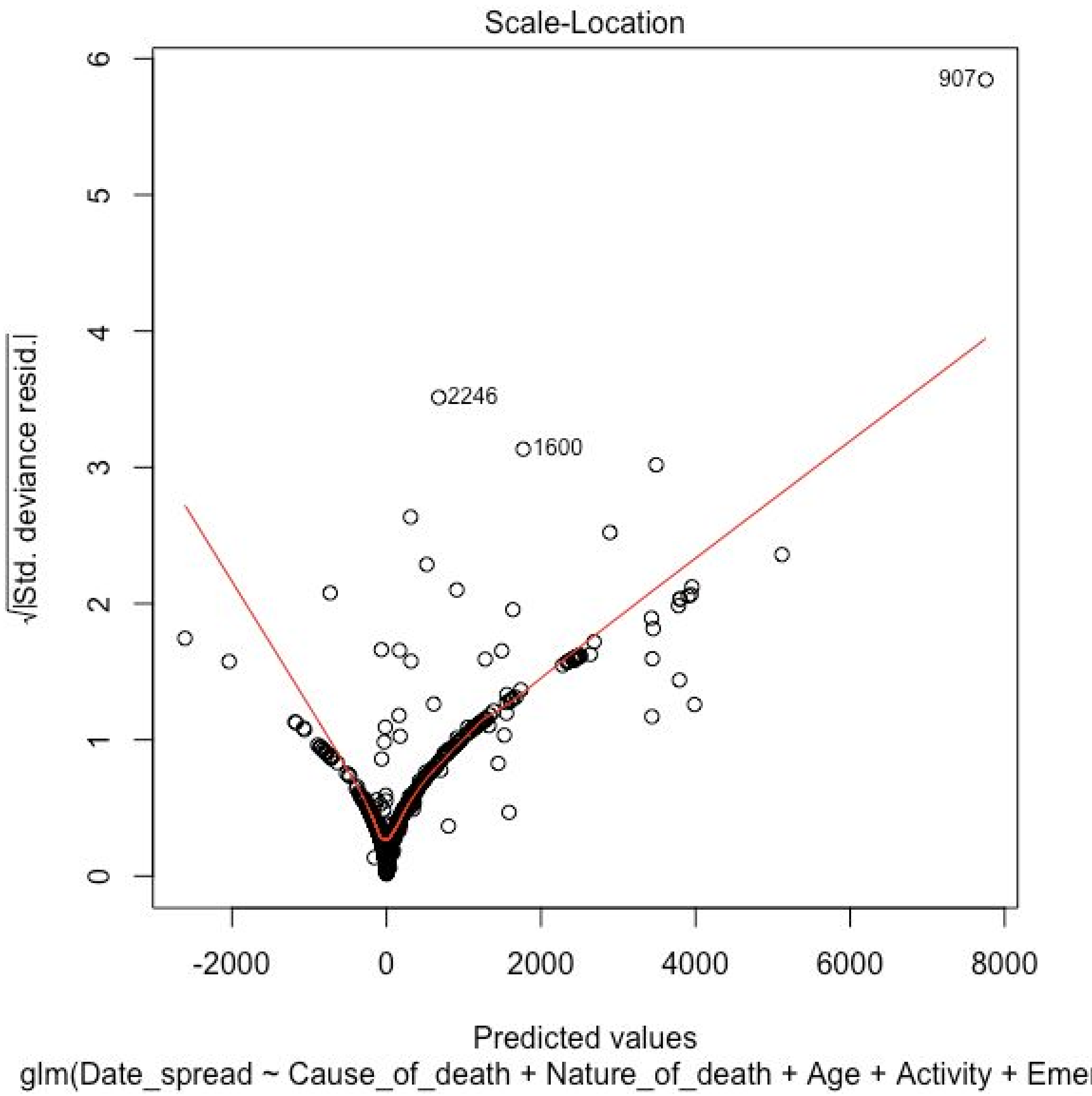

Scale-Location
907
2246
1600
0
1
2
3
4
5
6
√|Std. deviance resid.|
-2000
0
2000
4000
6000
8000
Predicted values
glm(Date_spread ~ Cause_of_death + Nature_of_death + Age + Activity + Emei

Figure 12

```
glm(formula = Emergency ~ Activity + Property_type + Age, family = binomial(link = "logit"),
    data = factTable)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.8522  -0.4399   0.2288   0.6836   2.8641

Coefficients:
                                                            Estimate Std. Error z value Pr(>|z|)
(Intercept)                                                1.214e+00  4.035e-01   3.009 0.002618 **
Activity                                                  -1.685e+00  6.574e-01  -2.563 0.010378 *
ActivityAdvance Hose Lines/Fire Attack (includes Wildland)  1.418e+00  4.506e-01   3.148 0.001646 **
ActivityDriving/Operating Vehicle/Apparatus               -1.260e+00  3.725e-01  -3.382 0.000719 ***
ActivityDriving/Riding Personal Vehicle                   -1.062e+00  3.969e-01  -2.675 0.007469 **
ActivityEMS/Patient Care                                   1.651e+00  1.087e+00   1.518 0.128925
ActivityExtrication                                        2.371e-02  1.150e+00   0.021 0.983542
ActivityFitness Activity                                  -4.789e+00  7.957e-01  -6.019 1.76e-09 ***
ActivityForcible Entry                                     1.434e+01  2.400e+03   0.006 0.995231
ActivityIn-Station Duties                                 -3.883e+00  5.057e-01  -7.678 1.61e-14 ***
ActivityIncident Command                                  -2.929e-01  5.161e-01  -0.568 0.570333
ActivityNot On Scene                                      -4.808e+00  5.333e-01  -9.015  < 2e-16 ***
ActivityOther                                             -2.567e+00  3.357e-01  -7.647 2.05e-14 ***
ActivityPump Operations                                   -6.383e-01  6.549e-01  -0.975 0.329744
ActivityResponding                                         1.468e+01  5.811e+02   0.025 0.979842
ActivityRiding Vehicle/Apparatus                          -1.086e+00  4.183e-01  -2.597 0.009403 **
ActivitySalvage and Overhaul                               1.475e+01  8.734e+02   0.017 0.986530
ActivityScene Safety                                      -2.808e-01  5.218e-01  -0.538 0.590527
ActivitySetup                                              1.429e+01  6.918e+02   0.021 0.983519
ActivityStandby                                           -2.207e+00  5.985e-01  -3.687 0.000227 ***
ActivitySupport                                           -8.530e-01  4.125e-01  -2.068 0.038645 *
ActivityUnknown                                           -1.511e+00  4.684e-01  -3.227 0.001252 **
ActivityVentilation                                        1.188e+00  1.074e+00   1.106 0.268627
ActivityWater Supply                                       2.456e-01  6.301e-01   0.390 0.696729
Property_type                                             -8.494e-01  3.228e-01  -2.631 0.008502 **
Property_typeEducational                                  -2.555e+00  1.120e+00  -2.282 0.022509 *
Property_typeIndustry                                      2.205e+00  8.577e-01   2.571 0.010150 *
Property_typeInstitutional                                -9.308e-01  7.656e-01  -1.216 0.224107
Property_typeManufacturing                                 2.251e+00  9.157e-01   2.458 0.013956 *
Property_typeN/A                                          -1.026e+00  4.469e-01  -2.296 0.021695 *
Property_typeOutdoor Property                              5.942e-01  2.393e-01   2.483 0.013019 *
Property_typePublic Assembly                               5.292e-01  7.380e-01   0.717 0.473353
Property_typeResidential                                   7.918e-01  2.345e-01   3.376 0.000735 ***
Property_typeStorage                                       2.297e-01  7.144e-01   0.322 0.747781
Property_typeStreet/Road                                   8.121e-01  2.400e-01   3.384 0.000714 ***
Property_typeVacant Property                              -3.062e-01  7.386e-01  -0.415 0.678429
Age                                                        5.875e-03  4.642e-03   1.266 0.205684
---
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 2613.6  on 1928  degrees of freedom
Residual deviance: 1499.5  on 1892  degrees of freedom
  (360 observations deleted due to missingness)
AIC: 1573.5

Number of Fisher Scoring iterations: 15
```

```
> summary(factTable$Duty)
   On-Scene Fire On-Scene Non-Fire     Other on-duty         Returning        Responding             After          Training              NA's
             951               180                 0                42               293               262               205               356
```

Figure 13 (continued from previous page)

```
 link  threshold nobs logLik   AIC     niter max.grad cond.H
 logit flexible  1577 -2112.24 4284.47 8(2)  9.95e-07 1.6e+06

Coefficients:
                                        Estimate Std. Error z value Pr(>|z|)
Age                                    -0.018534   0.003678  -5.040 4.67e-07 ***
Property_type                           0.873886   0.213973   4.084 4.42e-05 ***
Property_typeEducational                2.894121   0.774377   3.737 0.000186 ***
Property_typeIndustry                  -1.655414   0.598409  -2.766 0.005669 **
Property_typeInstitutional              1.182636   0.667600   1.771 0.076482 .
Property_typeManufacturing             -3.080249   0.780669  -3.946 7.96e-05 ***
Property_typeN/A                        0.837737   0.328348   2.551 0.010730 *
Property_typeOutdoor Property          -1.012117   0.215983  -4.686 2.78e-06 ***
Property_typePublic Assembly           -0.522767   0.766575  -0.682 0.495269
Property_typeResidential               -1.261978   0.195959  -6.440 1.19e-10 ***
Property_typeStorage                    0.309919   0.514229   0.603 0.546717
Property_typeStreet/Road               -0.153571   0.193231  -0.795 0.426758
Property_typeVacant Property           -2.203229   0.742557  -2.967 0.003006 **
Nature_of_death                        -1.599308   1.218184  -1.313 0.189229
Nature_of_deathAsphyxiation            -3.063644   0.278308 -11.008  < 2e-16 ***
Nature_of_deathBurns                   -4.900792   0.728940  -6.723 1.78e-11 ***
Nature_of_deathCerebrovascular Accident 0.360064   0.263098   1.369 0.171140
Nature_of_deathCrushed                 -3.178524   0.521550  -6.094 1.10e-09 ***
Nature_of_deathDrowning                 0.234932   0.596789   0.394 0.693832
Nature_of_deathElectrocution           -3.293302   1.070410  -3.077 0.002093 **
Nature_of_deathHeat Exhaustion          0.529892   0.800546   0.662 0.508027
Nature_of_deathOther                   -0.513787   0.276976  -1.855 0.063598 .
Nature_of_deathTrauma                  -0.958492   0.135081  -7.096 1.29e-12 ***
Nature_of_deathUnknown                  0.023380   0.843321   0.028 0.977882
Nature_of_deathViolence                -1.090085   0.490189  -2.224 0.026162 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Threshold coefficients:
                               Estimate Std. Error z value
On-Scene Fire|On-Scene Non-Fire  -2.7334     0.2691 -10.156
On-Scene Non-Fire|Returning      -2.0507     0.2662  -7.703
Returning|Responding             -1.9045     0.2656  -7.171
Responding|After                 -0.8350     0.2610  -3.199
After|Training                    0.4494     0.2611   1.721
(712 observations deleted due to missingness)
```

Figure 14

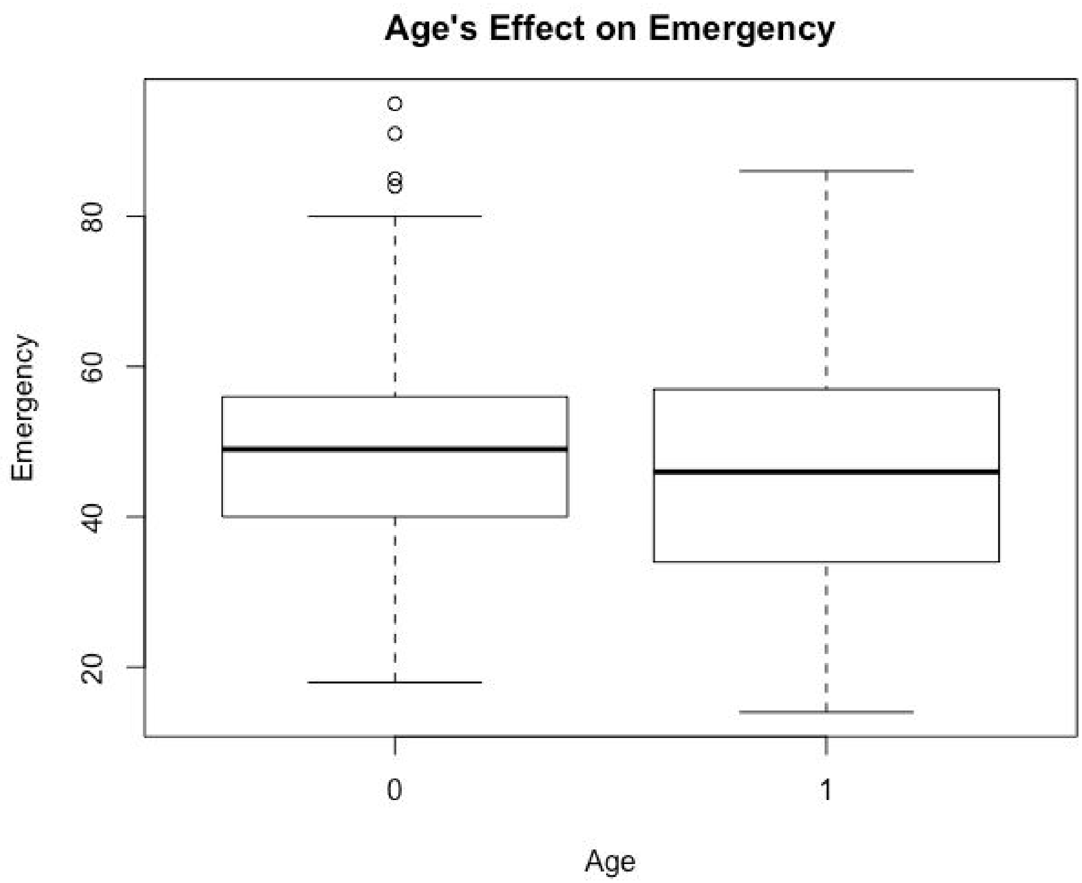


Figure 15

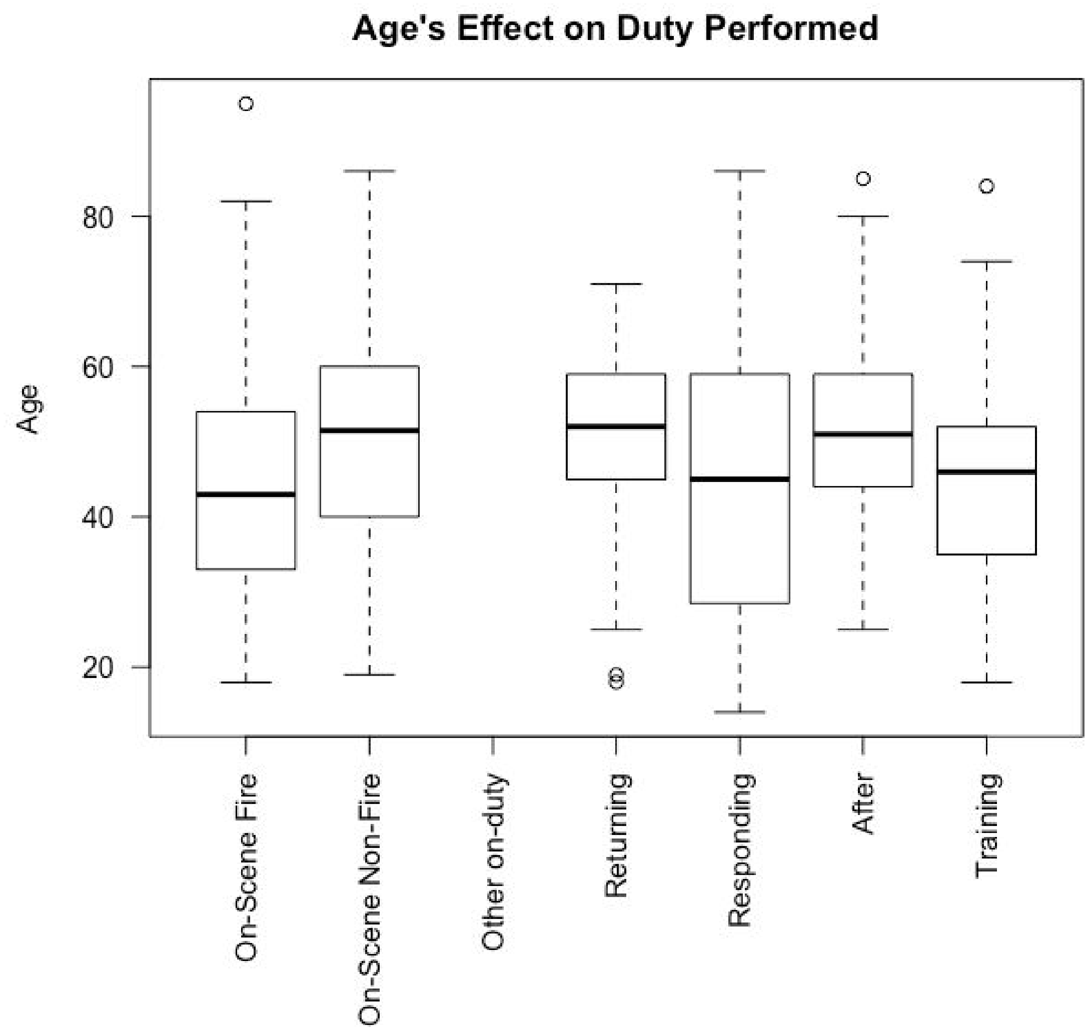


Figure 16

```
> summary(factTable$Duty)
   On-Scene Fire On-Scene Non-Fire      Other on-duty          Returning         Responding
             951               180                  0                 42                293
           After          Training               NA's
             262               205                356
```

Figure 17