# Detection and Characterization of Road Accident Clusters in Texas Counties

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# ABSTRACT

Traffic accidents count for one of the main causes of life losses globally as well as heavy burden of their consequents on societies, a matter which prompts researchers to discover the reasons of accidents occurrence and factors affect their severity. Therefore, in this study k-means clustering method is applied to analyze traffic accident data to identify the counties with the highest relatively severe accidents, considering all levels of crash severity, due to driver-related risk factors in Texas State. It analyzes recorded data of the statewide accidents occurred within 2013 to 2015, available from Texas Department of Transportation official website. As a result of this research the counties with similar status of crash severity were identified among which the counties in the most critical situation were distinguished, an outcome that can be useful for authorities such as transportation planners to make appropriate decisions in safety planning. Furthermore, some of the contributor factors that may intensify accidents were addressed.

**Keywords**: Traffic safety, Accident, Severity, K-Means, Clustering.

# ÖZ

Trafik kazaları günümüzde dünyadaki ölümlerin büyük bir oranını oluştururken, ayni zamanda toplumlar üzerindeki geri dönülemez etkileri de araştırmacılar tarafından büyük dikkat çekmekte ve araştırma konusu olmaktadır. Bu sebeple, bu araştırmada kümeleme metodu uygulanarak sürücü hatalarına bağlı trafik kazalarının Texastaki şehirlere göre olan oranları çıkarılmıştır. Teksas'ta 2013 yılından 2015 yılına kadar olan trafik kazaları bu bağlamda incelenmiş olup Ulaştırma Bakanlığınca yol güvenliğini sağlamak amacıyla yapılabilecek eylemler ve alınabilecek önlemler konusundaki icraatlara yönelik öneriler sunulmuştur. Bu öneriler trafik yönünden Teksas ile benzeşen diğer şehirlerde de kullanılabilir.

**Anahtar kelimeler:** Trafik güvenliği, Kaza, Ciddiyet, K-Means, Kümeleme.

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I express my gratitude to my dear parents who have always been encouraging and supporting me to acquire science to any extent I want, despite all hardships they have faced, and motivated and inspired me to keep on during the two years I did may master degree far from them.

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| | |
|---|---|
| WHO | World Health Organization |
| CA | Cluster Analysis |
| DUI | Driving Under the Influence |
| ASD | Alcohol Drunk, Speeding and Distraction |
| FOS | Figure of Severity |
| NHSTA | National Highway Traffic Safety Administration |
| MML | Minimum Message Length |
| SSE | Sum of Squared Errors |

# Chapter 1

# INTRODUCTION

## 1.1 Background

Transportation in general definition refers to displacement of people, goods and services that is tried to be efficiently and safely as much as possible. As a non-separable part of the life it has always played an important role in development of civilizations from distant past by realizing the requirement of people's travels and goods' transport. It shows a clear relation to the life quality and the lifestyle as a result of its dominant effect on economy, society, politics, and environment.

Side by side the benefits of development of transportation the tied-up hazards are always issues that are attempted to get minimized by efficient management. These potential problems come up through various shapes from environmental impact that is most often inevitable, to human safety issue that has a relatively more controllable nature. As its title suggests the principal threat of the human safety is transportation accident that has had a never stopping occurring from the earliest transportation in the history up to now. Among the three major way of air, marine and overland transportation, the overland transportation has the highest selectivity world-widely because of economy considerations and sometimes as a constraint. This in turns counts for the highest portion of the transportation accident, accounting for the highest ranked causes of life loss beside the fatal diseases. Based on World Health Organization (WHO) reports about 1.3 million deaths out of the overall 56.4 million in 2015 was due to road accidents (Figure 1) and averagely, the worldwide annually total number in the recent years has fixed on 1.25 million fatality, and it is predicted that by 2030 the number of fatalities resulted by the road traffic accidents will become the fifth main cause of the life losses globally. The highest rate of road accident fatality belongs to the low-income countries with approximately 24.1 life losses yearly per 100 thousand population significantly comparable with the global rate that is 17.4. From the total number of road accident deaths approximately half are pedestrians, cyclists and motorcyclists with 22%, 4% and 23% respectively who have the least protection, whereas the proportions of car occupants and the group of the other types are 31% and 21% respectively. (WHO, 2015)

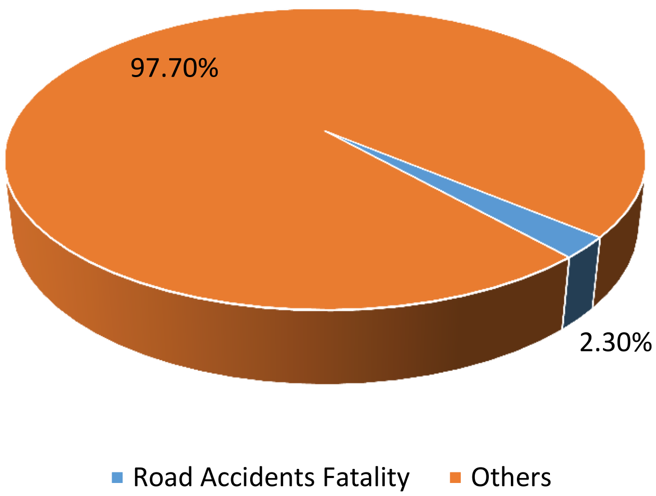


Figure 1: Proportion of Road Accident Deaths from All Deaths in 2015

The consequences of the transportation accidents are not limited to the fatalities only; if the involved persons are lucky enough to survive, they may face severe injuries, disabilities and mutilation that would annoy them and their families physically and psychically for the entire their rest life, let alone the economical burdens they would incur. Furthermore, besides the disastrous outcomes the involved persons suffer from, the social costs constrained to the society, including impact on development and health, is another detrimental result of the transportation accidents to an extent that the road traffic injuries claim a cost of almost 3 percent of GDP for the governments. (WHO, 2015).

## 1.2 Aim of study and scope

Perceiving such dreary statistics, most governments have always put endeavors to be taken to cope with this disaster at the top level of priorities that is important enough to assign huge budgets and resources to spend on researches, legislations and enforce the traffic regulations to strength the road safety such as reducing speed, increasing motorcycle helmet use, reducing drink–driving, increasing seat-belt use, increasing child restraint use, reducing drug–driving, reducing distracted driving, etc.

In this regard, in order to avoid of this calamitous phenomena, researchers have conducted numerous studies on various aspects adorably, in very narrow details, from trying to discover the roots and triggers to the efficient responses after the occurrence, so that the appropriate preventive and mitigating measures can be determined. From one aspect researchers can focus on the **occurrence** of the accidents (why does an accident happen?) while some others can focus on the accident **severity** issue (why does the severity level of the occurred accidents escalate?). The general trend for both is to identify the roots, which suggests the contributing factors, and then try to offer the efficient actions to prevent them, and in the second level of importance to mitigate the consequences after happening. To do that, digging data, analyze them and find the relationships between factors and the responses (dependent and independent variables) is most often a requisite that has been done using a broad spectrum of the old and novel offered methods and models.

Offering a model by which the predictions can be done, has always been as a concern for the researchers. No need to emphasize how importance the data circumstance is, as it is clear that most of the researches in this field are data based thus, accuracy and sufficiency of data is a vital prerequisite.

Hence, as the main goal of this study finding more facts about the transportation accidents has been aimed and in order to have a higher subtlety, the focus is on the severity of the accidents rather than the occurrence. Identification of factors that have influence on the severity of the accidents can undoubtedly help to lessen the traffic crashes death rate, as well as reducing the number of crashes with severe injuries.

The traffic safety improvement plans in the U.S. have most often been based on reduction of accidents frequency as the prioritization criteria of the safety projects; in other words, simply only the number of crashes are considered, or if the severe accident frequency has been considered, only the fatal accidents have been taken into account and the other levels of severity have not been measured often. Such an approach could be treated as a biased approach because it is not qualified as a perfect option for certain cases, for example in a county the number of accidents may be more than those occurred in another county while the crashes happened in the second county are much more severe and this fact gives more importance and higher priority to the second county. Similarly, as the second example, in a city although the number of fatal crashes are higher than those in another city, the number of serious injury accidents in the latter city may be significantly much greater in contrast to the first city. So the frequency-based approaches and fatal-crashes-frequency-based approaches are not suitable enough and introduce considerable errors (Milton, Shankar et al. 2008) and a more reliable and logically more accurate approach should be considered by which the above-mentioned contradictions would be resolved , which will be discussed further in chapter 3.

Besides, as a matter of additional scrutiny, among all factor categories including road-related, environment-related, vehicle-related and human-related factors, only the fourth category, and from that, only the drivers' risky behaviours (a subset of traffic violation behaviours) have been investigated in this study in order to have a narrower examination. The reason why only the drivers' risky behaviours were chosen to be analyzed is that from viewpoint of the author if the other factor categories (vehicle-related, road-related and environmental factors) can be improved even to the perfect level (assuming the best financial situation of the related agencies), the human-related factors are those which may stay unimproved yet as they completely depend on the human behaviours, out of control of the agencies to rectify. Hence, finding the roots of such erratic and hazardous behaviours, and the factors escalate the severity of the accidents due to these type of accidents, and then taking the appropriate countermeasures versus them is absolutely vital and underlying. To do that, in this study, data mining method has been used to identify counties with high-severity accidents. The locations of the accidents that are Texas counties, will be divided into some groups based on their similarities in terms of accident severity by using K-means clustering algorithm. As a result of this area partitioning the counties with different rate of accident severity will be identified that will be very helpful for managerial purposes for the involved parties such as legislators, implementers, and law enforcement agencies who could take advantages of more improvements, from aspects of making transportation rules and appropriate budget allocation, and by further studies on investigating some special suspect features which are somewhat similar between the counties in the same group, it can be understood what factors affect the severity of the crashes and caused these counties got around together in the same group. The objective of this study is to investigate the effectiveness of applying clustering analysis on the accident data.

The reason of using data mining instead of statistical models in this study is that the utilized dataset is rather large size and of course dimensional that makes usage of the traditional statistical techniques difficult because of the risk of offending their particular assumptions that can lead to incorrect results, as well as potential possibility of resulting in sparse data in large contingency tables (Chen, Jovanis et al. 2000).

## 1.3 Organization of thesis

The dissertation starts with a review on the former literature on applying clustering analysis in traffic safety, mainly the accident severity issue. Following that, the data-set and the study area is described in chapter three. Then, the methodology is discussed in chapter four. Afterward, analysis of the data and its result are presented respectively, and in the last chapter the thesis is concluded with a summary of the conducted study, and some recommendations for further studies are given as well as the limitations and shortcomings existed in this study.

# Chapter 2

# LITERATURE REVIEW

As it was mentioned before, the approach applied in this study is data mining. Data mining is analyzing data through different perspectives to achieve useful information especially discovering relationships between data and existing factors to solve problems. It can be described in other words as “ a novel technique to extract hidden and previously unknown information from the large amount of data”(Kumar and Toshniwal 2016), that includes 6 major classes of tasks, Anomaly detection (identifying unusual data by finding deviation, change and Outlier), Dependency modelling (explorations for relationships amid variables), Classification (to determine a new data belongs to which one of the predefined groups), Regression (trying to model the data with the least error by a function), Summarization (illustrating data in a compacted size information) and Clustering.

Clustering is the task of trying to group data (or objects) in a way that the data within a group has the highest similarity together but the similarity between data from different groups become as little as possible. Thus, a structure can be extracted from the data among which no known pattern was determined before. This method is known as an unsupervised learning algorithm because the true number of clusters and their shapes are not known. Another beneficial achievement of clustering besides grouping the similar data is reduction of the pre-existed heterogeneity between the data by creating groups (clusters) with higher homogeneous data that can raise the accuracy of the data analysis. As the description implies clustering is applied on the data which haven't been classified before and their output labels are not known. Hence, the best method to be applied on this study's data is clustering, since there are not pre-defined classes to generalize to each of these data. Therefore, in order to reach the highest interests of this study a broad literature review was directed.

Cluster analysis (CA) has been used in traffic safety with a relatively long history, when Karlaftis and Tarko (1998) classified Indiana State into three separate zones, urban, suburban and rural zones. Afterward, they examined if the age of the drivers had affected the accidents, by applying Negative Binomial (NB) regression models on the before segmented data in created clusters and once on the all the data integrated, and comparing the result of the two set of data a significant difference, statistically, was discovered.

Ng, Hung et al. (2002) used CA in combination with GIS (Geographic Information Systems) and NB regression models to create an algorithm by which he could estimate car-crash accidents number as well as assessment of the risks of the accidents.

Wong, Leung et al. (2004) clustered different traffic safety programs that was followed by a subgrouping process which grouped significant strategies of road safety as an evaluating method for a set of safety strategies that had been executed in Hong Kong.

Combining CA with probit model, Ma and Kockelman (2006) examined interdependency of Washington's accidents frequency with the usage characteristics, road geometry features and severity.

Solomon, Nguyen et al. (2006) used k-means and some other data-mining methods to assess the performance of red-light-signal monitoring cameras on improvement of traffic safety in the U.S. The outcome of that research was discovering relationships between fatal accidents and three variables, collision type, day time and drivers' demography.

Depaire, Wets et al. (2008) applied CA (Latent Class Cluster, LCC) to segment the accident data of occurred during 1997 to 1999 in Brussels, Belgium into seven clusters with different accident types and then used Multinomial Logit (MNL) models technique to analyze the data in the clusters once, and once the entire integrated data where comparing the results of those two a significant difference between them was revealed and hidden information as a result of clustering was discovered.

Analyzing a set of run-off accidents on two-lane roads data in Spain, by means of CA, Pardillo-Mayora, Dominguez-Lira et al. (2010) made a calibration on hazardous index.

Park and Lord (2009) used LCC in analysis of car-crash data. Also, this method was used by Park et al. (2010) for the same purpose.

De Ona, Lopez et al. (2013) segmented accident data on rural highways of Spain by means of LCC first, and then used Bayesian Networks (BNs) for identification of the principal factors involved in car-crash severity for the clustered data once and once for the whole data to see if there was any hidden relationship between the data variables. In that research clustering was done on the accidents (on the percentage of each variables' level at each of Slightly Injury and Fatal or Sever injury accidents) that created four clusters, then 13 not-characterizer variables were eliminated and only 5 variables remained by which the clusters were labeled (named). Then BN method was applied on the clusters once and once on the entire data to identify the most contributor factors of the crash severity and see if the clustering had any effect if clustering had discovered hidden relationships.

Alikhani, Nedaie et al. (2013) applied k-means and Self-Organizing Maps to demonstrate the effect of pre-clustering of data on the final accuracy of classifications, where 7035 recorded data related to accidents happened in 2011 in Iran was classified into six descriptive classes.

Dogru and Subasi (2015) tried to compare clustering models performance by evaluating their effectiveness on accident detection, by means of a simulated car-crash where they offered a model for detection of accidents based on position and velocity of the vehicles.

Mohammad M. Molla and Matthew L. Stone (2014) applied CA to verify the performance of Ordinary Kriging method that had been used for interpolation of a GIS data series where counties of Dakota were clustered into Cluster1 (Low), Cluster2 (Medium), Cluster3 (High) and Cluster4 (Severe) by single linkage method, based on the number of fatalities, then the revealed differences was justified by addressing the socio-economical characteristics of the corresponding counties to each cluster such as density and being business hubs. A limitation of this study is that the severity of the accidents has been rated based on the all influential factors including: human-related, road-related, vehicle-related and environment-related, hence, it is not possible to differentiate the effect weight of each of these factors. Also, only the fatal accidents have been considered and the accidents with other levels of severity (such as serious injury) have not been taken into account.

Sachin Kumar and Durga Toshniwal2 (2016) applied k-means to cluster 87 locations of Dehradun District of Uttarakhand State (India) into three groups, high-frequency, moderate-frequency and low-frequency accident zones based on their frequency count ( 7327 recorded road crashes occurred from 2009 to 2014) and then, used association rule mining method in order to characterize the obtained zones from clustering. A limitation of this study was that the dataset used did not contain accident-related information such as the drivers' related details (e.g. the vehicles' speed) and therefore, the result of the study was quite general. Also, the severity of the accidents were not taken into account and simply all accidents without differentiating the levels of severity were considered.

Mohammad M Molla (2016) clustered the U.S. states (using hierarchical clustering, single linkage method) into seven clusters based on 45 major driver-related factors that had contributed to the fatal accidents occurred in 38 years (1975-2012) in those states. These factors in turn identified 13 principal components, as a result of doing a principal components analysis. As a result of this research it was revealed that Texas, California, Mississippi, Florida, Pennsylvania, and Ohio had large number of traffic fatalities so that each one formed a one member cluster. Apart from the identified clusters, it was concluded that only 23 factors out of the primary 99 driver-related factors had affected the occurred accidents significantly. An issue of this study was that the scale of areas clustered was too big that still leaves somewhat heterogeneity; the scale could be minified to smaller district units such as counties of each state in order to obtain more detailed information. Moreover, the number of factors considered as the clustering variable was pretty high that suggests an improper distribution of significance-in-contribution, and focusing on lower number of factors with the highest effect on accident severity would have made more sense. Furthermore, that study also has focused on the fatal level of severity only, and the other severity levels such as serious injury have been ignored.

Using k-means Feng, Li et al. (2016) clustered bus drivers involved in fatal bus accidents in U.S. states during 2006 to 2010 years, into three clusters. In that study the risk factors of fatal bus accident severity were investigated to drivers in different types using an ordered logistic model. As a result of this study it was concluded that different types of drivers show different behaviors while confronting the same risk factors.

Chen, Li et al. (2016) used CA to identify the key contributing factors in high number fatality and injury accidents in China where four main factors among a total number of 49 were identified after a primary Principal Component Analysis of the data. In that research firstly an expert team identified 49 contributing factors based on two main references, then the author categorized the factors into 4 categories.

Afterward, Principal Component Analysis was done to order the factors ascendingly and obtain the most important factors and reduce the numbers of factors; and then these 4 factors were clustered into primary cluster c(including speeding 66.3% and overloading 32.6% ) and secondary cluster (roadside lack and slippery). Then groups with high principal component values were chosen for further analysis in order to prioritize countermeasures. Finally, the appropriate counteractions were suggested as prevention actions. The same limitation as those in the latter study exists in this research too and the researchers have considered the all category factors, not focusing on a certain category.

In this study it has been tried to focus on the above-expressed limitations in order to achieve more accurate results and to reveal more hidden facts. To realize this aim, the following considerations has been regarded:

1- Considering only the driver-related category of accident severity contributing factors; and among them only the three most important risky behaviors (a subset of traffic violation behaviors), accidents with: alcohol drunk drivers, distracted drivers and speed involved.

2- Clustering locations in a smaller scale (counties).

3- Considering other levels of accident severity in addition to fatalities (incapacitating injury accidents, non-incapacitating injury accidents, possible injury accidents and non- injury accidents).

# Chapter 3

# STUDY AREA AND DATA

## 3.1 Study Area

The study area is Texas, the second largest state of the United States of America by population and extent with 28.45 million population (estimated by 2017) and approximately 695,662 km$^2$ area, located on the south central area of the country's map as it can be seen in Figure 2 (Wikipedia). This state includes 254 counties counting for a total 473,375 kilometer long road network that has ranked Texas as the first among the U.S. states (Figure 3) (Jackson and Sharif 2016).

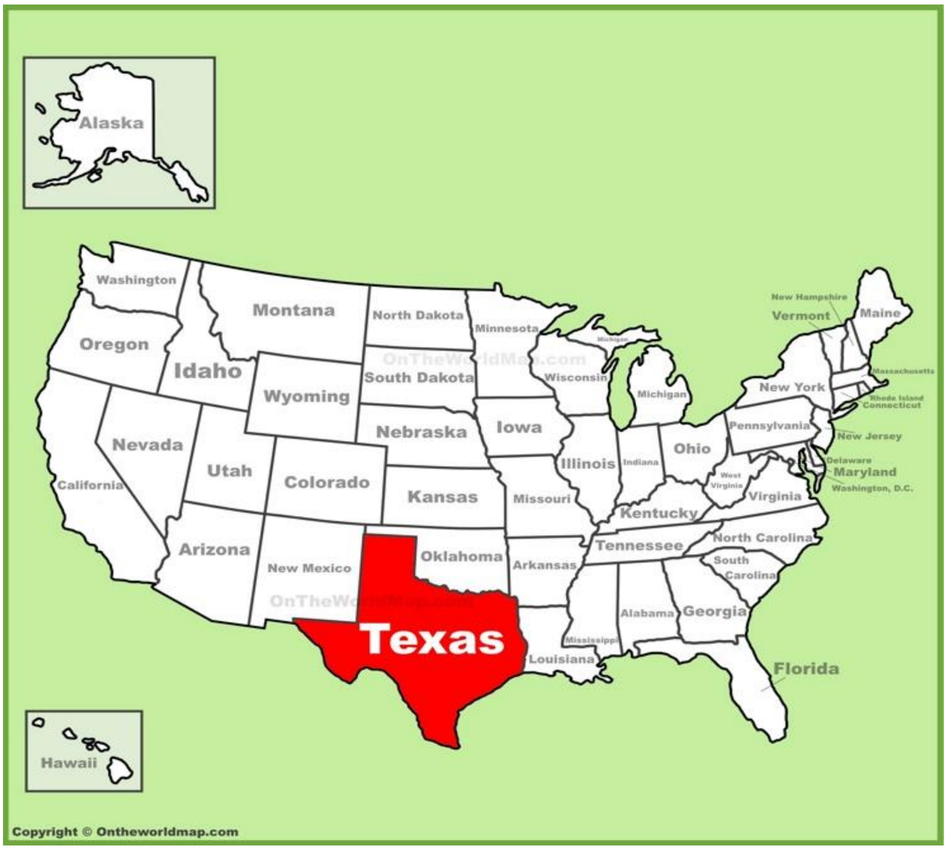


Figure 2: Geographical position of Texas in the United States

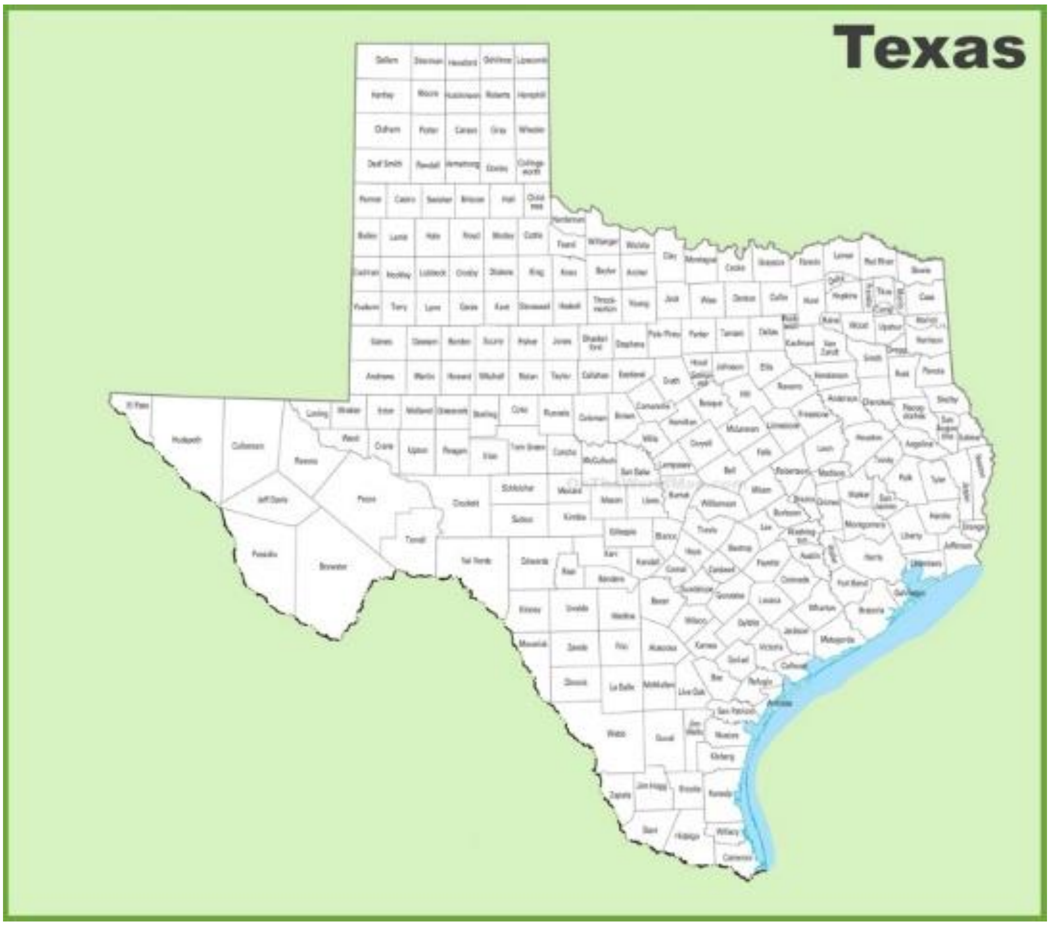


Figure 3: Texas Counties

Many relevant researches on identifying regions with severe traffic crashes have been conducted but for Texas counties specifically, no conducted research was found. Hence, this study will be the first one and unique research for the Texas district. Although, Jackson and Sharif (2016) carried out a study on the rain-related fatal accidents spatial distribution within Texas counties.

## 3.2 Data

The accident data analyzed in this study was obtained from official website of Texas Department of Transportation (available to public). From these data, we retrieved traffic accidents of 2013 to 2015 period. The reason why three years duration period was selected is that judging and inference on cause-and-effect relationship of traffic accidents is not easy over the short run, say one year; "This period should be short enough to embank structural changes in road and traffic conditions, but still long enough to limit any biased effects for random fluctuations." (Depaire, Wets et al. 2008).

The dataset on the mentioned online reference has been segmented into various classes such as zones, type of accidents, type of persons involved, involved contributing factors and etc. Furthermore, the number of accidents has been distributed according to the corresponding counties of Texas in which the accidents had happened, and categorized into crash severity levels (fatal, incapacitating, non-incapacitating, possible injury and non-injury accidents). The integrated data (statewide crashes, from 2013 to 2015) is enclosed in Appendix A.

The total number of the recorded accidents in Texas counties from 2013 to 2015 is 1,442,431 based on the dataset; that is summation of 445,899, 477,955 and 518,577crashes in 2013, 2014 and 2015 respectively. According to these statistics the number of accidents has increased by 7.2 percent rate from 2013 to 2014, while this rate grew to 8.5% from 2014 to 2015 that shows a rising acceleration in accident frequency. Nevertheless, the fatal accidents did not comply the same trend as the numbers promisingly indicate a 2% reduction in the period 2014 to 2015 from 3190 to 3138 fatal crashes respectively (Figure 4). Equivalently, Texas roadways Fatality Rate[1] in 2015 was 1.43 life losses per hundred million vehicle miles traveled that reflects 2.05% drop from the year before then. But contrariwise, comparing 2014 with 2013 a 5% upsurge was witnessed. (WHO).

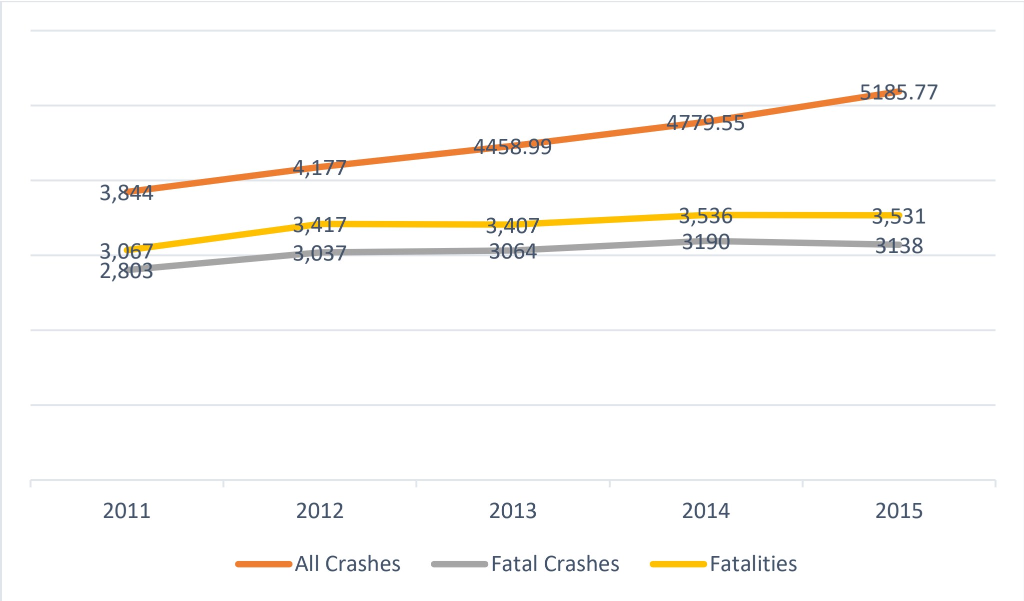

Figure 4: Changes in Accidents, Fatal Accidents and Fatalities during 2011-2015 period in Texas

As a primary and a general information Table 1 displays some interesting facts in relation to the total accidents happened in Texas counties within 2013 to 2015:

Table 1: Counties with the Maximum and Minimum Rates in 2013 to 2015 Period

| Variable | Maximum | Minimum |
|---|---|---|
| Accident frequency (All accidents) | Harris (299,296) | Foard (26) |
| Number of accidents per 100000 Daily Vehicle Mile (in 2015) | Jack (236) | Zavala (12) |
| $\frac{\text{Total accidents}}{\text{Registered Vehicles}} * 100$ | Loving (27.3%) | Zavala (1.5%) |
| Fatal accidents frequency | Harris (1,070) | Throckmorton (0) |
| $\frac{\text{Fatal accidents}}{\text{All accidents}} * 100$ | Coke (12%) | Briscoe (0%)<br>Throckmorton (0%) |

Since this study intends to focus on the main "drivers' hazardous behavior", only the accidents that involved three factors of alcohol drunk driver, over-speeding and distracted drivers have been considered and analyzed.

# Chapter 4

# METHODOLOGY

In this study K-means clustering method is applied to seek the possible existence of severe traffic accidents clusters among Texas counties by means of Python programming language as the language for writing the algorithm code. In order to accomplish the analysis, the pre-analysis steps were taken as follow:

1- Extract the required data
2- Calculate the ratios as the dimensions of the dataset and then transform them
3- Selecting the clustering type
4- Determining the number of the clusters
5- Writing the algorithm

All of the steps in the proposed method are depicted in Figure 5.

## 4.1 Extracting the required data

Since the focus was on the drivers' risky behavior factors, the data related to three principal contributor factors, corresponding to each of the counties, was selected to be analyzed: accidents with "Driving Under the Influence (DUI)[2] Alcohol drivers", "Speeding"[3] and "Distracted Drivers"[4] (ASD). These three factors were the only available driver-related factors in the dataset but important enough as they presented in almost half of the all occurred crashes ( averagely, 43% of the accidents had involved with these three) and more than half of the fatal crashes had involved with these three factors (56% averagely).

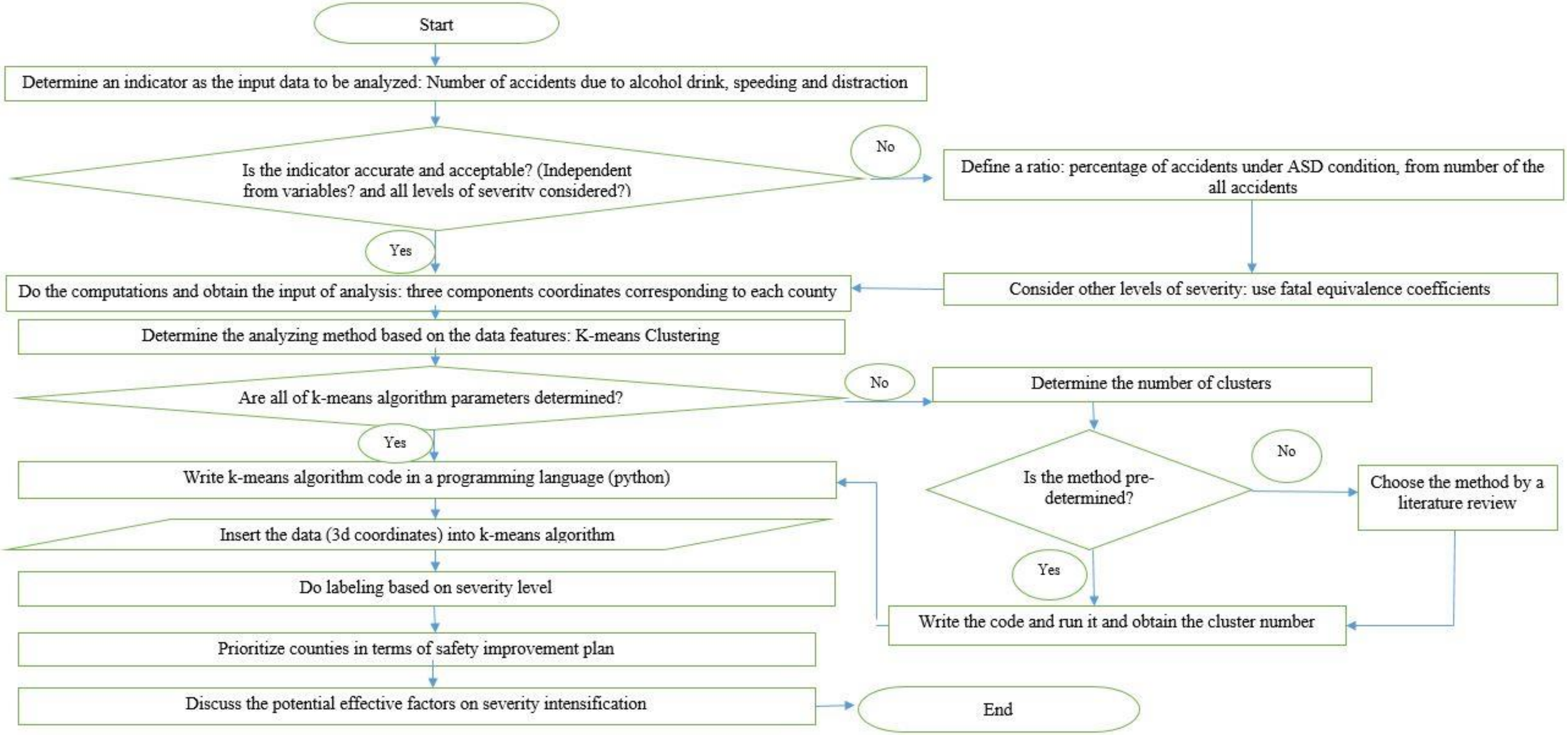


Figure 5: Process Chart of the Study Activities

## 4.2 Calculating the ratios and put them as the dimensions of the multidimensional dataset

To compliance with the argument about an acceptable severe-crashes-frequency-based approaches that was discussed earlier in introduction, and in order to attain a suitable and accurate measure as the criteria of accident severity that was required to be independent from variables such as population and vehicle number that vary wildly from a county to another one, firstly the equivalent impact of injury accidents relative to a fatal accidents was evaluated. To do that a literature review was done. Feng, Li et al. (2016) mentioned to the comprehensive fatality and injury relative values, offered by National Highway Traffic Safety Administration (NHSTA) through a publication (The Economic and Societal Impact of Motor Vehicle Crashes, 2010, revised by (Kahn 2015)) where each level of accident severity in terms of injury by body region had been given a fatal-equivalence coefficient based on average economic and societal costs each type of injury imposes. Based on that scale system (MAIS scale system) the second highest level (following fatality level, obviously, with coefficient 1) is level 5 that corresponds to an occupant with multiple injuries and has been given coefficient 0.6209, while other four lower levels have the coefficients 0.2790, 0.1183, 0.0484 and 0.0047 from level 4 to level 1 respectively. Then in order to accordance to a different nominal system which our dataset was presented based on it, KABCO scale that consists of levels, K: killed (fatality[5]), A: incapacitating injury[6], B: non-incapacitating injury[7], C: possible injury[8] and O: no apparent injury[9], a translation between these two scale systems was done that resulted in the coefficients as following:

Level K (killed): 1

Level A (incapacitating injury): 0.1107

Level B (non-incapacitating injury): 0.0310

Level C (possible injury): 0.0148

Level O (no apparent injury): 0.0049

Having obtained these coefficients, the number of accidents occurred at each level as the levels mentioned above was multiplied by the corresponding coefficients and then summed up within per each factor of the mentioned three driver-related factors (ASD) and the obtained figure was named Figure of severity (FOS).

Secondly, producing a ratio which could realize the issue of independency was essential. Therefore, five shapes for the best-indicator ratio were nominated as following:

(1) Portion of FOS of the 3 driver-related factors (ASD) from FOS OF all crashes.

    This ratio clearly reflects contribution of drivers' hazardous behaviour to the overall fatality, thus, it gives an appropriate module to identify the counties in which the drivers' fault highly affects the fatality of the accidents. But, if this ratio is concentrated on, the outcome would be limited to the shape of the distribution of accidents between different factors only, and therefore, the magnitude of the ASD-related accidents corresponding to each county could not be differentiated; for instance, it would not be possible to make sure county A is in more critical situation than county B.

(2) Portion of crashes with the 3 driver-related factors (ASD) from all crashes.

This ratio is a meaningful and usable criteria too, as it can be considered as an index showing the counties in which the drivers have the highest rate of recklessness (violation).

(3) Portion of the total FOS of all crashes from all crashes.

Although very general, this ratio is very reliable as a criteria to compare the vulnerability of different counties' vehicle occupants that suggests possible drawback in multiple variables such as weakness of the roadways, vehicles, human physics, rescue operations at after-accident time, etc.

(4) Portion of FOS of each of the 3 driver-related factors (ASD) from all crashes corresponding to each of the 3 driver-related factors.

This one can indicate a conditional probability that shows the probability of facing a severe accident threat due to driving under each of those three conditions and if the accident occurs.

(5) Portion of FOS of each of the 3 driver-related factors (ASD) from all crashes.

This ratio is a special case of the 3$^{rd}$ ratio, which focuses on vulnerability in terms of due to driver-related factors.

Each of these ratios could be used as a nifty criterion for analytical purposes, each one with different beneficial outcomes. But, for this study the most suitable one that would describe the main concept of severity weight effect of each of the three factors in the best way, was opted to be ratio 5, since it indicates the contribution and position of drivers' hazardous behaviours in the accidents severity well.

The obtained ratios including all five ratios are shown in Appendix B and their summary is shown in Table 2 in which the 3 most critical (most severe) counties in each case, are indicated.

Table 2: The Three Most Critical Counties in Case of Each of the 5 Ratios

| Ratio | Description | The 3 most critical counties |
|---|---|---|
| (1) | FOS of accidents with alcohol drink influence / FOS of all accidents | Knox (68%)<br>Collingsworth (66%)<br>Stonewall (53%) |
| | FOS of accidents with speeding involved / FOS of all accidents | Borden (68%)<br>Edwards (53%)<br>Jeff Davis (53%) |
| | FOS of accidents with distraction involved / FOS of all accidents | Cottle (71%)<br>Brewster (55%)<br>Bexar (47%) |
| (2) | Accidents with alcohol drink influence / all accidents | Blanco (17%)<br>Kent (16%)<br>Coke (15%) |
| | Accidents with speeding involved / all accidents | Real (44%)<br>Jeff Davis (39%)<br>Oldham (37%) |
| | Accidents with distraction involved / all accidents | Maverick (60%)<br>Bexar (52%)<br>Brewster (50%) |
| (3) | FOS of all accidents / all accidents | Coke (15%)<br>Foard (13%)<br>Zavala (10%) |
| (4) | FOS of accidents with alcohol drink influence / all accidents with alcohol drink influence | Motely (100%)<br>Hansford (53%)<br>Stonewall (50%) |
| | FOS of accidents with speeding involved / all accidents with speeding involved | Kinney (34%)<br>King (20%)<br>Collingsworth (19%) |
| | FOS of accidents with distraction involved / all accidents with distraction involved | Coke (35%)<br>Collingsworth (24%)<br>Foard (16%) |
| (5) | FOS of accidents with alcohol drink influence / all accidents | Collingsworth (6%)<br>Coke (4%)<br>Stonewall (4%) |
| | FOS of accidents with speeding involved / all accidents | Real (4%)<br>Borden (4%)<br>Sterling (3%) |
| | FOS of accidents with distraction involved / all accidents | Foard (4%)<br>Cottle (3%)<br>Coke (3%) |

The obtained numbers from the selected ratio, ratio 5, which was inserted into the clustering analysis as the input, is presented in Appendix C. As an example for obtaining ratio 5, the three obtained ratios for county *Anderson* is illustrated below:

Total crashes: 2540

Fatal crashes with alcohol drunk drivers: 6

Incapacitating crashes with alcohol drunk drivers: 15

Non-incapacitating crashes with alcohol drunk drivers: 43

Possible injury crashes with alcohol drunk drivers: 16

Non-injury crashes with alcohol drunk drivers: 72

→ FOS for crashes with alcohol drunk drivers = 6+ (0.1107)*(15) + (0.031)*(43) + (0.0148)*(16) + (0.0049)*(72) = 9.6

SO, alcohol related ratio equals to the quotient of the second obtained number by the first one, which is 9.6 divided by 2540 equal to 0.00378.

In the same way the ratios of the other two factors, speeding and distraction involved were obtained 0.00589 and 0.004599 respectively. Afterward, because the scale of the values was too small, a transformation was done by multiplying them in 1000. Thus, coordinates (dimensions) of county Anderson are [3.8, 5.9, 4.6].

## 4.3 Selecting the clustering type (K-means)

Generally speaking, some clustering models are probability model-based, where the created clusters differ from each other depending on their data probability distribution; while the other type of clustering techniques are similarity-based, meaning that the endeavor is to maximize the intra-cluster similarity and the inter-cluster dissimilarity. If the objects' features are continuous, some distance functions are used while for clustering data with qualitative features some similarity measures are applied (Depaire, Wets et al. 2008). The similarity-based techniques can be parted into two main approaches, partitioning approach (e.g. K-means) and hierarchical approach (e.g. Ward's method, single linkage method). Partitioning clustering divides the data into some non-overlapping clusters so that per each data necessarily belongs to exactly one cluster, whereas, the hierarchical clustering creates overlapping clusters with sub-clusters in turn that gives a set of nested clusters as a tree at the end.

Choosing the appropriate clustering model depends on the features of the data that is going to be analyzed, as well as the purposes of the analysis. Some of these factors are as following:

- number of clusters
- number of data
- shape of dataset
- distribution of data
- volume of clusters whether should be similar or could vary freely
- geometry (metric used)

The clustering model which fits the current data the best, and realizes the above mentioned factors, is K-means algorithm. K-means algorithm is a fast algorithm practically (it is among the fastest clustering algorithms), but it falls in local minima. That's why it can be useful to restart it several times. K-means clustering is a method by which the data are partitioned into some clusters so that the data placed in each cluster have the minimum possible distance from the centroid point of that cluster (as the similarity criteria) where the centroids of the clusters are determined randomly at first. The name k-means is derived from ‘k’ that is the number of the clusters that are selective and predetermined, and ‘means’ that refers to the means of the data in each cluster that is the so called centroid and therefore it underlies the centroid models. The algorithm of k-means is an iterative process consisted of five stages that starts with selecting the cluster numbers, which implies having a prior knowledge of the dataset, and is followed by the second step, choosing the initial centroids for the expected clusters where although can be randomly, a special care on choosing suitable points is very helpful since the number of iteration depends on these initial centroids. As the third step, each data is assigned to its nearest centroid and in this way the primary clusters are created that may not be optimum yet in terms of having the highest similarity (least distance to centroids). So, as the next step new centroids of these clusters are found and superseded to the primary centroids. Then, step three and four are repeated and this loop continues as long as the centroids converge enough and don’t change anymore. Mathematically, k-means function can be expressed as Equation 1:

$$D_i = \sum_{j=1}^{N_i} [d(Xij, Ci)]^2 \quad (1)$$

Where Di refers to the distortion of ith cluster, $N_i$ is the total number of objects that cluster i holds, $X_{ij}$ is the jth object in cluster i, $C_i$ is the central point (centroid) of cluster i and d ($X_{ij}$,$C_i$) shows the distance between object $X_{ij}$ and the centroid $C_i$. Consequently, summation of the all clusters’ distortions, $S_k$ (Presented in Equation 2), can be assessed a measure of quality of clustering by which the least summation indicates the best clustering result.

$$S_k = \sum_{i=1}^{k} D_i \quad (2)$$

Where k is the clusters number.

The reason of selection K-means among the various models is that:

1- The number of data is medium (254 data)
2- Not too many clusters are expected
3- Geometry is flat (not a specific shape is expected)
4- The similarity criterion is distance between points (distance between three coordinates corresponding to per each county that represent the ratios).

K-means is the one that suits these features very well, whereas, the other models of clustering do not adhere these factors better than k-means. For example, DBSCAN is used in data that have outliers and this algorithm excludes the outliers to be included in clusters, but here all data are real and should be taken into account. Similarly, Hierarchical clustering is sensitive to noise and outliers and also tends to break large clusters and is biased towards globular clusters.

## 4.4 Determining the number of the clusters

Number of clusters either could be predetermined beforehand of the analysis run or is determined automatically during running the clustering algorithm, depending on the type of the clustering; for example DBSCAN clustering doesn't need the number of clusters as an input since the number of clusters are determined during creation of the clusters simultaneously, whereas, k-means clustering requires the number of clusters as an input. Sometimes the purposed categorization determines the number of clusters, for example if the data under analysis must be grouped into 3 categories (low, medium and high), this value necessitates the number of clusters to be equal to three. But normally, in order to find the best value as the clusters number, clustering algorithms are run for a few times, while per time a different value of K is given and then based on a predefined criterion such as sum of cluster distortions, or a visually assessment (that can become complicated in multidimensional dataset (Pham, Dimov et al. 2005)) the value of K that yields the best result, is selected. Literature shows that a few methods have been used to determine the clusters number in most of the previous researches among which following methods have been applied more:

- Minimum Message Length (MML) criteria, used by Figueiredo and Jain (2002); in this approach when the number of the created clusters are relatively high some close clusters are merged together to reduce the MML criterion.

- Minimum Description Length (MDL) method, used by Hansen and Yu (2001); similarly to the above method, this method tries to reduce the description length by removing centroids (reducing k) to the least possible description of clusters.

- Bayes Information Criterion (BIC) and Akiake Information Criterion (AIC).

- Gap statistics, used by Tibshirani, Walther et al.(2001), Juan de O˜na et al, (2013) , Depaire et al, (2008) and Shumin Fenga et al, (2016) and Sachin Kumar (2016) .

- Dirichlet Process (DP), used by Ferguson, (1973) and Rasmussen, (2000);

- Silhouette analysis, used by Mahdi Alikhani(2013).

However, some other estimation models have been offered such as *Rule of Thumb* that is an empirical technique by which the number of clusters can be calculated by equation k = (n/2)^0,5, where n is the total number of data.

In this study we applied two methods which were found to be the best and the most used methods to obtain cluster number for k-means modeling, **Silhouette** analysis and **Elbow** method, since in the K-means algorithm, the criterion is to minimize clusters' distortion and these two techniques perform based on this criterion.

Furthermore, an addition visual assessment and a Minimum Message Length (MML) criteria were taken into account when the created clusters corresponding to three different values for k (k=3, 4, 5) were graphically assessed in order to attain a better result.

### 4.4.1 Silhouette analysis

Silhouette analysis is a technique with which the closeness between the points in one cluster to the points in adjacent clusters are measured, referred to as silhouette coefficient (Equation 3), and plotted graphically, thus the number of clusters can be assessed visually.

$$S = {}^{l_1 - l_2}/_{max(l_1, l_2)} \qquad (3)$$

Where $l_2$ is the average distance between an object in a cluster and all other objects belonging to the same cluster, and $l_1$ is the mean distance between an object and all other objects in the nearest adjacent cluster. (Alikhani, Nedaie et al. 2013).

In a simpler word, silhouette coefficient shows how well each object lies within its cluster (Rousseeuw 1987). The measured amount always gets a value in [-1,+1] range where closeness to bound +1 means the better result (greater matching of the clusters (Alikhani, Nedaie et al. 2013)), whereas, a close to zero value implies highest closeness of the sample to a decision boundary amid two adjacent clusters, and the negative values mean wrong allocations of the objects to the clusters.

In this study silhouette analysis was done, by using python programming language to write the algorithm code and run it, on a [2,50] range as the under-test values for k (Appendix D, Figure D-1).

The output is shown in Figure 6 and as it can be seen when the cluster number equals to 3, the highest silhouette coefficient is returned that is 0.514; although, the greatest value belongs to k=2 (S=0.567) that is ignored because of giving a too general information (description) in the case of selecting k=2 .

```
For n_clusters=2, The Silhouette Coefficient is 0.567202653322
For n_clusters=3, The Silhouette Coefficient is 0.514054588887
For n_clusters=4, The Silhouette Coefficient is 0.35103888371
For n_clusters=5, The Silhouette Coefficient is 0.338014672952
For n_clusters=6, The Silhouette Coefficient is 0.323695347451
For n_clusters=7, The Silhouette Coefficient is 0.359108156456
For n_clusters=8, The Silhouette Coefficient is 0.333654603169
For n_clusters=9, The Silhouette Coefficient is 0.310264691592
For n_clusters=10, The Silhouette Coefficient is 0.303775860294
For n_clusters=11, The Silhouette Coefficient is 0.299462456147
For n_clusters=12, The Silhouette Coefficient is 0.286969551101
For n_clusters=13, The Silhouette Coefficient is 0.313877033911
For n_clusters=14, The Silhouette Coefficient is 0.310031623185
For n_clusters=15, The Silhouette Coefficient is 0.282540570716
For n_clusters=16, The Silhouette Coefficient is 0.283844123767
For n_clusters=17, The Silhouette Coefficient is 0.275860491472
For n_clusters=18, The Silhouette Coefficient is 0.289282206809
For n_clusters=19, The Silhouette Coefficient is 0.294787027854
For n_clusters=20, The Silhouette Coefficient is 0.27941833858
For n_clusters=21, The Silhouette Coefficient is 0.284374980863
For n_clusters=22, The Silhouette Coefficient is 0.297755511431
For n_clusters=23, The Silhouette Coefficient is 0.267219223703
For n_clusters=24, The Silhouette Coefficient is 0.257852834031
For n_clusters=25, The Silhouette Coefficient is 0.267623493897
For n_clusters=26, The Silhouette Coefficient is 0.280404613484
For n_clusters=27, The Silhouette Coefficient is 0.274960691655
For n_clusters=28, The Silhouette Coefficient is 0.269047540512
For n_clusters=29, The Silhouette Coefficient is 0.260642336775
For n_clusters=30, The Silhouette Coefficient is 0.276099413617
```
Figure 6: Output of Silhouette Analysis

### 4.4.2 Elbow technique

In this technique the k-means algorithm is run several times for an ascending set of k values (for example k=2 to k=20) and the within-cluster Sum of Squared Errors (SSE) in each case is calculated (Equation 4). Then, a line chart is plotted for the obtained SSE versus values of k. If the shape of the chart is assumed as a human arm, the point corresponding to the elbow of this arm can be selected as the desired number of clusters, since it is the point which gives a small value of k while still keeps the SSE quantity low enough, and these two outcomes are the objectives of clustering.

$$\text{SSE} = \sum_{j=1}^{K} \sum_{i=1}^{n} \left(x_i - C_j\right)^2 \qquad (4)$$

Therefore, as the second method this technique was applied for determination of the cluster number, by trying k in the range [2, 50]. The code script written in python and the output is shown in Figures D-2 in Appendix D and Figures 7 respectively.

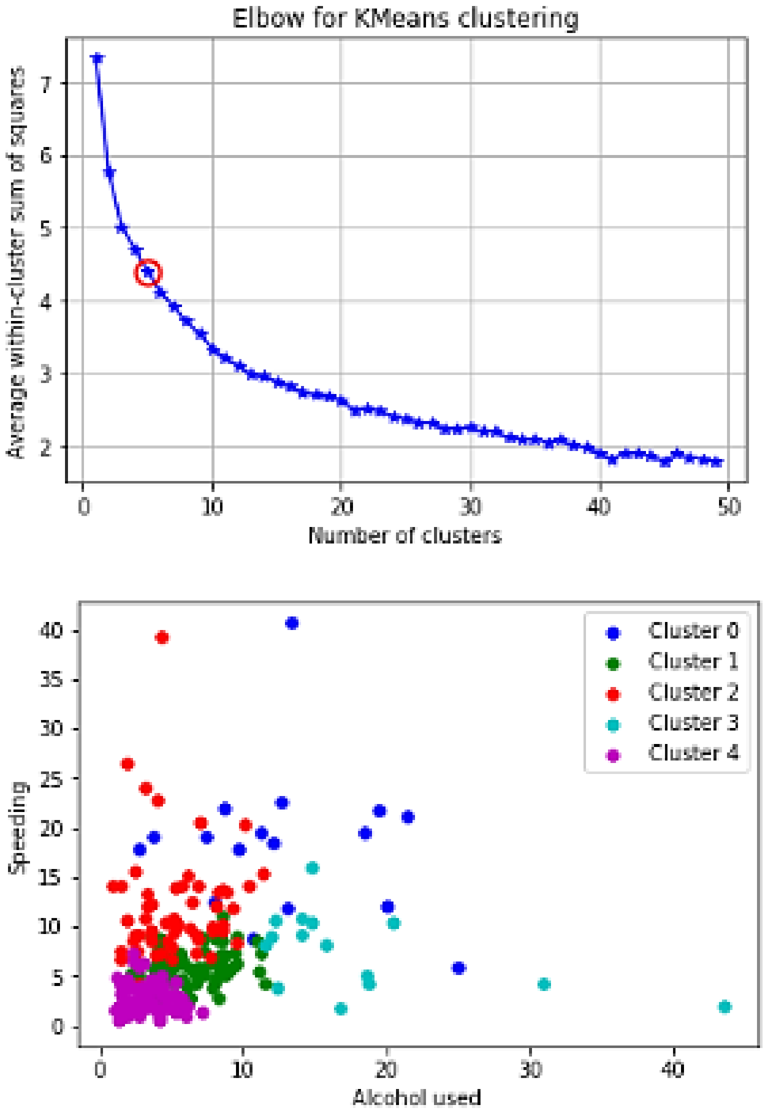


Figure 7: Output of Elbow Method

As it can be perceived from the chart, the elbow whereabouts is on k=8. However, the scatter chart (colored dots) shows a k=5 as the clusters number where a lack of cluster numbers can be seen though (for example, an extra cluster assigned to the farthermost blue dots).

Taking the results of the two used methods into account, two choices were selectable, k=3 and k=5. Therefore, the average of these two, k=4, was considered too; and then a visually assessment after doing the clustering was done as the supplementary criteria. Thus, the clustering was done for these three number of clusters, which is presented in the following section.

## 4.5 Writing the algorithm (firstly determine the parameters)

Having determined the clusters number, the algorithm can be written now. Thus, the algorithm code was scripted via python, based on the 5 step process explained in part three of this chapter. The other parameters besides the cluster number was defined as following:

- The initialization method (init) was determined to be ‘kmeans++’ that is a function in python by which the initial cluster centroids are selected in a way that the convergence speed rises up.

- The number of the k-means algorithm running times with different centroids (n_init), was given 100, to be high enough.

- Maximum repetition number of the algorithm for a single run (max_iter), was given 500, in order to reach a conservatively high accuracy.

- The Relative tolerance with regards to inertia to declare convergence, was given 0.0001 that is low enough comparing to the scale of the data values.

The k-means algorithm code written in python is shown in Figure D-3 in Appendix D. Afterward, in order to ensure the correct functionality of this algorithm it was tested on Iris dataset[10] that is a well-known dataset and the result of the analysis showed its correct performance. Figure D-4 and Figure D-5 show the code and the result respectively.

# Chapter 5

# ANALYSIS, RESULTS AND DISCUSSION

## 5.1 Run the algorithm and the results returned

The k-means algorithm was run in order to identify any structure among the data, and to classify different counties that are grouped in the separated clusters based on the characteristics of each cluster. Figures 8 to 10 display the three dimensional plot of the clustered counties for k=3, 4 and 5 respectively in which, the dots represents the three obtained ratios of each of the counties. The counties in the same cluster are differentiated with the same color.

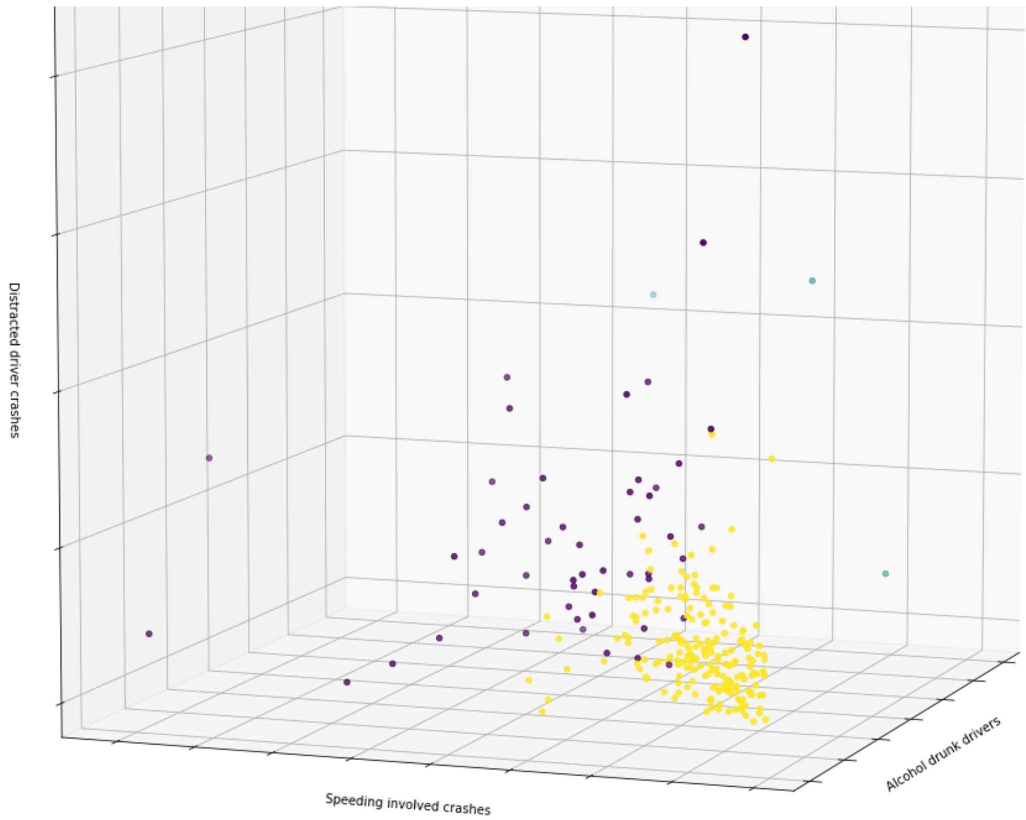


Figure 8: Three Dimensional Plot of the Clustered Counties, for k=3

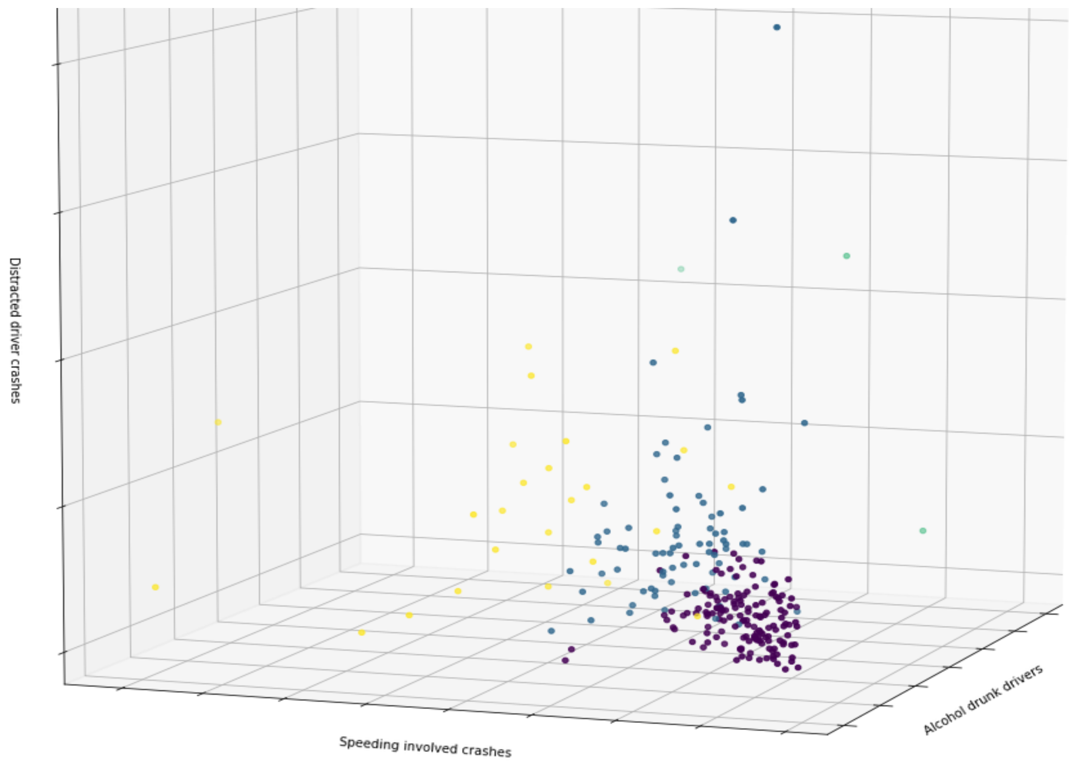


Figure 9: Three Dimensional Plot of the Clustered Counties, for k=4

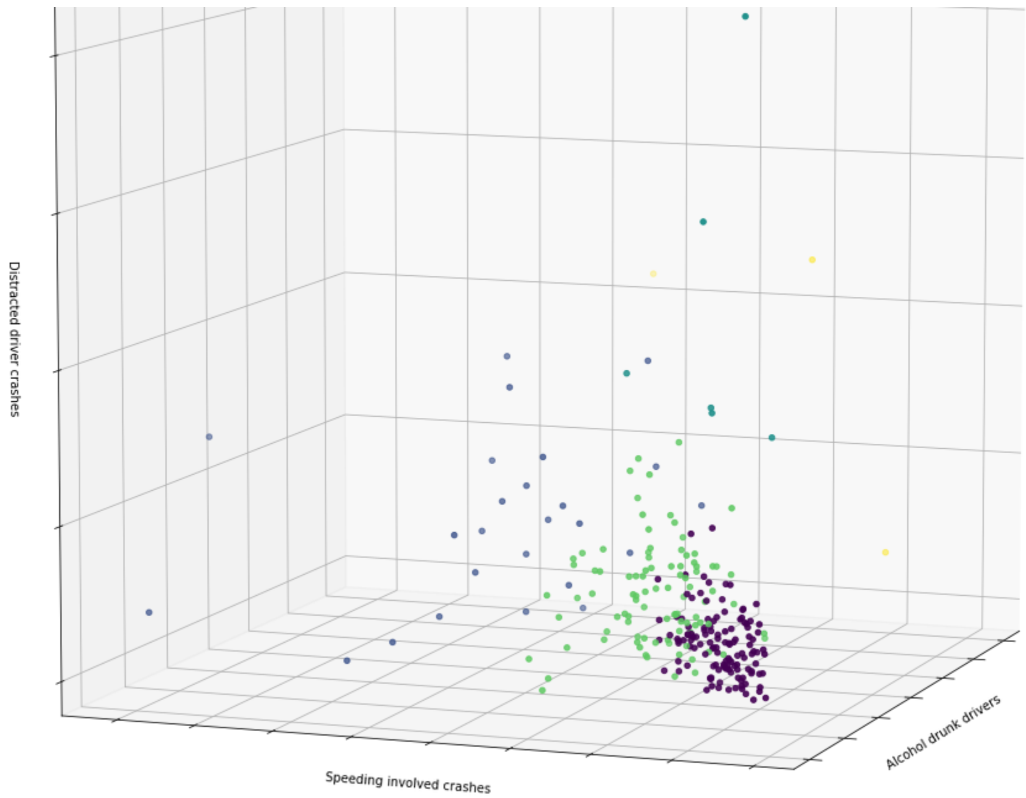


Figure 10: Three Dimensional Plot of the Clustered Counties, for k=5

The visual assessment implies that k=3 (Figure 9) look insufficient and in comparison with k=4, the latter one shows a better clustering. Besides the visual evaluation, the centroids of clusters created by each of the three k were compared pairwise. Table 3 shows how the clusters' features vary as the number of clusters changes.

Table 3: Variation of the Cluster Features by Varying the Cluster Number

| **Number of Clusters (k)** | **Number of Counties in Each Cluster** | **Centroids of The Clusters** |
|---|---|---|
| K=3 | C0: 50<br>C1:3<br>C2:201 | C0:[ 11, 15, 11]<br>C1:[ 47, 10, 17]<br>C2:[ 5, 5, 5] |
| K=4 | C0: 149<br>C1:77<br>C2:3<br>C3:25 | C0:[ 4, 4, 4]<br>C1:[ 7 , 9, 9]<br>C2:[ 47, 10, 17]<br>C3:[ 14, 20 , 9] |
| K=5 | C0:126<br>C1:25<br>C2:6<br>C3:94<br>C4:3 | C0:[ 4, 4, 4]<br>C1:[ 14, 20, 10]<br>C2:[ 4, 5, 25]<br>C3:[ 8, 9, 7]<br>C4:[ 47, 10, 17] |

Now, in order to choose one of the three possible results shown in Table 3, a good approach is comparing the range of centroids' coordinates in per each case of cluster size and find the one by which more succinct characterization of the clusters can be described that is actually using MML method. For the first case, k=3, distances between each pair centroids are significantly high, thus it is not reasonable to merge any pair. For k=4, although C0 and C1 are somewhat close to each other they can stay two separate clusters to provide a little more information. For k=5, C0 and C3 can be merged together as their centroids are too close to each other, and therefore this choice can be omitted. Thus, the final choice is k=4.

The obtained clusters for k=4 are presented in Table 4.

Table 4: Clusters

| **Cluster** | **Counties** | | | | |
|---|---|---|---|---|---|
| Cluster 0 | Anderson | Colorado | Hays | Maverick | Sherman |
| | Angelina | Comal | Hemphill | McLennan | Smith |
| | Aransas | Comanche | Henderson | McMullen | Starr |
| | Archer | Concho | Hidalgo | Medina | Swisher |
| | Atascosa | Coryell | Hockley | Menard | Tarrant |
| | Austin | Dallam | Hood | Midland | Taylor |
| | Bastrop | Dallas | Hopkins | Milam | Throckmorton |
| | Bee | Dawson | Houston | Montgomery | Titus |
| | Bell | Deaf Smith | Howard | Moore | Tom Green |
| | Bexar | Delta | Hunt | Motley | Travis |
| | Bowie | Denton | Jack | Nacogdoches | Upshur |
| | Brazoria | Dewitt | Jasper | Navarro | Uvalde |
| | Brazos | Dickens | Jefferson | Newton | Val Verde |
| | Briscoe | Ector | Jim Wells | Nolan | Van Zandt |
| | Brooks | El Paso | Johnson | Nueces | Victoria |
| | Brown | Ellis | Kaufman | Orange | Walker |
| | Burleson | Floyd | Kendall | Palo Pinto | Waller |
| | Caldwell | Fort Bend | Kenedy | Panola | Washington |
| | Calhoun | Freestone | Kent | Parker | Webb |
| | Callahan | Galveston | Kimble | Parmer | Wharton |
| | Cameron | Garza | King | Pecos | Wichita |
| | Camp | Gillespie | Kleberg | Polk | Wilbarger |
| | Castro | Gray | Lamar | Potter | Willacy |
| | Chambers | Gregg | Lampasas | Randall | Williamson |
| | Cherokee | Grimes | Lavaca | Robertson | Wilson |
| | Childress | Guadalupe | Liberty | Rockwall | Wise |
| | Clay | Hale | Limestone | Rusk | Yoakum |
| | Cochran | Hardin | Lipscomb | San Patricio | Young |
| | Coleman | Harris | Lubbock | Scurry | Zapata |
| | Collin | Harrison | Matagorda | Shelby | |

Table 4 (Continue): Clusters

| Cluster | Counties | | | | |
|---|---|---|---|---|---|
| Cluster 1 | Andrews | Erath | Irion | Madison | Reeves |
| | Armstrong | Falls | Jackson | Marion | Refugio |
| | Bailey | Fannin | Jim Hogg | Martin | Roberts |
| | Bosque | Fayette | Jones | Mason | Runnels |
| | Brewster | Foard | Karnes | McCulloch | San Jacinto |
| | Burnet | Frio | Kerr | Mills | Shackelford |
| | Carson | Gaines | Kinney | Mitchell | Stephens |
| | Cass | Glasscock | Lamb | Montague | Sutton |
| | Cooke | Goliad | Lasalle | Morris | Terry |
| | Cottle | Gonzales | Lee | Ochiltree | Trinity |
| | Crane | Grayson | Leon | Oldham | Tyler |
| | Crockett | Hall | Live Oak | Presidio | Ward |
| | Dimmit | Hardeman | Llano | Rains | Wheeler |
| | Donley | Hartley | Loving | Reagan | Winkler |
| | Duval | Hill | Lynn | Red River | Wood |
| | Eastland | Hutchinson | | | |
| Cluster 2 | Stonewall | Collingsworth | Coke | | |
| Cluster 3 | Bandera | Culberson | Hansford | Sabine | Sterling |
| | Baylor | Edwards | Haskell | San Augustine | Terrell |
| | Blanco | Fisher | Jeff Davis | San Saba | Upton |
| | Borden | Franklin | Knox | Schleicher | Zavala |
| | Crosby | Hamilton | Real | Somervell | Hudspeth |

## 5.2 Infer the results of the analysis

Having found the clusters, the next step is to characterize the clusters based on the similarity feature that had gathered counties in the same cluster. In this regard, the cluster centroids, that are the mean point of each cluster, were considered as the criterion of pairwise contrast between the clusters and the means of characterization since they represented the average amount of the counties' accident severity indices, and thus, they could show the characteristics of the counties in terms of influence of the three driver-related factors. Hence, using a Likert scale the clusters were categorized such that the coordinates below 5 were labeled as Low (L), those between 5 and 10 were labeled as Moderate (M) and the coordinates higher than 10, but below 15 were branded as High (H), and those above 15, Severe (S), referring to comparative severity extent of the accidents occurred due to each of the 3 main driver-related factors.

So, the clusters could be characterized as following:

Cluster 0: L. L. L

Cluster 1: M. M. M

Cluster 2: S. H. S

Cluster 3: H. S. M

As the labels suggest, cluster 2 contains the counties with the most critical situation since they have seized two severe ranks for alcohol and distraction and one high rank for speeding factor. These counties are: Stonewall, Collingsworth and Coke that have been shaded with black color in the map, shown in Figure 11.

Cluster 3 could be titled as the second critical cluster as it has gotten one high label, one severe and one medium for alcohol, speeding and distraction respectively (Figure 11, marked by red color). The third grade is given to cluster 1 whose counties have been categorized as medium ranked for the whole three factors; and finally the least critical situation belongs to cluster 0 as all counties situated in this cluster have been classified as low.

Hence, the aim of this study was achieved and in this way priority of rectification and safety improvement plans should be allocated to alcohol usage and distraction issues for the counties in cluster 2 and speed limit violation issue in the counties in cluster 3 which are in the severe degree.

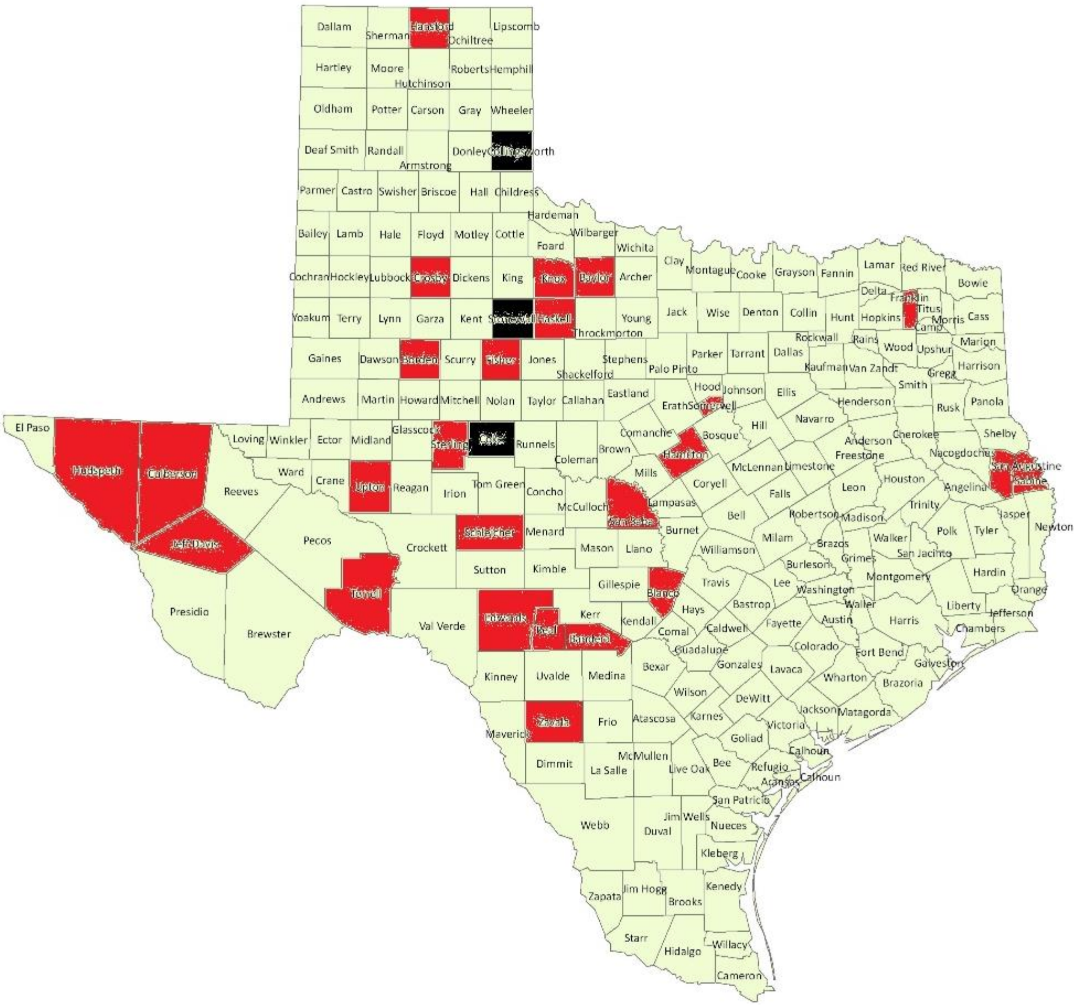


Figure 11: Counties in Cluster 2 and 3, the Most Critical Counties (Marked By Black and Red Color)

## 5.3 Discussion

Having identified the counties with different situations of traffic safety in terms of severity, the main question when comparing them together is that, why a county from cluster 2 (S.M.S), say Stonewall, suffers from higher proportion of severe accidents under ASD conditions, than the counties from the other three clusters? That makes us to identify the causes, roots and triggers. Afterward, following identification of the causes, the next task will be enacting appropriate countermeasures to prevent or mitigate them.

Generally, the factors which have influence on exacerbation of severity of the accidents when comparing a county with higher severity situation than another county, may be categorized into two general classes: the pre-accident related factors and the post-accident related factors.

### 5.3.1 Pre-accident related factors

As the pre-accident related factors many potential items can be addressed including but not limited to:

- Higher speed at the time of accident because of roads with higher speed limits: as it is clear the more the speed of the vehicle at the accident instant, the more severe the accident. So, maybe the average of speed at the time of accident for the involved vehicles in a county is greater than those ones' in the other county, leading to higher severity.

- Coincidence with other contributing factors such as not using seat belts: the possibility of existence of additional factors in the accidents happened in one county while absent in the other county can be an exacerbating cause of higher severity. As an instance, if due to insufficiency of safety regulation enforcements in a county, obedience of the vehicle occupants to buckling up the seat-belts, is lower than those in the other counties, the severity of injures will increase obviously.

- Higher weakness of the vehicles: if the periodic technical examinations of the vehicles are not done sufficiently in a county rather than the other counties, because of lower degree of cautiousness of the vehicle owners or because of foible in the police-inspection system, an accident occurred under the same conditions of the ASD in that county becomes more severe due to malfunction of the unsecured vehicles. Or, maybe difference in the economic situation can be addressed here rather than culture, which can affect the safety and security level of the vehicles, as the models and brands of the cars vary. To support this idea, the average of personal income at Texas counties were inquired and interestingly it was found out that almost all counties in clusters 2 and 3 are the counties in which the personal income is less than the mean of the whole Texas ($ 54,386 annually) that is shown in Figure 12 (Bureau of Economic Analysis, U.S. Department of Commerce). Counties in cluster 2 and cluster 3 are marked by black and red dots respectively.

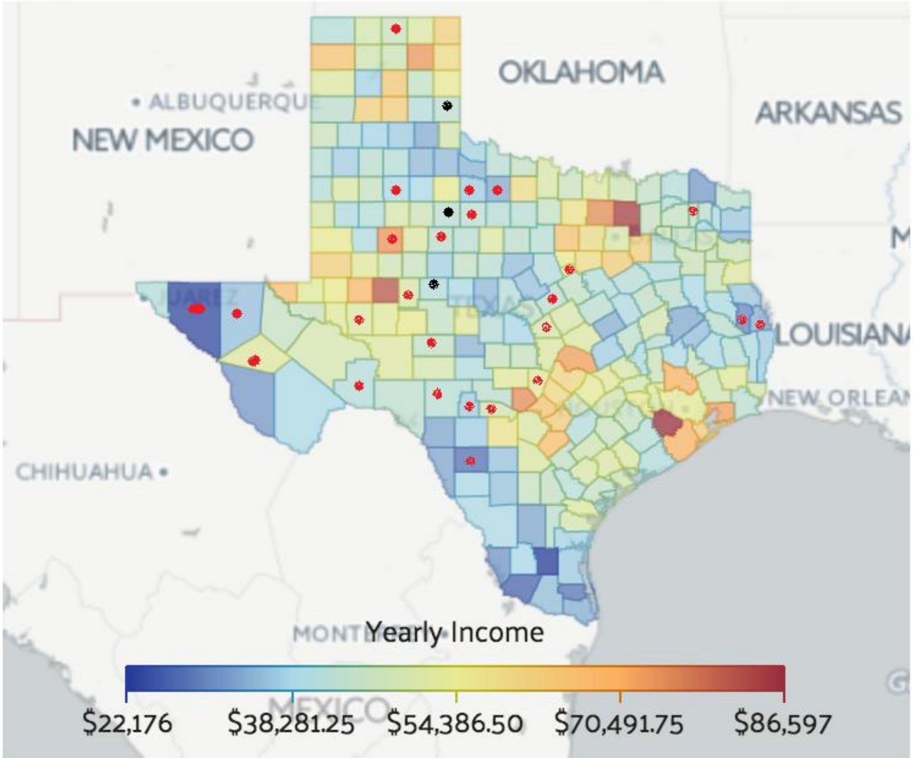

Figure 12: Personal Income of Texas Counties in 2015

- Higher degree of drunkenness: if the drivers consume larger amount of alcohol, normally their degree of unconsciousness will escalate, leading to increase in the secondary factor that is speeding or drop of their stamina or slower reaction.

- Greater number of the occupants present in the vehicles: if the average number of the vehicles' occupants in a county is higher comparing with those in the other counties, normally the probability by which an occupant gets injured hard and the accidents lies under severe accident category, rises up.

- Poor road-related and geographical-related factors: the areas with sloped roads, higher precipitation and therefore slippery pavements, have the ability to heighten the severity of the occurred accidents.

Meanwhile, besides the fore-mentioned factors two other factors that are very important but have not been determined in the data-set are:

- Type of the accidents depending on the road features: for example if because of the road features the accidents mostly tend to head-on collisions, the severity rises up.

- Type of the involved persons. For example, in the data-set collisions with pedestrians or cyclists, who have the least safety protections, have not been segmented.

### 5.3.2 Post-accident related factors

The factors which make the occupants involved in accidents face higher hardships and greater degrees of trauma, can be attributed to the following:

- Rescue operations level: Any lag in both informing the accident to the related organizations, and then dispatching the rescue team for delivering the emergency services can exacerbate the injured persons. Moreover, insufficiency of facilities, equipment, skills and treatments can strongly worsen the wounded persons. Hence, each of these factors should be concentrated and inquired in order to discover the factors that have caused the intensified severity of the accidents in the counties in cluster 2 and cluster3. If a significant insufficiency and drawback in terms of time and facilities will be disclosed, the appropriate treatments should be determined to improve the effectiveness of emergency services, reducing the rescue operation time and therefore lessening the number of victims or severity of injuries.

- Physical weakness of the involved occupants: the average age of the involved occupants in the accidents may affect their injury severity, as the older the involved persons are, the higher damage they incur. So, in a county the average age of the occupants might have been significantly higher, toward elderly, rather than those in the other counties, leading to greater level of severity. In the meantime, ethnicity of the vehicle occupants may affect the physical conditions so that those with certain ethnicity have lower stamina and resistance in comparison with the other people with different races (comparing whites, blacks, Hispanics and Asians together who are the predominant races in Texas). So, counties with higher population proportion of the ethnicity with the relatively lower stamina may be included hugely in the critical clusters. Based on this opinion, Nkhoma et al. (2016) conducted a study by which they showed that variation of ethnicity and gender had affected poisoning mortality, following identification clusters of accidental poisoning death amid Texas counties.

If the dataset encompassed further information describing the situation of the above-mentioned factors (drivers characteristics, type of accidents, etc.), it would be possible to discover the main causes by comparing them in two different counties.

From another viewpoint, answering that question (why a county from cluster 2 (S.M.S), say Stonewall, suffers from higher proportion of severe accidents under ASD conditions, than the counties from the other three clusters) depends in turn on the proportion of number of the accidents under ASD conditions from the overall number of the accidents. If the counties in cluster 2 have that ratio in higher amounts, it may imply that all the factors discussed above are in similar levels in all counties (because they were suggested for the case in which all counties were assumed to have almost identical ratio of accidents under ASD conditions from the overall number of the accidents) and different causes should be explored that are mostly frequency-related factors instead of severity-related factors. Actually, a new question would come up in this case: why a county from cluster 2 (S.M.S), say Stonewall, suffers from higher proportion of accidents under ASD conditions, than the counties from the other three clusters. Answering this question is less complicated and such factors as following can be pointed:

- Lack of strict enforcement on regarding the traffic safety regulations on behalf of police and other related agencies to the drivers and occupants, in that county.

- Commitment of drivers and occupants to obey the regulations related to alcohol consumption, speed limit violation and careless driving (using cell-phones, etc.) is not as much as what the drivers in other counties do.

Therefore, the counties with highest ratio of accidents under ASD conditions from the overall number of the accidents (ratio 2) were identified: for alcohol drunk, Blanco, Coke and Kent, for speeding, Oldham, Real and Jeff Davis and for distraction Bexar, Brewster and Maverick, while counties in cluster 2 are Stonewall, Collingsworth and Coke; so only Coke is the county that had the highest ratio of accidents with drunk driver and same time located in cluster 2, thus, all factors discussed in answering the first question should be investigated. After discovering the main effective factors, the appropriate countermeasures such as regular inspections, firm controlling, and guiding drivers by holding mandatory classes, special and tailored to each of those three factors (ASD) should be determined and enacted in the critical counties.

# Chapter 6

# CONCLUSION AND RECOMMENDATION

## 6.1 Conclusion

Road accidents count for one of the main reasons of deaths and disabilities globally, with other unpleasant outcomes impacting the society. Hence, never-stopping efforts to reduce the frequency and the severity of the accidents have been being made by identifying the causes by means of various scientific techniques and then proceeding appropriate countermeasures. A usual approach in this regard is identifying the locations with higher accident frequency or more severe accidents, so that the contributing factors special to those locations would be identified and treated properly by implementing strategic safety plans. Therefore, as a case study, Texas counties were selected and the dataset related to accidents occurred within three years of 2013 to 2015 were obtained, and in accordance to the data features, clustering analysis was chosen as the applied method, and among the various clustering techniques K-means was opted because of its compatibility with the selection criteria. Meanwhile, among various categories of effective factors, the driver-related factors were selected for analysis and from this category three driver-risky-behaviors, alcohol drunk, speeding and distraction of driver were considered in order to attain more detailed facts. Also, instead of just the occurrence issue, the severity of the accidents were focused on, where in addition of only the fatal crashes, the crashes with other levels of severity were considered too by assigning them fatality equivalence coefficients. As the input of the clustering analysis the most proper ratio among five possible ratio was firstly opted and then calculated for each of the counties. Next, based on two main techniques, silhouette and elbow, and supplement techniques (visual assessment and MML technique) the number of the clusters were selected to be four. Afterward, the analysis was carried out that resulted in identification of four clusters with 3, 25, 77 and 149 counties which the most critical cluster was the one with three counties (Stonewall, Collingsworth and Coke) and was labeled S.M.S (severe, medium, and severe, referring to the ASD ratios), and the second most critical cluster was the one with 25 counties (Bandera, Baylor, … Zavala) and the other two clusters with lower levels of severity were those with 77 and 149 counties respectively. After the analysis and labeling the counties, the suspect reasons of difference in severity of the accidents between the counties in two different clusters were discussed, where some potential factors categorized in two general groups (pre-accident and post-accident) were addressed.

## 6.2 Recommendation

A limitation of this study is absence of a secondary analysis on the counties in the most critical clusters to seek the main factors that have exacerbated the severity of the accidents under ASD conditions, which was because of nonexistence of the related data such as type of accidents that had not been distinguished separately for each county in the dataset source, and therefore, the existed numbers of the accidents and fatalities and injuries were summations of the all types like pedestrians, cyclists, buses, tractors, trucks, passenger cars, etc. Hence, as the further study data related to the addressed suspect factors pertaining to each of the counties should be gained and then be analyzed as sets of variables by using data-mining techniques such as Association Rule method to discover those of them which are identical between counties in same cluster and in this way it will be concluded that there are relationships between these factors and severity of accidents or in other word, variation of levels of these factors affects the severity level. Subsequently, following the state of the art of the improvement measures and corrective actions, new innovatory approaches can be offered in order to resolve the problem.

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# APPENDICES

## Appendix A: Number of Accidents of Each County and Each Year, and Obtained Ratio 3

| | All occurred accidents | | | | fatal crashes | | incapacitating crashes | | non-incapacitating crashes | | possible injury crashes | | non- injury crashes | | FOS | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| COUNTY | 2015 | 2014 | 2013 | TOTAL CRASHES | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | (3)- % of fatal crashes from all crashes |
| Anderson | 863 | 884 | 793 | **2540** | 26 | 1% | 68 | 3% | 408 | 16% | 390 | 15% | 1602 | 63% | 60 | 2% |
| Andrews | 225 | 366 | 294 | **885** | 29 | 3% | 47 | 5% | 171 | 19% | 89 | 10% | 528 | 60% | 43 | 5% |
| Angelina | 1709 | 1873 | 1831 | **5413** | 48 | 1% | 131 | 2% | 650 | 12% | 836 | 15% | 3619 | 67% | 113 | 2% |
| Aransas | 313 | 314 | 299 | **926** | 8 | 1% | 54 | 6% | 95 | 10% | 129 | 14% | 610 | 66% | 22 | 2% |
| Archer | 174 | 147 | 132 | **453** | 9 | 2% | 21 | 5% | 66 | 15% | 47 | 10% | 303 | 67% | 16 | 3% |
| Armstrong | 59 | 58 | 65 | **182** | 5 | 3% | 16 | 9% | 15 | 8% | 19 | 10% | 124 | 68% | 8 | 4% |
| Atascosa | 890 | 1006 | 933 | **2829** | 38 | 1% | 96 | 3% | 291 | 10% | 381 | 13% | 1975 | 70% | 73 | 3% |
| Austin | 610 | 514 | 515 | **1639** | 18 | 1% | 64 | 4% | 159 | 10% | 184 | 11% | 1189 | 73% | 39 | 2% |
| Bailey | 132 | 69 | 93 | **294** | 3 | 1% | 5 | 2% | 33 | 11% | 47 | 16% | 192 | 65% | 6 | 2% |
| Bandera | 304 | 324 | 287 | **915** | 22 | 2% | 79 | 9% | 181 | 20% | 86 | 9% | 523 | 57% | 40 | 4% |
| Bastrop | 1580 | 1312 | 1072 | **3964** | 50 | 1% | 221 | 6% | 476 | 12% | 581 | 15% | 2505 | 63% | 110 | 3% |
| Baylor | 76 | 61 | 71 | **208** | 12 | 6% | 15 | 7% | 33 | 16% | 25 | 12% | 122 | 59% | 16 | 8% |
| Bee | 350 | 419 | 446 | **1215** | 15 | 1% | 35 | 3% | 129 | 11% | 224 | 18% | 770 | 63% | 30 | 2% |
| Bell | 5524 | 5432 | 5463 | **16419** | 104 | 1% | 552 | 3% | 2208 | 13% | 2731 | 17% | 10327 | 63% | 325 | 2% |
| Bexar | 48289 | 42723 | 39694 | **130706** | 512 | 0% | 2780 | 2% | 11087 | 8% | 28217 | 22% | 80938 | 62% | 1978 | 2% |
| Blanco | 185 | 192 | 150 | **527** | 16 | 3% | 53 | 10% | 87 | 17% | 46 | 9% | 311 | 59% | 27 | 5% |
| Borden | 25 | 32 | 25 | **82** | 3 | 4% | 8 | 10% | 15 | 18% | 10 | 12% | 46 | 56% | 5 | 6% |
| Bosque | 160 | 170 | 153 | **483** | 12 | 2% | 26 | 5% | 86 | 18% | 69 | 14% | 286 | 59% | 20 | 4% |
| Bowie | 2154 | 1924 | 1869 | **5947** | 47 | 1% | 176 | 3% | 793 | 13% | 1198 | 20% | 3605 | 61% | 126 | 2% |
| Brazoria | 5244 | 4579 | 4400 | **14223** | 107 | 1% | 451 | 3% | 1505 | 11% | 2137 | 15% | 9709 | 68% | 283 | 2% |
| Brazos | 3842 | 3434 | 3286 | **10562** | 46 | 0% | 307 | 3% | 1844 | 17% | 1589 | 15% | 6549 | 62% | 193 | 2% |
| Brewster | 95 | 100 | 108 | **303** | 5 | 2% | 14 | 5% | 35 | 12% | 39 | 13% | 204 | 67% | 9 | 3% |
| Briscoe | 16 | 21 | 20 | **57** | 0 | 0% | 6 | 11% | 7 | 12% | 4 | 7% | 40 | 70% | 1 | 2% |
| Brooks | 154 | 203 | 200 | **557** | 12 | 2% | 28 | 5% | 41 | 7% | 83 | 15% | 387 | 69% | 19 | 4% |
| Brown | 586 | 576 | 536 | **1698** | 10 | 1% | 75 | 4% | 182 | 11% | 320 | 19% | 1062 | 63% | 34 | 2% |
| Burleson | 322 | 340 | 329 | **991** | 11 | 1% | 69 | 7% | 129 | 13% | 136 | 14% | 614 | 62% | 28 | 3% |

| | All occurred accidents | | | | fatal crashes | | incapacitating crashes | | non-incapacitating crashes | | possible injury crashes | | non- injury crashes | | FOS | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **COUNTY** | **2015** | **2014** | **2013** | **TOTAL CRASHES** | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | (3)- % of fatal crashes from all crashes |
| Burnet | 650 | 676 | 622 | **1948** | 35 | 2% | 135 | 7% | 301 | 15% | 291 | 15% | 1151 | 59% | 69 | 4% |
| Caldwell | 590 | 701 | 648 | **1939** | 24 | 1% | 79 | 4% | 219 | 11% | 325 | 17% | 1195 | 62% | 50 | 3% |
| Calhoun | 319 | 246 | 272 | **837** | 8 | 1% | 51 | 6% | 103 | 12% | 119 | 14% | 523 | 62% | 21 | 3% |
| Callahan | 316 | 284 | 268 | **868** | 16 | 2% | 23 | 3% | 101 | 12% | 97 | 11% | 623 | 72% | 26 | 3% |
| Cameron | 7649 | 6426 | 5879 | **19954** | 83 | 0% | 403 | 2% | 1756 | 9% | 4472 | 22% | 12254 | 61% | 308 | 2% |
| Camp | 204 | 169 | 174 | **547** | 7 | 1% | 35 | 6% | 63 | 12% | 87 | 16% | 341 | 62% | 16 | 3% |
| Carson | 123 | 116 | 115 | **354** | 10 | 3% | 27 | 8% | 63 | 18% | 10 | 3% | 239 | 68% | 16 | 5% |
| Cass | 478 | 396 | 454 | **1328** | 21 | 2% | 66 | 5% | 203 | 15% | 203 | 15% | 810 | 61% | 42 | 3% |
| Castro | 86 | 119 | 81 | **286** | 6 | 2% | 17 | 6% | 44 | 15% | 37 | 13% | 165 | 58% | 11 | 4% |
| Chambers | 1092 | 1042 | 1005 | **3139** | 44 | 1% | 133 | 4% | 350 | 11% | 326 | 10% | 2240 | 71% | 85 | 3% |
| Cherokee | 806 | 707 | 713 | **2226** | 32 | 1% | 100 | 4% | 310 | 14% | 329 | 15% | 1393 | 63% | 64 | 3% |
| Childress | 50 | 59 | 74 | **183** | 2 | 1% | 16 | 9% | 18 | 10% | 10 | 5% | 134 | 73% | 5 | 3% |
| Clay | 215 | 205 | 202 | **622** | 8 | 1% | 38 | 6% | 98 | 16% | 46 | 7% | 422 | 68% | 18 | 3% |
| Cochran | 37 | 26 | 30 | **93** | 2 | 2% | 6 | 6% | 24 | 26% | 9 | 10% | 50 | 54% | 4 | 4% |
| Coke | 29 | 41 | 15 | **85** | 10 | 12% | 13 | 15% | 24 | 28% | 11 | 13% | 26 | 31% | 12 | 15% |
| Coleman | 173 | 143 | 172 | **488** | 7 | 1% | 26 | 5% | 70 | 14% | 67 | 14% | 314 | 64% | 15 | 3% |
| Collin | 12849 | 11775 | 10477 | **35101** | 120 | 0% | 942 | 3% | 4711 | 13% | 6295 | 18% | 22305 | 64% | 573 | 2% |
| Collingswortl | 20 | 17 | 18 | **55** | 3 | 5% | 15 | 27% | 7 | 13% | 4 | 7% | 26 | 47% | 5 | 9% |
| Colorado | 640 | 573 | 547 | **1760** | 30 | 2% | 64 | 4% | 212 | 12% | 158 | 9% | 1281 | 73% | 52 | 3% |
| Comal | 2118 | 2025 | 1997 | **6140** | 57 | 1% | 226 | 4% | 732 | 12% | 997 | 16% | 3981 | 65% | 139 | 2% |
| Comanche | 185 | 160 | 139 | **484** | 7 | 1% | 22 | 5% | 78 | 16% | 51 | 11% | 323 | 67% | 14 | 3% |
| Concho | 52 | 54 | 30 | **136** | 3 | 2% | 15 | 11% | 20 | 15% | 18 | 13% | 77 | 57% | 6 | 4% |
| Cooke | 578 | 545 | 530 | **1653** | 30 | 2% | 92 | 6% | 240 | 15% | 268 | 16% | 978 | 59% | 56 | 3% |
| Coryell | 1002 | 911 | 1085 | **2998** | 21 | 1% | 119 | 4% | 443 | 15% | 394 | 13% | 1914 | 64% | 63 | 2% |
| Cottle | 8 | 16 | 16 | **40** | 1 | 3% | 3 | 8% | 7 | 18% | 6 | 15% | 22 | 55% | 2 | 4% |
| Crane | 61 | 75 | 71 | **207** | 6 | 3% | 4 | 2% | 41 | 20% | 19 | 9% | 134 | 65% | 9 | 4% |

| | All occurred accidents | | | | fatal crashes | | incapacitating crashes | | non-incapacitating crashes | | possible injury crashes | | non- injury crashes | | FOS | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| COUNTY | 2015 | 2014 | 2013 | TOTAL CRASHES | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | (3)- % of fatal crashes from all crashes |
| Crockett | 170 | 168 | 163 | 501 | 12 | 2% | 52 | 10% | 70 | 14% | 78 | 16% | 284 | 57% | 22 | 4% |
| Crosby | 54 | 74 | 54 | 182 | 5 | 3% | 14 | 8% | 31 | 17% | 22 | 12% | 108 | 59% | 8 | 5% |
| Culberson | 134 | 123 | 111 | 368 | 19 | 5% | 17 | 5% | 77 | 21% | 27 | 7% | 224 | 61% | 25 | 7% |
| Dallam | 222 | 166 | 180 | 568 | 9 | 2% | 16 | 3% | 52 | 9% | 29 | 5% | 440 | 77% | 15 | 3% |
| Dallas | 48999 | 43055 | 40894 | 132948 | 667 | 1% | 3724 | 3% | 16361 | 12% | 30456 | 23% | 74743 | 56% | 2403 | 2% |
| Dawson | 83 | 154 | 176 | 413 | 10 | 2% | 13 | 3% | 51 | 12% | 54 | 13% | 278 | 67% | 15 | 4% |
| Deaf Smith | 272 | 249 | 221 | 742 | 6 | 1% | 27 | 4% | 63 | 8% | 70 | 9% | 559 | 75% | 15 | 2% |
| Delta | 66 | 49 | 60 | 175 | 2 | 1% | 15 | 9% | 34 | 19% | 16 | 9% | 107 | 61% | 5 | 3% |
| Denton | 11649 | 9865 | 9039 | 30553 | 108 | 0% | 774 | 3% | 3368 | 11% | 5134 | 17% | 20308 | 66% | 474 | 2% |
| Dewitt | 417 | 411 | 376 | 1204 | 16 | 1% | 50 | 4% | 121 | 10% | 196 | 16% | 781 | 65% | 32 | 3% |
| Dickens | 37 | 34 | 22 | 93 | 1 | 1% | 4 | 4% | 10 | 11% | 9 | 10% | 69 | 74% | 2 | 2% |
| Dimmit | 215 | 241 | 305 | 761 | 22 | 3% | 37 | 5% | 58 | 8% | 176 | 23% | 435 | 57% | 33 | 4% |
| Donley | 76 | 80 | 67 | 223 | 4 | 2% | 17 | 8% | 19 | 9% | 15 | 7% | 167 | 75% | 8 | 3% |
| Duval | 154 | 146 | 180 | 480 | 12 | 3% | 29 | 6% | 65 | 14% | 84 | 18% | 268 | 56% | 20 | 4% |
| Eastland | 415 | 354 | 385 | 1154 | 22 | 2% | 38 | 3% | 126 | 11% | 140 | 12% | 816 | 71% | 36 | 3% |
| Ector | 2985 | 3306 | 3077 | 9368 | 137 | 1% | 265 | 3% | 1581 | 17% | 1521 | 16% | 5264 | 56% | 264 | 3% |
| Edwards | 42 | 54 | 37 | 133 | 2 | 2% | 18 | 14% | 41 | 31% | 10 | 8% | 58 | 44% | 6 | 4% |
| Ellis | 2393 | 2171 | 1901 | 6465 | 65 | 1% | 343 | 5% | 782 | 12% | 1030 | 16% | 4134 | 64% | 163 | 3% |
| El Paso | 18521 | 14322 | 13899 | 46742 | 173 | 0% | 668 | 1% | 4574 | 10% | 9111 | 19% | 30560 | 65% | 673 | 1% |
| Erath | 693 | 630 | 505 | 1828 | 35 | 2% | 115 | 6% | 304 | 17% | 251 | 14% | 1099 | 60% | 66 | 4% |
| Falls | 252 | 277 | 240 | 769 | 17 | 2% | 43 | 6% | 142 | 18% | 84 | 11% | 472 | 61% | 30 | 4% |
| Fannin | 337 | 329 | 337 | 1003 | 19 | 2% | 63 | 6% | 116 | 12% | 169 | 17% | 622 | 62% | 35 | 4% |
| Fayette | 545 | 476 | 511 | 1532 | 33 | 2% | 77 | 5% | 195 | 13% | 222 | 14% | 988 | 64% | 56 | 4% |
| Fisher | 99 | 83 | 79 | 261 | 8 | 3% | 16 | 6% | 25 | 10% | 27 | 10% | 182 | 70% | 12 | 5% |
| Floyd | 67 | 43 | 49 | 159 | 3 | 2% | 3 | 2% | 14 | 9% | 29 | 18% | 99 | 62% | 5 | 3% |
| Foard | 7 | 7 | 12 | 26 | 3 | 12% | 1 | 4% | 9 | 35% | 1 | 4% | 12 | 46% | 3 | 13% |

| | All occurred accidents | | | | fatal crashes | | incapacitating crashes | | non-incapacitating crashes | | possible injury crashes | | non- injury crashes | | FOS | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **COUNTY** | **2015** | **2014** | **2013** | **TOTAL CRASHES** | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | (3)- % of fatal crashes from all crashes |
| Fort Bend | 8808 | 7993 | 7224 | **24025** | 118 | 0% | 497 | 2% | 2208 | 9% | 3768 | 16% | 16939 | 71% | 380 | 2% |
| Franklin | 139 | 77 | 84 | **300** | 9 | 3% | 20 | 7% | 46 | 15% | 49 | 16% | 174 | 58% | 14 | 5% |
| Freestone | 560 | 584 | 486 | **1630** | 20 | 1% | 74 | 5% | 181 | 11% | 235 | 14% | 1092 | 67% | 43 | 3% |
| Frio | 216 | 230 | 192 | **638** | 15 | 2% | 43 | 7% | 106 | 17% | 92 | 14% | 372 | 58% | 26 | 4% |
| Gaines | 273 | 263 | 198 | **734** | 25 | 3% | 59 | 8% | 159 | 22% | 59 | 8% | 419 | 57% | 39 | 5% |
| Galveston | 6287 | 5520 | 5179 | **16986** | 97 | 1% | 398 | 2% | 1500 | 9% | 2507 | 15% | 11936 | 70% | 283 | 2% |
| Garza | 137 | 155 | 103 | **395** | 8 | 2% | 17 | 4% | 50 | 13% | 42 | 11% | 274 | 69% | 13 | 3% |
| Gillespie | 443 | 454 | 459 | **1356** | 14 | 1% | 100 | 7% | 195 | 14% | 143 | 11% | 888 | 65% | 38 | 3% |
| Glasscock | 84 | 126 | 102 | **312** | 12 | 4% | 23 | 7% | 60 | 19% | 27 | 9% | 190 | 61% | 18 | 6% |
| Goliad | 109 | 123 | 139 | **371** | 9 | 2% | 19 | 5% | 61 | 16% | 48 | 13% | 228 | 61% | 15 | 4% |
| Gonzales | 386 | 479 | 471 | **1336** | 31 | 2% | 72 | 5% | 198 | 15% | 191 | 14% | 822 | 62% | 52 | 4% |
| Gray | 463 | 419 | 407 | **1289** | 12 | 1% | 36 | 3% | 111 | 9% | 143 | 11% | 975 | 76% | 26 | 2% |
| Grayson | 1643 | 1563 | 1454 | **4660** | 64 | 1% | 274 | 6% | 915 | 20% | 775 | 17% | 2465 | 53% | 146 | 3% |
| Gregg | 3244 | 3251 | 3103 | **9598** | 64 | 1% | 201 | 2% | 1042 | 11% | 2477 | 26% | 5650 | 59% | 183 | 2% |
| Grimes | 649 | 576 | 510 | **1735** | 29 | 2% | 82 | 5% | 279 | 16% | 234 | 13% | 1075 | 62% | 55 | 3% |
| Guadalupe | 2261 | 2068 | 1948 | **6277** | 48 | 1% | 236 | 4% | 679 | 11% | 803 | 13% | 4375 | 70% | 128 | 2% |
| Hale | 595 | 487 | 432 | **1514** | 13 | 1% | 60 | 4% | 136 | 9% | 188 | 12% | 1060 | 70% | 32 | 2% |
| Hall | 64 | 55 | 69 | **188** | 4 | 2% | 10 | 5% | 24 | 13% | 12 | 6% | 137 | 73% | 7 | 4% |
| Hamilton | 81 | 117 | 121 | **319** | 14 | 4% | 41 | 13% | 53 | 17% | 24 | 8% | 183 | 57% | 21 | 7% |
| Hansford | 17 | 44 | 40 | **101** | 6 | 6% | 8 | 8% | 18 | 18% | 5 | 5% | 64 | 63% | 8 | 8% |
| Hardeman | 87 | 55 | 50 | **192** | 5 | 3% | 13 | 7% | 30 | 16% | 22 | 11% | 121 | 63% | 8 | 4% |
| Hardin | 763 | 797 | 726 | **2286** | 29 | 1% | 100 | 4% | 307 | 13% | 364 | 16% | 1447 | 63% | 62 | 3% |
| Harris | 110489 | 101814 | 86993 | **299296** | 1070 | 0% | 5550 | 2% | 23174 | 8% | 60777 | 20% | 198351 | 66% | 4274 | 1% |
| Harrison | 1563 | 1377 | 1343 | **4283** | 57 | 1% | 197 | 5% | 461 | 11% | 667 | 16% | 2821 | 66% | 117 | 3% |
| Hartley | 129 | 102 | 114 | **345** | 11 | 3% | 20 | 6% | 64 | 19% | 23 | 7% | 222 | 64% | 17 | 5% |
| Haskell | 75 | 108 | 77 | **260** | 13 | 5% | 15 | 6% | 37 | 14% | 26 | 10% | 164 | 63% | 17 | 7% |

| | All occurred accidents | | | | fatal crashes | | incapacitating crashes | | non-incapacitating crashes | | possible injury crashes | | non- injury crashes | | FOS | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| COUNTY | 2015 | 2014 | 2013 | TOTAL CRASHES | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | (3)- % of fatal crashes from all crashes |
| Hays | 3056 | 2562 | 2328 | **7946** | 52 | 1% | 323 | 4% | 1140 | 14% | 1205 | 15% | 5002 | 63% | 165 | 2% |
| Hemphill | 82 | 116 | 111 | **309** | 4 | 1% | 16 | 5% | 23 | 7% | 23 | 7% | 233 | 75% | 8 | 3% |
| Henderson | 916 | 907 | 868 | **2691** | 35 | 1% | 130 | 5% | 426 | 16% | 522 | 19% | 1536 | 57% | 78 | 3% |
| Hidalgo | 13535 | 12825 | 11497 | **37857** | 177 | 0% | 577 | 2% | 3701 | 10% | 10636 | 28% | 21042 | 56% | 616 | 2% |
| Hill | 764 | 675 | 706 | **2145** | 40 | 2% | 56 | 3% | 241 | 11% | 285 | 13% | 1497 | 70% | 65 | 3% |
| Hockley | 394 | 367 | 302 | **1063** | 16 | 2% | 34 | 3% | 153 | 14% | 158 | 15% | 693 | 65% | 30 | 3% |
| Hood | 752 | 753 | 657 | **2162** | 16 | 1% | 76 | 4% | 254 | 12% | 402 | 19% | 1383 | 64% | 45 | 2% |
| Hopkins | 599 | 526 | 567 | **1692** | 21 | 1% | 66 | 4% | 225 | 13% | 146 | 9% | 1204 | 71% | 43 | 3% |
| Houston | 344 | 332 | 287 | **963** | 18 | 2% | 70 | 7% | 161 | 17% | 139 | 14% | 560 | 58% | 36 | 4% |
| Howard | 694 | 789 | 727 | **2210** | 26 | 1% | 59 | 3% | 268 | 12% | 281 | 13% | 1499 | 68% | 52 | 2% |
| Hudspeth | 233 | 183 | 183 | **599** | 29 | 5% | 32 | 5% | 130 | 22% | 44 | 7% | 358 | 60% | 39 | 7% |
| Hunt | 1321 | 1112 | 974 | **3407** | 49 | 1% | 172 | 5% | 410 | 12% | 671 | 20% | 2020 | 59% | 101 | 3% |
| Hutchinson | 244 | 276 | 255 | **775** | 18 | 2% | 25 | 3% | 83 | 11% | 97 | 13% | 523 | 67% | 27 | 4% |
| Irion | 58 | 106 | 79 | **243** | 12 | 5% | 24 | 10% | 37 | 15% | 34 | 14% | 135 | 56% | 17 | 7% |
| Jack | 136 | 798 | 172 | **1106** | 12 | 1% | 22 | 2% | 40 | 4% | 65 | 6% | 366 | 33% | 18 | 2% |
| Jackson | 223 | 197 | 226 | **646** | 16 | 2% | 38 | 6% | 82 | 13% | 59 | 9% | 445 | 69% | 26 | 4% |
| Jasper | 447 | 497 | 490 | **1434** | 21 | 1% | 39 | 3% | 171 | 12% | 267 | 19% | 925 | 65% | 39 | 3% |
| Jeff Davis | 50 | 53 | 67 | **170** | 5 | 3% | 11 | 6% | 26 | 15% | 8 | 5% | 120 | 71% | 8 | 5% |
| Jefferson | 6233 | 5668 | 5255 | **17156** | 75 | 0% | 375 | 2% | 1866 | 11% | 3593 | 21% | 10851 | 63% | 281 | 2% |
| Jim Hogg | 50 | 61 | 49 | **160** | 5 | 3% | 5 | 3% | 12 | 8% | 65 | 41% | 66 | 41% | 7 | 5% |
| Jim Wells | 902 | 855 | 912 | **2669** | 32 | 1% | 67 | 3% | 251 | 9% | 600 | 22% | 1606 | 60% | 64 | 2% |
| Johnson | 2020 | 2001 | 2047 | **6068** | 58 | 1% | 335 | 6% | 896 | 15% | 933 | 15% | 3665 | 60% | 155 | 3% |
| Jones | 163 | 190 | 181 | **534** | 18 | 3% | 35 | 7% | 97 | 18% | 50 | 9% | 314 | 59% | 27 | 5% |
| Karnes | 401 | 512 | 404 | **1317** | 23 | 2% | 50 | 4% | 200 | 15% | 171 | 13% | 862 | 65% | 41 | 3% |
| Kaufman | 1751 | 1482 | 1416 | **4649** | 51 | 1% | 221 | 5% | 455 | 10% | 703 | 15% | 2524 | 54% | 112 | 2% |
| Kendall | 750 | 689 | 606 | **2045** | 20 | 1% | 75 | 4% | 271 | 13% | 197 | 10% | 1456 | 71% | 47 | 2% |

| | All occurred accidents | | | | fatal crashes | | incapacitating crashes | | non-incapacitating crashes | | possible injury crashes | | non- injury crashes | | FOS | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| COUNTY | 2015 | 2014 | 2013 | TOTAL CRASHES | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | (3)- % of fatal crashes from all crashes |
| Kenedy | 72 | 62 | 69 | **203** | 4 | 2% | 12 | 6% | 20 | 10% | 44 | 22% | 119 | 59% | 7 | 4% |
| Kent | 15 | 20 | 20 | **55** | 1 | 2% | 9 | 16% | 9 | 16% | 4 | 7% | 31 | 56% | 2 | 5% |
| Kerr | 838 | 772 | 805 | **2415** | 36 | 1% | 169 | 7% | 321 | 13% | 348 | 14% | 1501 | 62% | 77 | 3% |
| Kimble | 135 | 125 | 105 | **365** | 7 | 2% | 29 | 8% | 56 | 15% | 50 | 14% | 222 | 61% | 14 | 4% |
| King | 25 | 25 | 22 | **72** | 1 | 1% | 6 | 8% | 8 | 11% | 5 | 7% | 52 | 72% | 2 | 3% |
| Kinney | 25 | 43 | 29 | **97** | 4 | 4% | 3 | 3% | 14 | 14% | 16 | 16% | 60 | 62% | 5 | 5% |
| Kleberg | 406 | 433 | 436 | **1275** | 14 | 1% | 45 | 4% | 100 | 8% | 274 | 21% | 834 | 65% | 30 | 2% |
| Knox | 40 | 49 | 34 | **123** | 3 | 2% | 4 | 3% | 23 | 19% | 26 | 21% | 60 | 49% | 5 | 4% |
| Lamar | 1095 | 968 | 914 | **2977** | 24 | 1% | 114 | 4% | 316 | 11% | 463 | 16% | 2001 | 67% | 63 | 2% |
| Lamb | 156 | 166 | 182 | **504** | 12 | 2% | 16 | 3% | 66 | 13% | 62 | 12% | 340 | 67% | 18 | 4% |
| Lampasas | 306 | 269 | 230 | **805** | 7 | 1% | 41 | 5% | 152 | 19% | 91 | 11% | 494 | 61% | 20 | 2% |
| Lasalle | 154 | 174 | 232 | **560** | 24 | 4% | 39 | 7% | 93 | 17% | 65 | 12% | 334 | 60% | 34 | 6% |
| Lavaca | 232 | 230 | 232 | **694** | 13 | 2% | 40 | 6% | 80 | 12% | 84 | 12% | 459 | 66% | 23 | 3% |
| Lee | 472 | 403 | 301 | **1176** | 26 | 2% | 61 | 5% | 169 | 14% | 109 | 9% | 800 | 68% | 44 | 4% |
| Leon | 406 | 480 | 416 | **1302** | 27 | 2% | 96 | 7% | 178 | 14% | 104 | 8% | 893 | 69% | 49 | 4% |
| Liberty | 1135 | 1194 | 1195 | **3524** | 52 | 1% | 184 | 5% | 436 | 12% | 518 | 15% | 2259 | 64% | 105 | 3% |
| Limestone | 370 | 358 | 353 | **1081** | 16 | 1% | 66 | 6% | 155 | 14% | 121 | 11% | 695 | 64% | 33 | 3% |
| Lipscomb | 18 | 20 | 22 | **60** | 1 | 2% | 7 | 12% | 7 | 12% | 4 | 7% | 40 | 67% | 2 | 4% |
| Live Oak | 381 | 487 | 498 | **1366** | 32 | 2% | 72 | 5% | 160 | 12% | 196 | 14% | 887 | 65% | 52 | 4% |
| Llano | 227 | 254 | 247 | **728** | 9 | 1% | 66 | 9% | 92 | 13% | 67 | 9% | 482 | 66% | 23 | 3% |
| Loving | 13 | 25 | 18 | **56** | 3 | 5% | 7 | 13% | 593 | 1059% | 1 | 2% | 33 | 59% | 4 | 8% |
| Lubbock | 7019 | 6925 | 6926 | **20870** | 100 | 0% | 286 | 1% | 1241 | 6% | 5820 | 28% | 11363 | 54% | 330 | 2% |
| Lynn | 92 | 93 | 74 | **259** | 5 | 2% | 25 | 10% | 60 | 23% | 21 | 8% | 175 | 68% | 10 | 4% |
| Madison | 296 | 325 | 274 | **895** | 21 | 2% | 43 | 5% | 81 | 9% | 120 | 13% | 594 | 66% | 34 | 4% |
| Marion | 167 | 155 | 126 | **448** | 12 | 3% | 32 | 7% | 85 | 19% | 80 | 18% | 254 | 57% | 20 | 4% |
| Martin | 211 | 239 | 153 | **603** | 18 | 3% | 34 | 6% | 84 | 14% | 60 | 10% | 359 | 60% | 28 | 5% |

| | All occurred accidents | | | | fatal crashes | | incapacitating crashes | | non-incapacitating crashes | | possible injury crashes | | non- injury crashes | | FOS | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| COUNTY | 2015 | 2014 | 2013 | TOTAL CRASHES | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | (3)- % of fatal crashes from all crashes |
| Mason | 41 | 56 | 43 | **140** | 2 | 1% | 31 | 22% | 85 | 61% | 17 | 12% | 81 | 58% | 6 | 5% |
| Matagorda | 753 | 575 | 545 | **1873** | 25 | 1% | 77 | 4% | 179 | 10% | 369 | 20% | 1107 | 59% | 52 | 3% |
| Maverick | 854 | 844 | 707 | **2405** | 15 | 1% | 29 | 1% | 58 | 2% | 456 | 19% | 1772 | 74% | 36 | 1% |
| McCulloch | 188 | 193 | 161 | **542** | 9 | 2% | 42 | 8% | 1365 | 252% | 92 | 17% | 336 | 62% | 18 | 3% |
| McLennan | 5218 | 4921 | 4603 | **14742** | 93 | 1% | 432 | 3% | 662 | 4% | 2696 | 18% | 9018 | 61% | 287 | 2% |
| McMullen | 67 | 121 | 107 | **295** | 7 | 2% | 19 | 6% | 161 | 55% | 56 | 19% | 179 | 61% | 12 | 4% |
| Medina | 730 | 664 | 656 | **2050** | 22 | 1% | 83 | 4% | 111 | 5% | 244 | 12% | 1381 | 67% | 50 | 2% |
| Menard | 42 | 45 | 24 | **111** | 2 | 2% | 11 | 10% | 832 | 750% | 14 | 13% | 71 | 64% | 4 | 4% |
| Midland | 4283 | 4919 | 4212 | **13414** | 117 | 1% | 278 | 2% | 555 | 4% | 1780 | 13% | 9414 | 70% | 260 | 2% |
| Milam | 447 | 495 | 463 | **1405** | 16 | 1% | 59 | 4% | 89 | 6% | 175 | 12% | 946 | 67% | 35 | 3% |
| Mills | 85 | 66 | 94 | **245** | 5 | 2% | 20 | 8% | 36 | 15% | 24 | 10% | 161 | 66% | 9 | 4% |
| Mitchell | 170 | 178 | 148 | **496** | 10 | 2% | 27 | 5% | 81 | 16% | 64 | 13% | 343 | 69% | 17 | 3% |
| Montague | 253 | 274 | 286 | **813** | 9 | 1% | 53 | 7% | 1863 | 229% | 83 | 10% | 572 | 70% | 22 | 3% |
| Montgomery | 9928 | 8812 | 8009 | **26749** | 151 | 1% | 775 | 3% | 1042 | 4% | 4202 | 16% | 18287 | 68% | 475 | 2% |
| Moore | 409 | 366 | 363 | **1138** | 19 | 2% | 35 | 3% | 111 | 10% | 61 | 5% | 813 | 71% | 32 | 3% |
| Morris | 150 | 131 | 153 | **434** | 7 | 2% | 30 | 7% | 35 | 8% | 86 | 20% | 226 | 52% | 15 | 4% |
| Motley | 27 | 36 | 25 | **88** | 2 | 2% | 3 | 3% | 231 | 263% | 17 | 19% | 59 | 67% | 3 | 4% |
| Nacogdoche | 1122 | 971 | 1087 | **3180** | 39 | 1% | 131 | 4% | 336 | 11% | 613 | 19% | 1986 | 62% | 84 | 3% |
| Navarro | 1253 | 1072 | 969 | **3294** | 31 | 1% | 108 | 3% | 166 | 5% | 437 | 13% | 2288 | 69% | 71 | 2% |
| Newton | 201 | 183 | 165 | **549** | 11 | 2% | 23 | 4% | 118 | 21% | 106 | 19% | 331 | 60% | 19 | 3% |
| Nolan | 399 | 424 | 431 | **1254** | 15 | 1% | 56 | 4% | 1449 | 116% | 136 | 11% | 895 | 71% | 32 | 3% |
| Nueces | 3064 | 4486 | 7559 | **15109** | 97 | 1% | 459 | 3% | 434 | 3% | 2822 | 19% | 8961 | 59% | 289 | 2% |
| Ochiltree | 158 | 162 | 139 | **459** | 10 | 2% | 21 | 5% | 46 | 10% | 30 | 7% | 323 | 70% | 16 | 4% |
| Oldham | 171 | 100 | 121 | **392** | 10 | 3% | 24 | 6% | 403 | 103% | 20 | 5% | 288 | 73% | 16 | 4% |
| Orange | 1775 | 1633 | 1440 | **4848** | 55 | 1% | 246 | 5% | 366 | 8% | 662 | 14% | 3228 | 67% | 126 | 3% |
| Palo Pinto | 549 | 535 | 544 | **1628** | 27 | 2% | 71 | 4% | 159 | 10% | 114 | 7% | 1124 | 69% | 49 | 3% |

| | All occurred accidents | | | | fatal crashes | | incapacitating crashes | | non-incapacitating crashes | | possible injury crashes | | non- injury crashes | | FOS | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **COUNTY** | **2015** | **2014** | **2013** | **TOTAL CRASHES** | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | (3)- % of fatal crashes from all crashes |
| Panola | 469 | 458 | 426 | **1353** | 26 | 2% | 82 | 6% | 530 | 39% | 179 | 13% | 870 | 64% | 47 | 3% |
| Parker | 1990 | 2011 | 1829 | **5830** | 46 | 1% | 191 | 3% | 287 | 5% | 764 | 13% | 3983 | 68% | 120 | 2% |
| Parmer | 147 | 135 | 103 | **385** | 8 | 2% | 29 | 8% | 151 | 39% | 34 | 9% | 252 | 65% | 15 | 4% |
| Pecos | 381 | 427 | 334 | **1142** | 25 | 2% | 51 | 4% | 279 | 24% | 142 | 12% | 716 | 63% | 42 | 4% |
| Polk | 742 | 767 | 796 | **2305** | 38 | 2% | 154 | 7% | 719 | 31% | 265 | 11% | 1469 | 64% | 76 | 3% |
| Potter | 3431 | 2854 | 2597 | **8882** | 70 | 1% | 287 | 3% | 343 | 4% | 1534 | 17% | 5380 | 61% | 180 | 2% |
| Presidio | 59 | 66 | 63 | **188** | 2 | 1% | 19 | 10% | 38 | 20% | 12 | 6% | 123 | 65% | 6 | 3% |
| Rains | 115 | 91 | 122 | **328** | 5 | 2% | 29 | 9% | 371 | 113% | 69 | 21% | 183 | 56% | 11 | 3% |
| Randall | 2121 | 1871 | 1564 | **5556** | 38 | 1% | 164 | 3% | 229 | 4% | 840 | 15% | 3614 | 65% | 104 | 2% |
| Reagan | 122 | 118 | 116 | **356** | 11 | 3% | 42 | 12% | 42 | 12% | 32 | 9% | 225 | 63% | 19 | 5% |
| Real | 72 | 66 | 82 | **220** | 10 | 5% | 65 | 30% | 54 | 25% | 25 | 11% | 81 | 37% | 19 | 9% |
| Red River | 163 | 115 | 122 | **400** | 8 | 2% | 43 | 11% | 148 | 37% | 41 | 10% | 231 | 58% | 17 | 4% |
| Reeves | 421 | 479 | 406 | **1306** | 45 | 3% | 67 | 5% | 124 | 9% | 80 | 6% | 909 | 70% | 64 | 5% |
| Refugio | 216 | 219 | 167 | **602** | 17 | 3% | 31 | 5% | 24 | 4% | 62 | 10% | 416 | 69% | 25 | 4% |
| Roberts | 28 | 41 | 48 | **117** | 5 | 4% | 11 | 9% | 69 | 59% | 13 | 11% | 74 | 63% | 7 | 6% |
| Robertson | 341 | 285 | 298 | **924** | 12 | 1% | 68 | 7% | 225 | 24% | 107 | 12% | 607 | 66% | 27 | 3% |
| Rockwall | 1313 | 1097 | 1052 | **3462** | 14 | 0% | 82 | 2% | 149 | 4% | 536 | 15% | 2507 | 72% | 52 | 2% |
| Runnels | 115 | 129 | 120 | **364** | 9 | 2% | 20 | 5% | 189 | 52% | 22 | 6% | 241 | 66% | 15 | 4% |
| Rusk | 725 | 697 | 756 | **2178** | 48 | 2% | 109 | 5% | 144 | 7% | 375 | 17% | 1342 | 62% | 80 | 4% |
| Sabine | 125 | 104 | 122 | **351** | 11 | 3% | 22 | 6% | 60 | 17% | 36 | 10% | 210 | 60% | 17 | 5% |
| San Augusti | 120 | 108 | 124 | **352** | 12 | 3% | 16 | 5% | 124 | 35% | 49 | 14% | 206 | 59% | 17 | 5% |
| San Jacinto | 402 | 344 | 334 | **1080** | 22 | 2% | 92 | 9% | 283 | 26% | 103 | 10% | 655 | 61% | 42 | 4% |
| San Patricio | 1134 | 1025 | 1118 | **3277** | 34 | 1% | 136 | 4% | 125 | 4% | 460 | 14% | 2200 | 67% | 77 | 2% |
| San Saba | 48 | 47 | 49 | **144** | 5 | 3% | 18 | 13% | 27 | 19% | 18 | 13% | 76 | 53% | 8 | 6% |
| Schleicher | 45 | 44 | 39 | **128** | 5 | 4% | 8 | 6% | 85 | 66% | 8 | 6% | 75 | 59% | 7 | 6% |
| Scurry | 194 | 318 | 289 | **801** | 14 | 2% | 46 | 6% | 56 | 7% | 140 | 17% | 476 | 59% | 27 | 3% |

| | All occurred accidents | | | | fatal crashes | | incapacitating crashes | | non-incapacitating crashes | | possible injury crashes | | non- injury crashes | | FOS | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| COUNTY | 2015 | 2014 | 2013 | TOTAL CRASHES | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | (3)- % of fatal crashes from all crashes |
| Shackelford | 51 | 47 | 60 | **158** | 4 | 3% | 13 | 8% | 140 | 89% | 16 | 10% | 85 | 54% | 7 | 5% |
| Shelby | 406 | 426 | 365 | **1197** | 26 | 2% | 40 | 3% | 72 | 6% | 168 | 14% | 738 | 62% | 43 | 4% |
| Sherman | 74 | 42 | 70 | **186** | 3 | 2% | 16 | 9% | 1138 | 612% | 10 | 5% | 136 | 73% | 6 | 3% |
| Smith | 5715 | 5379 | 5163 | **16257** | 120 | 1% | 415 | 3% | 671 | 4% | 2918 | 18% | 10652 | 66% | 316 | 2% |
| Somervell | 134 | 132 | 138 | **404** | 8 | 2% | 30 | 7% | 165 | 41% | 52 | 13% | 254 | 63% | 15 | 4% |
| Starr | 600 | 665 | 692 | **1957** | 19 | 1% | 39 | 2% | 73 | 4% | 302 | 15% | 1298 | 66% | 40 | 2% |
| Stephens | 92 | 111 | 126 | **329** | 4 | 1% | 17 | 5% | 23 | 7% | 46 | 14% | 206 | 63% | 9 | 3% |
| Sterling | 25 | 34 | 36 | **95** | 5 | 5% | 4 | 4% | 19 | 20% | 10 | 11% | 57 | 60% | 6 | 7% |
| Stonewall | 19 | 33 | 20 | **72** | 4 | 6% | 8 | 11% | 42 | 58% | 6 | 8% | 37 | 51% | 6 | 8% |
| Sutton | 126 | 155 | 132 | **413** | 11 | 3% | 44 | 11% | 45 | 11% | 64 | 15% | 231 | 56% | 20 | 5% |
| Swisher | 81 | 95 | 111 | **287** | 4 | 1% | 26 | 9% | 7777 | 2710% | 24 | 8% | 188 | 66% | 9 | 3% |
| Tarrant | 30805 | 28246 | 27951 | **87002** | 407 | 0% | 3181 | 4% | 4796 | 6% | 18991 | 22% | 49076 | 56% | 1642 | 2% |
| Taylor | 3608 | 3691 | 3497 | **10796** | 69 | 1% | 256 | 2% | 499 | 5% | 1807 | 17% | 7023 | 65% | 202 | 2% |
| Terrell | 14 | 24 | 17 | **55** | 2 | 4% | 5 | 9% | 48 | 87% | 3 | 5% | 33 | 60% | 3 | 5% |
| Terry | 172 | 185 | 183 | **540** | 7 | 1% | 26 | 5% | 39 | 7% | 68 | 13% | 353 | 65% | 15 | 3% |
| Throckmorto | 34 | 31 | 18 | **83** | 0 | 0% | 2 | 2% | 191 | 230% | 11 | 13% | 56 | 67% | 1 | 1% |
| Titus | 795 | 797 | 785 | **2377** | 19 | 1% | 78 | 3% | 726 | 31% | 349 | 15% | 1588 | 67% | 49 | 2% |
| Tom Green | 2187 | 2595 | 2397 | **7179** | 42 | 1% | 156 | 2% | 7610 | 106% | 1182 | 16% | 4852 | 68% | 128 | 2% |
| Travis | 17804 | 15475 | 16107 | **49386** | 322 | 1% | 1721 | 3% | 3437 | 7% | 11076 | 22% | 24116 | 49% | 1127 | 2% |
| Trinity | 113 | 130 | 143 | **386** | 11 | 3% | 36 | 9% | 89 | 23% | 47 | 12% | 211 | 55% | 19 | 5% |
| Tyler | 185 | 166 | 232 | **583** | 21 | 4% | 30 | 5% | 222 | 38% | 60 | 10% | 359 | 62% | 30 | 5% |
| Upshur | 560 | 516 | 511 | **1587** | 20 | 1% | 80 | 5% | 97 | 6% | 245 | 15% | 949 | 60% | 45 | 3% |
| Upton | 63 | 92 | 66 | **221** | 12 | 5% | 27 | 12% | 90 | 41% | 29 | 13% | 122 | 55% | 17 | 8% |
| Uvalde | 449 | 482 | 471 | **1402** | 13 | 1% | 62 | 4% | 181 | 13% | 243 | 17% | 951 | 68% | 32 | 2% |
| Val Verde | 852 | 759 | 674 | **2285** | 17 | 1% | 51 | 2% | 238 | 10% | 426 | 19% | 1477 | 65% | 43 | 2% |
| Van Zandt | 914 | 804 | 790 | **2508** | 42 | 2% | 139 | 6% | 509 | 20% | 464 | 19% | 1522 | 61% | 80 | 3% |

| | All occurred accidents | | | | fatal crashes | | incapacitating crashes | | non-incapacitating crashes | | possible injury crashes | | non- injury crashes | | FOS | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| COUNTY | 2015 | 2014 | 2013 | TOTAL CRASHES | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | % from the all crashes | Total | (3)- % of fatal crashes from all crashes |
| Victoria | 958 | 989 | 1053 | **3000** | 40 | 1% | 173 | 6% | 399 | 13% | 572 | 19% | 1638 | 55% | 93 | 3% |
| Walker | 1506 | 1405 | 1364 | **4275** | 36 | 1% | 123 | 3% | 260 | 6% | 569 | 13% | 3078 | 72% | 85 | 2% |
| Waller | 693 | 610 | 586 | **1889** | 35 | 2% | 97 | 5% | 179 | 9% | 391 | 21% | 1114 | 59% | 63 | 3% |
| Ward | 237 | 299 | 283 | **819** | 27 | 3% | 34 | 4% | 210 | 26% | 54 | 7% | 546 | 67% | 39 | 5% |
| Washington | 853 | 806 | 793 | **2452** | 26 | 1% | 70 | 3% | 1340 | 55% | 257 | 10% | 1789 | 73% | 54 | 2% |
| Webb | 5869 | 5618 | 5455 | **16942** | 55 | 0% | 331 | 2% | 717 | 4% | 3823 | 23% | 10205 | 60% | 254 | 1% |
| Wharton | 657 | 709 | 637 | **2003** | 25 | 1% | 78 | 4% | 110 | 5% | 269 | 13% | 1337 | 67% | 52 | 3% |
| Wheeler | 112 | 122 | 123 | **357** | 9 | 3% | 29 | 8% | 463 | 130% | 28 | 8% | 231 | 65% | 15 | 4% |
| Wichita | 2283 | 2343 | 2340 | **6966** | 34 | 0% | 111 | 2% | 257 | 4% | 735 | 11% | 5086 | 73% | 102 | 1% |
| Wilbarger | 295 | 269 | 290 | **854** | 13 | 2% | 32 | 4% | 86 | 10% | 97 | 11% | 598 | 70% | 24 | 3% |
| Willacy | 143 | 121 | 152 | **416** | 5 | 1% | 19 | 5% | 1622 | 390% | 55 | 13% | 262 | 63% | 11 | 3% |
| Williamson | 6018 | 5531 | 4381 | **15930** | 99 | 1% | 585 | 4% | 972 | 6% | 2372 | 15% | 10112 | 63% | 325 | 2% |
| Wilson | 629 | 637 | 624 | **1890** | 28 | 1% | 91 | 5% | 109 | 6% | 273 | 14% | 1275 | 67% | 54 | 3% |
| Winkler | 136 | 161 | 130 | **427** | 15 | 4% | 11 | 3% | 243 | 57% | 56 | 13% | 276 | 65% | 20 | 5% |
| Wise | 803 | 927 | 913 | **2643** | 39 | 1% | 114 | 4% | 227 | 9% | 267 | 10% | 1864 | 71% | 75 | 3% |
| Wood | 515 | 484 | 495 | **1494** | 34 | 2% | 100 | 7% | 88 | 6% | 209 | 14% | 950 | 64% | 59 | 4% |
| Yoakum | 109 | 111 | 107 | **327** | 6 | 2% | 20 | 6% | 61 | 19% | 23 | 7% | 238 | 73% | 11 | 3% |
| Young | 242 | 254 | 246 | **742** | 6 | 1% | 32 | 4% | 43 | 6% | 100 | 13% | 520 | 70% | 16 | 2% |
| Zapata | 105 | 112 | 131 | **348** | 4 | 1% | 9 | 3% | 34 | 10% | 65 | 19% | 242 | 70% | 8 | 2% |
| Zavala | 56 | 47 | 30 | **133** | 9 | 7% | 20 | 15% | 7 | 5% | 12 | 9% | 53 | 40% | 13 | 10% |

## Appendix B: Obtained Figure of Severity (FOS) for Counties, and Obtained Ratios 1, 4 and 5 for the Three Factors (ASD)

| | Crashes with Alcohol Drunk Drivers | | | | | | Speed Involved Crashes | | | | | | Distracted Diver Crashes | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | # of all crashes with Alcohol drunk driver | (2)- Accidents with Alc / all accidents | **Alc FOS** | (5)_FOS of accidents with Alc / all accidents | (4)_FOS of accidents with Alc / all accidents with Alc | (1)_FOS of accidents with Alc / FOS of all accidents | # of all speed involved crashes | (2)- Accidents with Spd / all accidents | **Spd inv cr FOS** | (5)_FOS of accidents with Spd / all accidents | (4)_FOS of accidents with Spd / all accidents with Spd | (1)_FOS of accidents with Spd / FOS of all accidents | # of all crashes with Dist D | (2)- Accidents with Dist / all accidents | **Dist inv cra FOS** | (5)_FOS of accidents with Dist / all accidents | (4)_FOS of accidents with Dist / all accidents with Dist | (1)_FOS of accidents with Dist / FOS of all accidents |
| **COUNTY** | Total | | **Total** | | | | Total | | **Total** | | | | Total | | **Total** | | | |
| Anderson | 160 | 6.3% | 10 | 0.4% | 6.0% | 16.0% | 399 | 15.7% | 15 | 0.6% | 3.8% | 25.0% | 439 | 17.3% | 12 | 0.5% | 2.7% | 19.5% |
| Andrews | 71 | 8.0% | 16 | 1.8% | 22.2% | 36.3% | 167 | 18.9% | 8 | 0.9% | 5.0% | 19.0% | 182 | 20.6% | 4 | 0.5% | 2.5% | 10.3% |
| Angelina | 279 | 5.2% | 12 | 0.2% | 4.4% | 11.0% | 354 | 6.5% | 13 | 0.2% | 3.7% | 11.7% | 450 | 8.3% | 12 | 0.2% | 2.8% | 11.0% |
| Aransas | 82 | 8.9% | 3 | 0.3% | 3.6% | 13.7% | 76 | 8.2% | 4 | 0.4% | 4.9% | 16.9% | 215 | 23.2% | 5 | 0.6% | 2.5% | 25.0% |
| Archer | 44 | 9.7% | 4 | 0.9% | 9.4% | 26.6% | 86 | 19.0% | 3 | 0.7% | 3.5% | 19.3% | 41 | 9.1% | 1 | 0.1% | 1.6% | 4.2% |
| Armstrong | 5 | 2.7% | 1 | 0.6% | 22.5% | 13.9% | 34 | 18.7% | 2 | 1.4% | 7.3% | 30.4% | 18 | 9.9% | 1 | 0.8% | 8.3% | 18.4% |
| Atascosa | 176 | 6.2% | 10 | 0.4% | 5.9% | 14.2% | 289 | 10.2% | 9 | 0.3% | 3.1% | 12.3% | 845 | 29.9% | 15 | 0.5% | 1.7% | 20.0% |
| Austin | 93 | 5.7% | 6 | 0.4% | 6.9% | 16.5% | 272 | 16.6% | 13 | 0.8% | 4.6% | 32.7% | 354 | 21.6% | 7 | 0.4% | 1.9% | 17.5% |
| Bailey | 24 | 8.2% | 2 | 0.8% | 10.2% | 39.6% | 51 | 17.3% | 2 | 0.6% | 3.4% | 27.7% | 86 | 29.3% | 2 | 0.6% | 2.1% | 29.0% |
| Bandera | 116 | 12.7% | 11 | 1.2% | 9.4% | 27.0% | 215 | 23.5% | 14 | 1.5% | 6.5% | 34.7% | 207 | 22.6% | 6 | 0.6% | 2.7% | 14.0% |
| Bastrop | 203 | 5.1% | 21 | 0.5% | 10.2% | 18.7% | 301 | 7.6% | 15 | 0.4% | 5.1% | 13.9% | 1187 | 29.9% | 31 | 0.8% | 2.6% | 27.9% |
| Baylor | 20 | 9.6% | 5 | 2.2% | 22.5% | 28.8% | 44 | 21.2% | 5 | 2.3% | 10.7% | 30.0% | 42 | 20.2% | 3 | 1.3% | 6.3% | 16.9% |
| Bee | 85 | 7.0% | 6 | 0.5% | 6.6% | 18.8% | 130 | 10.7% | 3 | 0.3% | 2.4% | 10.4% | 223 | 18.4% | 7 | 0.5% | 3.0% | 22.2% |
| Bell | 837 | 5.1% | 48 | 0.3% | 5.7% | 14.6% | 1416 | 8.6% | 57 | 0.3% | 4.0% | 17.5% | 2683 | 16.3% | 49 | 0.3% | 1.8% | 15.2% |
| Bexar | 6664 | 5.1% | 264 | 0.2% | 4.0% | 13.4% | 4737 | 3.6% | 167 | 0.1% | 3.5% | 8.5% | 67835 | 51.9% | 922 | 0.7% | 1.4% | 46.6% |
| Blanco | 87 | 16.5% | 9 | 1.7% | 10.2% | 33.2% | 139 | 26.4% | 9 | 1.8% | 6.7% | 35.0% | 125 | 23.7% | 5 | 1.0% | 4.1% | 19.0% |
| Borden | 2 | 2.4% | 0 | 0.0% | 1.0% | 0.4% | 18 | 22.0% | 3 | 3.9% | 17.9% | 68.0% | 14 | 17.1% | 0 | 0.4% | 2.5% | 7.3% |
| Bosque | 44 | 9.1% | 5 | 1.0% | 10.8% | 23.8% | 144 | 29.8% | 7 | 1.4% | 4.8% | 34.4% | 93 | 19.3% | 3 | 0.6% | 2.9% | 13.6% |
| Bowie | 245 | 4.1% | 16 | 0.3% | 6.5% | 12.5% | 401 | 6.7% | 18 | 0.3% | 4.4% | 13.9% | 891 | 15.0% | 19 | 0.3% | 2.1% | 15.1% |
| Brazoria | 776 | 5.5% | 49 | 0.3% | 6.3% | 17.2% | 902 | 6.3% | 35 | 0.2% | 3.9% | 12.4% | 3286 | 23.1% | 52 | 0.4% | 1.6% | 18.5% |
| Brazos | 721 | 6.8% | 23 | 0.2% | 3.2% | 11.9% | 408 | 3.9% | 17 | 0.2% | 4.1% | 8.7% | 1596 | 15.1% | 29 | 0.3% | 1.8% | 15.2% |
| Brewster | 28 | 9.2% | 2 | 0.8% | 8.8% | 26.7% | 21 | 6.9% | 1 | 0.2% | 2.4% | 5.6% | 151 | 49.8% | 5 | 1.7% | 3.4% | 55.3% |
| Briscoe | 1 | 1.8% | 0 | 0.1% | 3.1% | 2.7% | 8 | 14.0% | 0 | 0.5% | 3.8% | 26.7% | 14 | 24.6% | 1 | 0.9% | 3.6% | 44.1% |
| Brooks | 14 | 2.5% | 1 | 0.2% | 9.3% | 6.7% | 138 | 24.8% | 4 | 0.7% | 3.0% | 21.0% | 134 | 24.1% | 3 | 0.6% | 2.3% | 16.0% |
| Brown | 108 | 6.4% | 5 | 0.3% | 4.8% | 15.3% | 246 | 14.5% | 6 | 0.4% | 2.4% | 17.6% | 285 | 16.8% | 5 | 0.3% | 1.7% | 14.2% |
| Burleson | 72 | 7.3% | 5 | 0.5% | 7.1% | 18.5% | 155 | 15.6% | 5 | 0.5% | 3.1% | 17.3% | 202 | 20.4% | 4 | 0.4% | 2.0% | 14.3% |
| Burnet | 184 | 9.4% | 16 | 0.8% | 8.5% | 22.5% | 333 | 17.1% | 17 | 0.9% | 5.2% | 24.9% | 451 | 23.2% | 13 | 0.7% | 2.9% | 19.2% |
| Caldwell | 169 | 8.7% | 11 | 0.6% | 6.5% | 22.0% | 371 | 19.1% | 11 | 0.6% | 3.0% | 22.4% | 428 | 22.1% | 8 | 0.4% | 1.9% | 16.3% |

| | Crashes with Alcohol Drunk Drivers | | | | | | Speed Involved Crashes | | | | | | Distracted Diver Crashes | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | # of all crashes with Alcohol drunk driver | (2)- Accidents with Alc / all accidents | Alc FOS | (5)_FOS of accidents with Alc / all accidents | (4)_FOS of accidents with Alc / all accidents with Alc | (1)_FOS of accidents with Alc / FOS of all accidents | # of all speed involved crashes | (2)- Accidents with Spd / all accidents | Spd inv cr FOS | (5)_FOS of accidents with Spd / all accidents | (4)_FOS of accidents with Spd / all accidents with Spd | (1)_FOS of accidents with Spd / FOS of all accidents | # of all crashes with Dist D | (2)- Accidents with Dist / all accidents | Dist inv cra FOS | (5)_FOS of accidents with Dist / all accidents | (4)_FOS of accidents with Dist / all accidents with Dist | (1)_FOS of accidents with Dist / FOS of all accidents |
| **COUNTY** | Total | | **Total** | | | | Total | | **Total** | | | | Total | | **Total** | | | |
| Calhoun | 58 | 6.9% | 4 | 0.5% | 7.3% | 20.0% | 42 | 5.0% | 2 | 0.3% | 5.6% | 11.0% | 231 | 27.6% | 5 | 0.6% | 2.3% | 24.6% |
| Callahan | 34 | 3.9% | 4 | 0.4% | 10.4% | 13.5% | 282 | 32.5% | 6 | 0.7% | 2.0% | 21.7% | 117 | 13.5% | 3 | 0.4% | 2.9% | 13.2% |
| Cameron | 1130 | 5.7% | 45 | 0.2% | 4.0% | 14.5% | 890 | 4.5% | 30 | 0.1% | 3.3% | 9.6% | 1475 | 7.4% | 19 | 0.1% | 1.3% | 6.3% |
| Camp | 39 | 7.1% | 3 | 0.6% | 7.9% | 19.5% | 53 | 9.7% | 4 | 0.8% | 7.8% | 26.2% | 154 | 28.2% | 2 | 0.4% | 1.4% | 13.5% |
| Carson | 27 | 7.6% | 1 | 0.3% | 3.7% | 6.1% | 85 | 24.0% | 1 | 0.4% | 1.8% | 9.2% | 55 | 15.5% | 7 | 1.9% | 12.1% | 40.9% |
| Cass | 103 | 7.8% | 9 | 0.7% | 8.6% | 21.3% | 331 | 24.9% | 13 | 1.0% | 3.9% | 31.2% | 376 | 28.3% | 8 | 0.6% | 2.2% | 19.8% |
| Castro | 18 | 6.3% | 3 | 0.9% | 14.5% | 24.7% | 75 | 26.2% | 2 | 0.8% | 2.9% | 20.6% | 46 | 16.1% | 1 | 0.3% | 1.6% | 6.8% |
| Chambers | 238 | 7.6% | 14 | 0.5% | 6.0% | 16.7% | 291 | 9.3% | 11 | 0.3% | 3.8% | 12.8% | 410 | 13.1% | 10 | 0.3% | 2.3% | 11.2% |
| Cherokee | 159 | 7.1% | 13 | 0.6% | 8.3% | 20.5% | 420 | 18.9% | 14 | 0.6% | 3.3% | 21.2% | 449 | 20.2% | 9 | 0.4% | 2.1% | 14.7% |
| Childress | 12 | 6.6% | 1 | 0.7% | 10.8% | 25.2% | 35 | 19.1% | 2 | 0.9% | 4.5% | 30.8% | 26 | 14.2% | 1 | 0.3% | 2.5% | 12.4% |
| Clay | 40 | 6.4% | 4 | 0.7% | 11.2% | 24.8% | 161 | 25.9% | 6 | 0.9% | 3.6% | 32.1% | 77 | 12.4% | 2 | 0.3% | 2.1% | 9.1% |
| Cochran | 7 | 7.5% | 0 | 0.3% | 3.5% | 6.5% | 13 | 14.0% | 0 | 0.1% | 0.9% | 3.2% | 18 | 19.4% | 0 | 0.5% | 2.7% | 12.7% |
| Coke | 13 | 15.3% | 3 | 4.0% | 25.8% | 26.9% | 16 | 18.8% | 1 | 0.6% | 3.2% | 4.1% | 6 | 7.1% | 2 | 2.5% | 35.4% | 17.0% |
| Coleman | 38 | 7.8% | 3 | 0.6% | 7.1% | 18.6% | 104 | 21.3% | 1 | 0.3% | 1.3% | 9.6% | 134 | 27.5% | 3 | 0.6% | 2.3% | 20.8% |
| Collin | 1835 | 5.2% | 75 | 0.2% | 4.1% | 13.1% | 1614 | 4.6% | 55 | 0.2% | 3.4% | 9.6% | 9060 | 25.8% | 136 | 0.4% | 1.5% | 23.8% |
| Collingsworth | 7 | 12.7% | 3 | 6.1% | 47.8% | 66.1% | 6 | 10.9% | 1 | 2.1% | 19.4% | 23.0% | 5 | 9.1% | 1 | 2.1% | 23.6% | 23.3% |
| Colorado | 95 | 5.4% | 7 | 0.4% | 7.1% | 13.0% | 441 | 25.1% | 16 | 0.9% | 3.5% | 29.9% | 226 | 12.8% | 6 | 0.4% | 2.8% | 12.0% |
| Comal | 461 | 7.5% | 24 | 0.4% | 5.2% | 17.3% | 682 | 11.1% | 25 | 0.4% | 3.7% | 17.9% | 1058 | 17.2% | 27 | 0.4% | 2.6% | 19.7% |
| Comanche | 34 | 7.0% | 2 | 0.4% | 6.0% | 14.3% | 97 | 20.0% | 3 | 0.7% | 3.3% | 22.7% | 127 | 26.2% | 3 | 0.6% | 2.1% | 19.2% |
| Concho | 9 | 6.6% | 1 | 1.0% | 14.6% | 22.2% | 27 | 19.9% | 1 | 0.5% | 2.5% | 11.5% | 33 | 24.3% | 0 | 0.3% | 1.1% | 6.1% |
| Cooke | 177 | 10.7% | 16 | 1.0% | 9.0% | 28.2% | 331 | 20.0% | 16 | 1.0% | 4.8% | 28.3% | 513 | 31.0% | 14 | 0.9% | 2.8% | 25.1% |
| Coryell | 147 | 4.9% | 12 | 0.4% | 8.1% | 18.9% | 313 | 10.4% | 9 | 0.3% | 2.9% | 14.4% | 376 | 12.5% | 8 | 0.3% | 2.2% | 13.2% |
| Cottle | 0 | 0.0% | 0 | 0.0% | 0.0% | 0.0% | 5 | 12.5% | 0 | 0.4% | 3.3% | 9.5% | 11 | 27.5% | 1 | 3.1% | 11.3% | 70.9% |
| Crane | 21 | 10.1% | 2 | 1.2% | 11.9% | 28.8% | 21 | 10.1% | 2 | 1.1% | 10.8% | 26.1% | 52 | 25.1% | 1 | 0.3% | 1.2% | 7.4% |
| Crockett | 23 | 4.6% | 3 | 0.5% | 11.9% | 12.1% | 120 | 24.0% | 5 | 1.0% | 4.1% | 22.1% | 78 | 15.6% | 4 | 0.8% | 5.0% | 17.4% |
| Crosby | 18 | 9.9% | 4 | 2.1% | 20.9% | 44.9% | 23 | 12.6% | 2 | 0.9% | 7.0% | 19.3% | 65 | 35.7% | 2 | 1.1% | 3.0% | 23.3% |
| Culberson | 10 | 2.7% | 1 | 0.3% | 10.7% | 4.3% | 118 | 32.1% | 7 | 2.0% | 6.3% | 30.2% | 44 | 12.0% | 4 | 1.0% | 8.4% | 15.0% |
| Dallam | 19 | 3.3% | 0 | 0.1% | 2.1% | 2.7% | 87 | 15.3% | 2 | 0.4% | 2.5% | 14.5% | 87 | 15.3% | 1 | 0.2% | 1.6% | 9.0% |

| | Crashes with Alcohol Drunk Drivers | | | | | | Speed Involved Crashes | | | | | | Distracted Diver Crashes | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| COUNTY | # of all crashes with Alcohol drunk driver Total | (2)- Accidents with Alc / all accidents | Alc FOS Total | (5)_FOS of accidents with Alc / all accidents | (4)_FOS of accidents with Alc / all accidents with Alc | (1)_FOS of accidents with Alc / FOS of all accidents | # of all speed involved crashes Total | (2)- Accidents with Spd / all accidents | Spd inv cr FOS Total | (5)_FOS of accidents with Spd / all accidents | (4)_FOS of accidents with Spd / all accidents with Spd | (1)_FOS of accidents with Spd / FOS of all accidents | # of all crashes with Dist D Total | (2)- Accidents with Dist / all accidents | Dist inv cra FOS Total | (5)_FOS of accidents with Dist / all accidents | (4)_FOS of accidents with Dist / all accidents with Dist | (1)_FOS of accidents with Dist / FOS of all accidents |
| Dallas | 7073 | 5.3% | 347 | 0.3% | 4.9% | 14.4% | 6037 | 4.5% | 295 | 0.2% | 4.9% | 12.3% | 18243 | 13.7% | 301 | 0.2% | 1.7% | 12.5% |
| Dawson | 30 | 7.3% | 2 | 0.6% | 8.1% | 16.0% | 70 | 16.9% | 2 | 0.4% | 2.5% | 11.5% | 140 | 33.9% | 3 | 0.7% | 2.0% | 18.2% |
| Deaf Smith | 43 | 5.8% | 3 | 0.4% | 6.3% | 18.5% | 82 | 11.1% | 1 | 0.2% | 1.5% | 8.4% | 97 | 13.1% | 2 | 0.3% | 2.3% | 15.4% |
| Delta | 12 | 6.9% | 1 | 0.7% | 10.1% | 22.1% | 23 | 13.1% | 0 | 0.2% | 1.7% | 7.3% | 25 | 14.3% | 1 | 0.3% | 2.3% | 10.6% |
| Denton | 1654 | 5.4% | 56 | 0.2% | 3.4% | 11.8% | 1349 | 4.4% | 52 | 0.2% | 3.9% | 11.1% | 6270 | 20.5% | 90 | 0.3% | 1.4% | 19.0% |
| Dewitt | 68 | 5.6% | 4 | 0.3% | 5.5% | 11.6% | 117 | 9.7% | 5 | 0.4% | 4.5% | 16.3% | 246 | 20.4% | 6 | 0.5% | 2.6% | 19.9% |
| Dickens | 6 | 6.5% | 0 | 0.3% | 4.6% | 12.5% | 16 | 17.2% | 0 | 0.3% | 1.6% | 11.5% | 9 | 9.7% | 0 | 0.2% | 1.6% | 6.4% |
| Dimmit | 29 | 3.8% | 4 | 0.5% | 14.4% | 12.8% | 69 | 9.1% | 9 | 1.2% | 13.3% | 28.2% | 300 | 39.4% | 6 | 0.8% | 2.0% | 18.8% |
| Donley | 10 | 4.5% | 0 | 0.1% | 2.7% | 3.6% | 60 | 26.9% | 3 | 1.4% | 5.2% | 41.8% | 24 | 10.8% | 2 | 0.7% | 6.4% | 20.3% |
| Duval | 28 | 5.8% | 2 | 0.3% | 5.8% | 8.2% | 74 | 15.4% | 2 | 0.4% | 2.8% | 10.5% | 110 | 22.9% | 6 | 1.1% | 5.0% | 27.8% |
| Eastland | 63 | 5.5% | 8 | 0.7% | 12.7% | 22.0% | 334 | 28.9% | 15 | 1.3% | 4.3% | 40.1% | 211 | 18.3% | 7 | 0.6% | 3.5% | 20.3% |
| Ector | 996 | 10.6% | 63 | 0.7% | 6.3% | 23.9% | 759 | 8.1% | 32 | 0.3% | 4.3% | 12.3% | 1136 | 12.1% | 29 | 0.3% | 2.5% | 10.9% |
| Edwards | 7 | 5.3% | 1 | 0.9% | 17.1% | 21.0% | 39 | 29.3% | 3 | 2.3% | 7.8% | 53.2% | 21 | 15.8% | 1 | 0.4% | 2.5% | 9.3% |
| Ellis | 386 | 6.0% | 27 | 0.4% | 7.1% | 16.9% | 842 | 13.0% | 32 | 0.5% | 3.8% | 19.9% | 2127 | 32.9% | 54 | 0.8% | 2.5% | 32.9% |
| El Paso | 2536 | 5.4% | 102 | 0.2% | 4.0% | 15.2% | 660 | 1.4% | 43 | 0.1% | 6.5% | 6.4% | 9919 | 21.2% | 125 | 0.3% | 1.3% | 18.6% |
| Erath | 151 | 8.3% | 9 | 0.5% | 6.1% | 14.0% | 379 | 20.7% | 13 | 0.7% | 3.5% | 19.9% | 481 | 26.3% | 16 | 0.9% | 3.3% | 23.9% |
| Falls | 43 | 5.6% | 7 | 0.9% | 16.7% | 24.1% | 195 | 25.4% | 5 | 0.7% | 2.6% | 17.2% | 92 | 12.0% | 4 | 0.5% | 4.2% | 12.9% |
| Fannin | 81 | 8.1% | 5 | 0.5% | 5.8% | 13.4% | 155 | 15.5% | 6 | 0.6% | 3.7% | 16.3% | 391 | 39.0% | 9 | 0.9% | 2.3% | 25.9% |
| Fayette | 95 | 6.2% | 13 | 0.9% | 13.8% | 23.5% | 296 | 19.3% | 11 | 0.7% | 3.8% | 20.3% | 336 | 21.9% | 14 | 0.9% | 4.2% | 25.6% |
| Fisher | 21 | 8.0% | 2 | 0.9% | 11.3% | 20.0% | 89 | 34.1% | 5 | 2.1% | 6.0% | 45.2% | 31 | 11.9% | 2 | 0.7% | 5.9% | 15.3% |
| Floyd | 9 | 5.7% | 0 | 0.1% | 1.4% | 2.7% | 10 | 6.3% | 0 | 0.0% | 0.8% | 1.7% | 61 | 38.4% | 1 | 0.4% | 1.1% | 13.9% |
| Foard | 2 | 7.7% | 0 | 0.1% | 1.8% | 1.0% | 5 | 19.2% | 0 | 0.2% | 1.0% | 1.5% | 7 | 26.9% | 1 | 4.4% | 16.2% | 32.7% |
| Fort Bend | 848 | 3.5% | 53 | 0.2% | 6.2% | 13.9% | 619 | 2.6% | 39 | 0.2% | 6.2% | 10.1% | 4252 | 17.7% | 64 | 0.3% | 1.5% | 16.7% |
| Franklin | 30 | 10.0% | 6 | 1.9% | 19.0% | 40.1% | 84 | 28.0% | 3 | 1.1% | 3.8% | 22.2% | 32 | 10.7% | 1 | 0.2% | 1.7% | 3.9% |
| Freestone | 73 | 4.5% | 2 | 0.2% | 3.4% | 5.8% | 241 | 14.8% | 5 | 0.3% | 2.1% | 11.8% | 211 | 12.9% | 9 | 0.5% | 4.1% | 20.1% |
| Frio | 43 | 6.7% | 6 | 0.9% | 13.9% | 22.7% | 83 | 13.0% | 7 | 1.1% | 8.3% | 26.2% | 192 | 30.1% | 9 | 1.4% | 4.7% | 34.2% |
| Gaines | 69 | 9.4% | 7 | 0.9% | 9.4% | 16.5% | 110 | 15.0% | 6 | 0.8% | 5.4% | 15.2% | 105 | 14.3% | 8 | 1.1% | 8.0% | 21.3% |
| Galveston | 766 | 4.5% | 41 | 0.2% | 5.4% | 14.5% | 514 | 3.0% | 30 | 0.2% | 5.8% | 10.5% | 4932 | 29.0% | 75 | 0.4% | 1.5% | 26.4% |

| | Crashes with Alcohol Drunk Drivers | | | | | | Speed Involved Crashes | | | | | | Distracted Diver Crashes | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | # of all crashes with Alcohol drunk driver | (2)- Accidents with Alc / all accidents | Alc FOS | (5)_FOS of accidents with Alc / all accidents | (4)_FOS of accidents with Alc / all accidents with Alc | (1)_FOS of accidents with Alc / FOS of all accidents | # of all speed involved crashes | (2)- Accidents with Spd / all accidents | Spd inv cr FOS | (5)_FOS of accidents with Spd / all accidents | (4)_FOS of accidents with Spd / all accidents with Spd | (1)_FOS of accidents with Spd / FOS of all accidents | # of all crashes with Dist D | (2)- Accidents with Dist / all accidents | Dist inv cra FOS | (5)_FOS of accidents with Dist / all accidents | (4)_FOS of accidents with Dist / all accidents with Dist | (1)_FOS of accidents with Dist / FOS of all accidents |
| COUNTY | Total | | Total | | | | Total | | Total | | | | Total | | Total | | | |
| Garza | 15 | 3.8% | 1 | 0.2% | 4.0% | 4.5% | 76 | 19.2% | 3 | 0.9% | 4.6% | 25.9% | 112 | 28.4% | 3 | 0.7% | 2.5% | 21.3% |
| Gillespie | 92 | 6.8% | 4 | 0.3% | 4.6% | 11.2% | 206 | 15.2% | 8 | 0.6% | 3.8% | 20.9% | 354 | 26.1% | 10 | 0.7% | 2.8% | 26.2% |
| Glasscock | 11 | 3.5% | 1 | 0.4% | 10.6% | 6.6% | 34 | 10.9% | 3 | 0.9% | 7.8% | 15.0% | 35 | 11.2% | 3 | 0.8% | 7.6% | 14.9% |
| Goliad | 26 | 7.0% | 2 | 0.5% | 6.9% | 12.0% | 73 | 19.7% | 3 | 0.9% | 4.4% | 21.4% | 78 | 21.0% | 4 | 1.1% | 5.2% | 27.4% |
| Gonzales | 109 | 8.2% | 8 | 0.6% | 7.1% | 15.0% | 258 | 19.3% | 13 | 1.0% | 5.0% | 24.7% | 286 | 21.4% | 10 | 0.8% | 3.7% | 20.1% |
| Gray | 45 | 3.5% | 5 | 0.4% | 11.1% | 18.9% | 158 | 12.3% | 5 | 0.4% | 3.3% | 19.5% | 78 | 6.1% | 2 | 0.1% | 2.2% | 6.6% |
| Grayson | 438 | 9.4% | 31 | 0.7% | 7.2% | 21.4% | 653 | 14.0% | 29 | 0.6% | 4.4% | 19.6% | 1507 | 32.3% | 44 | 0.9% | 2.9% | 29.8% |
| Gregg | 441 | 4.6% | 26 | 0.3% | 5.8% | 14.1% | 936 | 9.8% | 30 | 0.3% | 3.2% | 16.3% | 1544 | 16.1% | 42 | 0.4% | 2.7% | 23.0% |
| Grimes | 115 | 6.6% | 8 | 0.5% | 7.2% | 14.8% | 233 | 13.4% | 8 | 0.5% | 3.4% | 14.1% | 313 | 18.0% | 9 | 0.5% | 3.0% | 17.0% |
| Guadalupe | 336 | 5.4% | 17 | 0.3% | 5.0% | 13.1% | 481 | 7.7% | 18 | 0.3% | 3.7% | 13.7% | 1672 | 26.6% | 28 | 0.4% | 1.7% | 21.8% |
| Hale | 103 | 6.8% | 7 | 0.4% | 6.4% | 20.8% | 206 | 13.6% | 8 | 0.6% | 4.1% | 26.7% | 447 | 29.5% | 6 | 0.4% | 1.3% | 17.6% |
| Hall | 7 | 3.7% | 1 | 0.6% | 17.0% | 17.7% | 23 | 12.2% | 1 | 0.7% | 5.7% | 19.4% | 62 | 33.0% | 2 | 0.9% | 2.6% | 24.0% |
| Hamilton | 19 | 6.0% | 3 | 0.8% | 14.0% | 12.4% | 70 | 21.9% | 5 | 1.6% | 7.3% | 23.9% | 75 | 23.5% | 5 | 1.5% | 6.3% | 21.9% |
| Hansford | 4 | 4.0% | 2 | 2.1% | 52.9% | 27.0% | 12 | 11.9% | 1 | 1.2% | 10.0% | 15.3% | 18 | 17.8% | 1 | 1.3% | 7.3% | 16.8% |
| Hardeman | 10 | 5.2% | 1 | 0.7% | 14.2% | 17.2% | 41 | 21.4% | 2 | 0.9% | 4.3% | 21.1% | 47 | 24.5% | 3 | 1.4% | 5.8% | 32.7% |
| Hardin | 98 | 4.3% | 12 | 0.5% | 12.1% | 19.2% | 314 | 13.7% | 12 | 0.5% | 3.7% | 18.8% | 313 | 13.7% | 10 | 0.4% | 3.3% | 16.5% |
| Harris | 8811 | 2.9% | 525 | 0.2% | 6.0% | 12.3% | 4540 | 1.5% | 302 | 0.1% | 6.6% | 7.1% | 39945 | 13.3% | 478 | 0.2% | 1.2% | 11.2% |
| Harrison | 260 | 6.1% | 26 | 0.6% | 9.9% | 22.0% | 755 | 17.6% | 27 | 0.6% | 3.5% | 22.7% | 850 | 19.8% | 17 | 0.4% | 2.0% | 14.5% |
| Hartley | 21 | 6.1% | 1 | 0.4% | 6.8% | 8.5% | 67 | 19.4% | 3 | 0.9% | 4.5% | 18.2% | 33 | 9.6% | 3 | 0.8% | 8.4% | 16.7% |
| Haskell | 26 | 10.0% | 4 | 1.4% | 13.8% | 21.1% | 65 | 25.0% | 5 | 1.9% | 7.8% | 29.8% | 31 | 11.9% | 5 | 1.8% | 15.5% | 28.2% |
| Hays | 697 | 8.8% | 31 | 0.4% | 4.4% | 18.6% | 777 | 9.8% | 34 | 0.4% | 4.4% | 20.7% | 2402 | 30.2% | 31 | 0.4% | 1.3% | 18.6% |
| Hemphill | 13 | 4.2% | 0 | 0.1% | 2.4% | 4.0% | 35 | 11.3% | 1 | 0.2% | 1.8% | 7.9% | 93 | 30.1% | 2 | 0.6% | 2.0% | 23.9% |
| Henderson | 202 | 7.5% | 16 | 0.6% | 7.9% | 20.4% | 403 | 15.0% | 14 | 0.5% | 3.5% | 18.0% | 565 | 21.0% | 18 | 0.7% | 3.1% | 22.6% |
| Hidalgo | 2377 | 6.3% | 85 | 0.2% | 3.6% | 13.9% | 2265 | 6.0% | 74 | 0.2% | 3.3% | 12.0% | 3273 | 8.6% | 50 | 0.1% | 1.5% | 8.1% |
| Hill | 123 | 5.7% | 11 | 0.5% | 8.6% | 16.1% | 498 | 23.2% | 13 | 0.6% | 2.7% | 20.5% | 759 | 35.4% | 20 | 0.9% | 2.7% | 31.1% |
| Hockley | 68 | 6.4% | 5 | 0.5% | 7.1% | 15.9% | 106 | 10.0% | 6 | 0.5% | 5.3% | 18.5% | 208 | 19.6% | 8 | 0.7% | 3.7% | 25.2% |
| Hood | 147 | 6.8% | 5 | 0.2% | 3.2% | 10.6% | 336 | 15.5% | 9 | 0.4% | 2.8% | 20.9% | 166 | 7.7% | 3 | 0.1% | 1.8% | 6.7% |
| Hopkins | 97 | 5.7% | 6 | 0.3% | 5.7% | 12.7% | 205 | 12.1% | 11 | 0.6% | 5.2% | 24.8% | 217 | 12.8% | 5 | 0.3% | 2.3% | 11.5% |

| | Crashes with Alcohol Drunk Drivers | | | | | | Speed Involved Crashes | | | | | | Distracted Diver Crashes | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | # of all crashes with Alcohol drunk driver | (2)- Accidents with Alc / all accidents | Alc FOS | (5)_FOS of accidents with Alc / all accidents | (4)_FOS of accidents with Alc / all accidents with Alc | (1)_FOS of accidents with Alc / FOS of all accidents | # of all speed involved crashes | (2)- Accidents with Spd / all accidents | Spd inv cr FOS | (5)_FOS of accidents with Spd / all accidents | (4)_FOS of accidents with Spd / all accidents with Spd | (1)_FOS of accidents with Spd / FOS of all accidents | # of all crashes with Dist D | (2)- Accidents with Dist / all accidents | Dist inv cra FOS | (5)_FOS of accidents with Dist / all accidents | (4)_FOS of accidents with Dist / all accidents with Dist | (1)_FOS of accidents with Dist / FOS of all accidents |
| COUNTY | Total | | Total | | | | Total | | Total | | | | Total | | Total | | | |
| Houston | 71 | 7.4% | 5 | 0.5% | 7.3% | 14.7% | 141 | 14.6% | 7 | 0.7% | 4.8% | 19.1% | 196 | 20.4% | 5 | 0.6% | 2.7% | 15.1% |
| Howard | 110 | 5.0% | 4 | 0.2% | 3.9% | 8.2% | 193 | 8.7% | 9 | 0.4% | 4.6% | 16.8% | 327 | 14.8% | 4 | 0.2% | 1.1% | 7.2% |
| Hudspeth | 29 | 4.8% | 8 | 1.4% | 28.9% | 21.5% | 180 | 30.1% | 11 | 1.8% | 6.1% | 28.3% | 132 | 22.0% | 7 | 1.2% | 5.5% | 18.6% |
| Hunt | 189 | 5.5% | 15 | 0.4% | 7.7% | 14.5% | 392 | 11.5% | 13 | 0.4% | 3.2% | 12.6% | 823 | 24.2% | 21 | 0.6% | 2.5% | 20.7% |
| Hutchinson | 66 | 8.5% | 7 | 0.9% | 10.9% | 26.3% | 64 | 8.3% | 4 | 0.5% | 6.5% | 15.2% | 238 | 30.7% | 6 | 0.8% | 2.7% | 23.5% |
| Irion | 19 | 7.8% | 3 | 1.1% | 14.3% | 16.0% | 53 | 21.8% | 2 | 0.8% | 3.7% | 11.7% | 34 | 14.0% | 4 | 1.6% | 11.3% | 22.7% |
| Jack | 22 | 2.0% | 2 | 0.2% | 11.3% | 13.5% | 93 | 8.4% | 4 | 0.3% | 3.8% | 19.0% | 91 | 8.2% | 3 | 0.3% | 3.4% | 16.9% |
| Jackson | 45 | 7.0% | 7 | 1.1% | 15.3% | 26.8% | 77 | 11.9% | 4 | 0.7% | 5.8% | 17.3% | 144 | 22.3% | 5 | 0.8% | 3.5% | 19.3% |
| Jasper | 87 | 6.1% | 5 | 0.3% | 5.6% | 12.4% | 259 | 18.1% | 9 | 0.6% | 3.5% | 23.4% | 277 | 19.3% | 6 | 0.4% | 2.2% | 15.4% |
| Jeff Davis | 12 | 7.1% | 0 | 0.2% | 2.9% | 4.5% | 66 | 38.8% | 4 | 2.4% | 6.2% | 52.8% | 17 | 10.0% | 1 | 0.3% | 3.1% | 6.8% |
| Jefferson | 477 | 2.8% | 25 | 0.1% | 5.3% | 9.0% | 565 | 3.3% | 16 | 0.1% | 2.8% | 5.6% | 2194 | 12.8% | 33 | 0.2% | 1.5% | 11.6% |
| Jim Hogg | 9 | 5.6% | 1 | 0.7% | 12.1% | 15.1% | 10 | 6.3% | 1 | 0.7% | 11.9% | 16.4% | 61 | 38.1% | 2 | 1.1% | 2.9% | 24.9% |
| Jim Wells | 158 | 5.9% | 8 | 0.3% | 5.1% | 12.6% | 203 | 7.6% | 8 | 0.3% | 4.2% | 13.3% | 233 | 8.7% | 4 | 0.1% | 1.6% | 5.8% |
| Johnson | 380 | 6.3% | 24 | 0.4% | 6.2% | 15.3% | 673 | 11.1% | 27 | 0.4% | 4.0% | 17.6% | 1469 | 24.2% | 30 | 0.5% | 2.0% | 19.2% |
| Jones | 52 | 9.7% | 6 | 1.2% | 12.3% | 23.5% | 144 | 27.0% | 5 | 1.0% | 3.8% | 20.1% | 99 | 18.5% | 5 | 0.9% | 4.6% | 16.9% |
| Karnes | 71 | 5.4% | 8 | 0.6% | 10.9% | 18.7% | 156 | 11.8% | 8 | 0.6% | 4.9% | 18.5% | 443 | 33.6% | 11 | 0.9% | 2.6% | 27.5% |
| Kaufman | 261 | 5.6% | 21 | 0.5% | 8.1% | 18.9% | 589 | 12.7% | 17 | 0.4% | 3.0% | 15.5% | 1054 | 22.7% | 19 | 0.4% | 1.8% | 17.2% |
| Kendall | 97 | 4.7% | 10 | 0.5% | 10.6% | 22.1% | 212 | 10.4% | 14 | 0.7% | 6.6% | 29.9% | 645 | 31.5% | 8 | 0.4% | 1.3% | 17.9% |
| Kenedy | 5 | 2.5% | 0 | 0.1% | 3.2% | 2.2% | 41 | 20.2% | 1 | 0.7% | 3.5% | 20.0% | 57 | 28.1% | 2 | 0.8% | 3.0% | 23.7% |
| Kent | 9 | 16.4% | 0 | 0.8% | 4.6% | 16.6% | 16 | 29.1% | 1 | 0.9% | 3.2% | 20.5% | 6 | 10.9% | 0 | 0.2% | 2.3% | 5.4% |
| Kerr | 201 | 8.3% | 13 | 0.5% | 6.3% | 16.3% | 276 | 11.4% | 15 | 0.6% | 5.6% | 19.9% | 812 | 33.6% | 19 | 0.8% | 2.4% | 25.0% |
| Kimble | 17 | 4.7% | 1 | 0.4% | 8.1% | 10.0% | 98 | 26.8% | 2 | 0.5% | 1.7% | 12.2% | 95 | 26.0% | 3 | 0.8% | 3.1% | 21.1% |
| King | 1 | 1.4% | 0 | 0.0% | 3.1% | 1.4% | 5 | 6.9% | 1 | 1.4% | 20.4% | 45.5% | 4 | 5.6% | 0 | 0.1% | 1.6% | 2.9% |
| Kinney | 6 | 6.2% | 1 | 1.1% | 17.2% | 19.5% | 3 | 3.1% | 1 | 1.1% | 34.3% | 19.4% | 16 | 16.5% | 1 | 1.2% | 7.4% | 22.3% |
| Kleberg | 86 | 6.7% | 4 | 0.3% | 4.3% | 12.3% | 83 | 6.5% | 4 | 0.3% | 5.1% | 14.1% | 296 | 23.2% | 4 | 0.3% | 1.4% | 13.6% |
| Knox | 16 | 13.0% | 3 | 2.7% | 20.6% | 68.3% | 19 | 15.4% | 2 | 1.8% | 11.6% | 45.5% | 28 | 22.8% | 0 | 0.3% | 1.2% | 6.8% |
| Lamar | 124 | 4.2% | 9 | 0.3% | 7.4% | 14.5% | 188 | 6.3% | 9 | 0.3% | 5.0% | 14.9% | 679 | 22.8% | 13 | 0.4% | 1.9% | 20.0% |
| Lamb | 31 | 6.2% | 5 | 1.0% | 16.4% | 27.6% | 94 | 18.7% | 4 | 0.7% | 3.8% | 19.6% | 83 | 16.5% | 2 | 0.4% | 2.3% | 10.6% |

| COUNTY | Crashes with Alcohol Drunk Drivers | | | | | | Speed Involved Crashes | | | | | | Distracted Diver Crashes | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | # of all crashes with Alcohol drunk driver Total | (2)- Accidents with Alc / all accidents | Alc FOS Total | (5)_FOS of accidents with Alc / all accidents | (4)_FOS of accidents with Alc / all accidents with Alc | (1)_FOS of accidents with Alc / FOS of all accidents | # of all speed involved crashes Total | (2)- Accidents with Spd / all accidents | Spd inv cr FOS Total | (5)_FOS of accidents with Spd / all accidents | (4)_FOS of accidents with Spd / all accidents with Spd | (1)_FOS of accidents with Spd / FOS of all accidents | # of all crashes with Dist D Total | (2)- Accidents with Dist / all accidents | Dist inv cra FOS Total | (5)_FOS of accidents with Dist / all accidents | (4)_FOS of accidents with Dist / all accidents with Dist | (1)_FOS of accidents with Dist / FOS of all accidents |
| Lampasas | 47 | 5.8% | 1 | 0.1% | 1.4% | 3.3% | 115 | 14.3% | 4 | 0.5% | 3.6% | 20.4% | 210 | 26.1% | 3 | 0.4% | 1.6% | 17.2% |
| Lasalle | 30 | 5.4% | 4 | 0.7% | 13.0% | 11.5% | 93 | 16.6% | 6 | 1.0% | 6.3% | 17.3% | 159 | 28.4% | 11 | 2.1% | 7.2% | 34.0% |
| Lavaca | 59 | 8.5% | 5 | 0.6% | 7.6% | 19.3% | 86 | 12.4% | 3 | 0.5% | 4.0% | 14.8% | 140 | 20.2% | 5 | 0.7% | 3.5% | 21.0% |
| Lee | 66 | 5.6% | 8 | 0.6% | 11.5% | 17.4% | 241 | 20.5% | 13 | 1.1% | 5.3% | 29.4% | 240 | 20.4% | 6 | 0.5% | 2.5% | 13.7% |
| Leon | 68 | 5.2% | 7 | 0.6% | 10.9% | 15.1% | 235 | 18.0% | 10 | 0.8% | 4.2% | 20.1% | 252 | 19.4% | 9 | 0.7% | 3.7% | 19.2% |
| Liberty | 177 | 5.0% | 17 | 0.5% | 9.5% | 16.1% | 387 | 11.0% | 16 | 0.5% | 4.2% | 15.4% | 474 | 13.5% | 13 | 0.4% | 2.7% | 12.4% |
| Limestone | 67 | 6.2% | 7 | 0.6% | 10.3% | 20.6% | 143 | 13.2% | 6 | 0.5% | 4.1% | 17.7% | 290 | 26.8% | 5 | 0.5% | 1.8% | 15.4% |
| Lipscomb | 8 | 13.3% | 0 | 0.8% | 6.2% | 22.0% | 9 | 15.0% | 0 | 0.5% | 3.5% | 14.1% | 16 | 26.7% | 0 | 0.2% | 0.8% | 5.5% |
| Live Oak | 70 | 5.1% | 4 | 0.3% | 5.2% | 7.0% | 193 | 14.1% | 7 | 0.5% | 3.9% | 14.3% | 300 | 22.0% | 15 | 1.1% | 5.1% | 29.1% |
| Llano | 103 | 14.1% | 6 | 0.8% | 5.5% | 25.1% | 145 | 19.9% | 8 | 1.1% | 5.3% | 34.0% | 151 | 20.7% | 3 | 0.5% | 2.2% | 14.9% |
| Loving | 3 | 5.4% | 1 | 1.8% | 33.7% | 23.4% | 11 | 19.6% | 0 | 0.4% | 2.2% | 5.5% | 4 | 7.1% | 0 | 0.3% | 3.8% | 3.5% |
| Lubbock | 1194 | 5.7% | 54 | 0.3% | 4.5% | 16.3% | 1166 | 5.6% | 43 | 0.2% | 3.7% | 13.0% | 2496 | 12.0% | 40 | 0.2% | 1.6% | 12.0% |
| Lynn | 20 | 7.7% | 2 | 0.8% | 10.7% | 21.6% | 86 | 33.2% | 4 | 1.4% | 4.1% | 35.4% | 29 | 11.2% | 2 | 0.9% | 7.8% | 22.9% |
| Madison | 45 | 5.0% | 6 | 0.7% | 13.7% | 18.3% | 172 | 19.2% | 3 | 0.4% | 2.0% | 10.3% | 216 | 24.1% | 11 | 1.2% | 5.1% | 32.7% |
| Marion | 51 | 11.4% | 5 | 1.1% | 10.0% | 25.9% | 91 | 20.3% | 5 | 1.0% | 5.1% | 23.6% | 82 | 18.3% | 2 | 0.5% | 2.8% | 11.7% |
| Martin | 29 | 4.8% | 2 | 0.3% | 6.4% | 6.5% | 113 | 18.7% | 5 | 0.9% | 4.8% | 19.0% | 84 | 13.9% | 4 | 0.7% | 5.0% | 14.7% |
| Mason | 20 | 14.3% | 1 | 0.7% | 4.7% | 14.6% | 19 | 13.6% | 1 | 0.5% | 3.8% | 11.3% | 29 | 20.7% | 3 | 1.9% | 9.0% | 41.1% |
| Matagorda | 144 | 7.7% | 15 | 0.8% | 10.2% | 28.4% | 203 | 10.8% | 14 | 0.7% | 6.8% | 26.5% | 366 | 19.5% | 8 | 0.4% | 2.2% | 15.2% |
| Maverick | 116 | 4.8% | 3 | 0.1% | 2.6% | 8.5% | 51 | 2.1% | 2 | 0.1% | 4.4% | 6.2% | 1439 | 59.8% | 14 | 0.6% | 1.0% | 39.8% |
| McCulloch | 52 | 9.6% | 4 | 0.7% | 7.6% | 22.2% | 89 | 16.4% | 4 | 0.8% | 4.9% | 24.2% | 225 | 41.5% | 3 | 0.5% | 1.2% | 15.2% |
| McLennan | 774 | 5.3% | 48 | 0.3% | 6.1% | 16.6% | 1316 | 8.9% | 40 | 0.3% | 3.1% | 14.0% | 2563 | 17.4% | 44 | 0.3% | 1.7% | 15.3% |
| McMullen | 14 | 4.7% | 1 | 0.4% | 9.1% | 10.8% | 35 | 11.9% | 1 | 0.2% | 2.0% | 6.0% | 42 | 14.2% | 2 | 0.5% | 3.8% | 13.7% |
| Medina | 212 | 10.3% | 7 | 0.4% | 3.4% | 14.7% | 367 | 17.9% | 12 | 0.6% | 3.2% | 24.0% | 621 | 30.3% | 10 | 0.5% | 1.7% | 21.1% |
| Menard | 4 | 3.6% | 0 | 0.2% | 6.0% | 5.8% | 30 | 27.0% | 2 | 1.4% | 5.3% | 37.8% | 21 | 18.9% | 0 | 0.1% | 0.8% | 3.8% |
| Midland | 769 | 5.7% | 58 | 0.4% | 7.6% | 22.5% | 741 | 5.5% | 34 | 0.3% | 4.6% | 13.1% | 2850 | 21.2% | 44 | 0.3% | 1.6% | 17.0% |
| Milam | 101 | 7.2% | 6 | 0.4% | 5.6% | 16.1% | 242 | 17.2% | 8 | 0.6% | 3.3% | 22.8% | 350 | 24.9% | 6 | 0.5% | 1.9% | 18.4% |
| Mills | 14 | 5.7% | 1 | 0.5% | 8.1% | 12.1% | 52 | 21.2% | 2 | 0.9% | 4.2% | 23.2% | 57 | 23.3% | 3 | 1.2% | 5.1% | 31.1% |
| Mitchell | 26 | 5.2% | 5 | 1.1% | 21.1% | 32.1% | 101 | 20.4% | 4 | 0.7% | 3.6% | 21.6% | 92 | 18.5% | 3 | 0.7% | 3.6% | 19.3% |

| | Crashes with Alcohol Drunk Drivers | | | | | | Speed Involved Crashes | | | | | | Distracted Diver Crashes | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| COUNTY | # of all crashes with Alcohol drunk driver Total | (2)-Accidents with Alc / all accidents | Alc FOS Total | (5)_FOS of accidents with Alc / all accidents | (4)_FOS of accidents with Alc / all accidents with Alc | (1)_FOS of accidents with Alc / FOS of all accidents | # of all speed involved crashes Total | (2)-Accidents with Spd / all accidents | Spd inv cr FOS Total | (5)_FOS of accidents with Spd / all accidents | (4)_FOS of accidents with Spd / all accidents with Spd | (1)_FOS of accidents with Spd / FOS of all accidents | # of all crashes with Dist D Total | (2)-Accidents with Dist / all accidents | Dist inv cra FOS Total | (5)_FOS of accidents with Dist / all accidents | (4)_FOS of accidents with Dist / all accidents with Dist | (1)_FOS of accidents with Dist / FOS of all accidents |
| Montague | 62 | 7.6% | 6 | 0.7% | 9.1% | 26.1% | 178 | 21.9% | 8 | 0.9% | 4.2% | 34.9% | 183 | 22.5% | 5 | 0.7% | 3.0% | 25.3% |
| Montgomery | 1559 | 5.8% | 82 | 0.3% | 5.3% | 17.3% | 1853 | 6.9% | 71 | 0.3% | 3.8% | 15.0% | 5108 | 19.1% | 72 | 0.3% | 1.4% | 15.2% |
| Moore | 66 | 5.8% | 9 | 0.8% | 13.1% | 27.1% | 146 | 12.8% | 5 | 0.5% | 3.7% | 16.9% | 96 | 8.4% | 1 | 0.1% | 1.4% | 4.1% |
| Morris | 33 | 7.6% | 3 | 0.7% | 8.8% | 19.2% | 86 | 19.8% | 6 | 1.4% | 6.9% | 39.2% | 146 | 33.6% | 4 | 0.9% | 2.5% | 24.4% |
| Motley | 1 | 1.1% | 1 | 1.1% | 100.0% | 32.4% | 16 | 18.2% | 0 | 0.3% | 1.6% | 8.1% | 19 | 21.6% | 0 | 0.4% | 1.8% | 11.2% |
| Nacogdoches | 228 | 7.2% | 16 | 0.5% | 7.0% | 19.1% | 343 | 10.8% | 15 | 0.5% | 4.4% | 17.9% | 245 | 7.7% | 6 | 0.2% | 2.3% | 6.8% |
| Navarro | 193 | 5.9% | 11 | 0.3% | 5.6% | 15.4% | 438 | 13.3% | 9 | 0.3% | 2.1% | 13.3% | 586 | 17.8% | 15 | 0.5% | 2.6% | 21.2% |
| Newton | 48 | 8.7% | 4 | 0.8% | 8.6% | 22.0% | 146 | 26.6% | 4 | 0.8% | 2.8% | 22.0% | 27 | 4.9% | 1 | 0.1% | 2.7% | 3.9% |
| Nolan | 62 | 4.9% | 6 | 0.5% | 9.3% | 18.0% | 352 | 28.1% | 11 | 0.9% | 3.1% | 34.4% | 200 | 15.9% | 5 | 0.4% | 2.6% | 16.0% |
| Nueces | 1036 | 6.9% | 56 | 0.4% | 5.5% | 19.5% | 496 | 3.3% | 22 | 0.1% | 4.4% | 7.6% | 1997 | 13.2% | 37 | 0.2% | 1.8% | 12.6% |
| Ochiltree | 29 | 6.3% | 2 | 0.4% | 6.4% | 11.5% | 78 | 17.0% | 3 | 0.6% | 3.8% | 18.3% | 81 | 17.6% | 4 | 0.8% | 4.7% | 23.6% |
| Oldham | 11 | 2.8% | 1 | 0.3% | 11.9% | 8.3% | 144 | 36.7% | 5 | 1.3% | 3.6% | 33.1% | 18 | 4.6% | 1 | 0.3% | 7.2% | 8.2% |
| Orange | 285 | 5.9% | 16 | 0.3% | 5.5% | 12.5% | 420 | 8.7% | 17 | 0.3% | 4.0% | 13.2% | 568 | 11.7% | 13 | 0.3% | 2.3% | 10.6% |
| Palo Pinto | 105 | 6.4% | 8 | 0.5% | 7.8% | 16.6% | 256 | 15.7% | 9 | 0.6% | 3.7% | 19.3% | 429 | 26.4% | 7 | 0.4% | 1.6% | 14.2% |
| Panola | 105 | 7.8% | 8 | 0.6% | 7.6% | 17.0% | 286 | 21.1% | 13 | 1.0% | 4.5% | 27.4% | 144 | 10.6% | 5 | 0.4% | 3.4% | 10.4% |
| Parker | 388 | 6.7% | 13 | 0.2% | 3.4% | 10.9% | 891 | 15.3% | 22 | 0.4% | 2.4% | 18.0% | 1415 | 24.3% | 22 | 0.4% | 1.6% | 18.4% |
| Parmer | 18 | 4.7% | 1 | 0.4% | 7.5% | 9.2% | 90 | 23.4% | 3 | 0.7% | 3.1% | 19.2% | 62 | 16.1% | 1 | 0.2% | 1.4% | 5.9% |
| Pecos | 43 | 3.8% | 5 | 0.4% | 11.4% | 11.7% | 108 | 9.5% | 7 | 0.6% | 6.8% | 17.3% | 154 | 13.5% | 6 | 0.6% | 4.1% | 15.0% |
| Polk | 142 | 6.2% | 16 | 0.7% | 11.2% | 21.0% | 266 | 11.5% | 11 | 0.5% | 4.1% | 14.3% | 248 | 10.8% | 10 | 0.4% | 4.0% | 13.0% |
| Potter | 403 | 4.5% | 30 | 0.3% | 7.4% | 16.6% | 428 | 4.8% | 22 | 0.2% | 5.1% | 12.2% | 642 | 7.2% | 14 | 0.2% | 2.3% | 8.0% |
| Presidio | 20 | 10.6% | 0 | 0.2% | 2.1% | 7.1% | 37 | 19.7% | 2 | 1.1% | 5.6% | 35.5% | 28 | 14.9% | 2 | 0.8% | 5.7% | 27.3% |
| Rains | 22 | 6.7% | 2 | 0.6% | 8.7% | 16.9% | 29 | 8.8% | 3 | 0.9% | 9.8% | 25.1% | 96 | 29.3% | 3 | 0.8% | 2.9% | 24.4% |
| Randall | 275 | 4.9% | 19 | 0.3% | 6.9% | 18.2% | 317 | 5.7% | 14 | 0.2% | 4.4% | 13.3% | 528 | 9.5% | 11 | 0.2% | 2.1% | 10.6% |
| Reagan | 10 | 2.8% | 1 | 0.4% | 12.8% | 6.9% | 51 | 14.3% | 5 | 1.4% | 9.7% | 26.5% | 94 | 26.4% | 2 | 0.5% | 2.0% | 9.9% |
| Real | 10 | 4.5% | 4 | 2.0% | 43.7% | 22.9% | 96 | 43.6% | 9 | 4.1% | 9.3% | 46.9% | 67 | 30.5% | 3 | 1.3% | 4.4% | 15.4% |
| Red River | 35 | 8.8% | 6 | 1.5% | 17.0% | 35.8% | 52 | 13.0% | 3 | 0.8% | 6.5% | 20.4% | 60 | 15.0% | 1 | 0.2% | 1.5% | 5.6% |
| Reeves | 59 | 4.5% | 9 | 0.7% | 15.8% | 14.6% | 232 | 17.8% | 12 | 0.9% | 5.1% | 18.4% | 276 | 21.1% | 12 | 0.9% | 4.5% | 19.3% |
| Refugio | 29 | 4.8% | 4 | 0.6% | 12.3% | 14.0% | 129 | 21.4% | 6 | 1.0% | 4.7% | 23.8% | 169 | 28.1% | 3 | 0.5% | 1.9% | 12.4% |

| | Crashes with Alcohol Drunk Drivers | | | | | | Speed Involved Crashes | | | | | | Distracted Diver Crashes | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| COUNTY | # of all crashes with Alcohol drunk driver Total | (2)- Accidents with Alc / all accidents | Alc FOS Total | (5)_FOS of accidents with Alc / all accidents | (4)_FOS of accidents with Alc / all accidents with Alc | (1)_FOS of accidents with Alc / FOS of all accidents | # of all speed involved crashes Total | (2)- Accidents with Spd / all accidents | Spd inv cr FOS Total | (5)_FOS of accidents with Spd / all accidents | (4)_FOS of accidents with Spd / all accidents with Spd | (1)_FOS of accidents with Spd / FOS of all accidents | # of all crashes with Dist D Total | (2)- Accidents with Dist / all accidents | Dist inv cra FOS Total | (5)_FOS of accidents with Dist / all accidents | (4)_FOS of accidents with Dist / all accidents with Dist | (1)_FOS of accidents with Dist / FOS of all accidents |
| Roberts | 3 | 2.6% | 1 | 1.0% | 40.7% | 17.2% | 34 | 29.1% | 2 | 1.4% | 4.9% | 23.5% | 16 | 13.7% | 1 | 1.0% | 7.6% | 17.1% |
| Robertson | 70 | 7.6% | 7 | 0.8% | 10.0% | 25.7% | 114 | 12.3% | 6 | 0.6% | 4.8% | 20.3% | 247 | 26.7% | 5 | 0.5% | 1.8% | 16.6% |
| Rockwall | 137 | 4.0% | 8 | 0.2% | 5.8% | 15.1% | 126 | 3.6% | 3 | 0.1% | 2.5% | 5.9% | 1214 | 35.1% | 14 | 0.4% | 1.2% | 27.5% |
| Runnels | 31 | 8.5% | 5 | 1.3% | 14.8% | 30.9% | 82 | 22.5% | 2 | 0.7% | 2.9% | 16.1% | 56 | 15.4% | 1 | 0.2% | 1.5% | 5.7% |
| Rusk | 124 | 5.7% | 12 | 0.6% | 9.7% | 14.9% | 356 | 16.3% | 15 | 0.7% | 4.1% | 18.1% | 269 | 12.4% | 11 | 0.5% | 4.2% | 14.0% |
| Sabine | 37 | 10.5% | 6 | 1.7% | 16.0% | 34.9% | 101 | 28.8% | 7 | 1.9% | 6.7% | 39.6% | 35 | 10.0% | 3 | 0.7% | 7.3% | 15.1% |
| San Augustine | 31 | 8.8% | 6 | 1.6% | 18.5% | 32.9% | 69 | 19.6% | 4 | 1.2% | 6.3% | 25.0% | 54 | 15.3% | 3 | 0.8% | 5.2% | 15.9% |
| San Jacinto | 91 | 8.4% | 11 | 1.0% | 11.7% | 25.5% | 269 | 24.9% | 13 | 1.2% | 5.0% | 31.8% | 58 | 5.4% | 4 | 0.4% | 6.7% | 9.3% |
| San Patricio | 234 | 7.1% | 15 | 0.5% | 6.4% | 19.5% | 456 | 13.9% | 17 | 0.5% | 3.6% | 21.5% | 913 | 27.9% | 16 | 0.5% | 1.7% | 20.6% |
| San Saba | 17 | 11.8% | 3 | 2.0% | 16.7% | 33.8% | 31 | 21.5% | 2 | 1.2% | 5.6% | 20.7% | 48 | 33.3% | 3 | 2.0% | 6.0% | 34.2% |
| Schleicher | 8 | 6.3% | 2 | 1.6% | 25.9% | 28.3% | 19 | 14.8% | 2 | 1.9% | 12.8% | 33.2% | 29 | 22.7% | 0 | 0.4% | 1.6% | 6.4% |
| Scurry | 44 | 5.5% | 5 | 0.6% | 11.4% | 18.9% | 149 | 18.6% | 5 | 0.7% | 3.5% | 19.6% | 138 | 17.2% | 4 | 0.5% | 2.9% | 15.0% |
| Shackelford | 18 | 11.4% | 2 | 1.0% | 8.4% | 21.1% | 32 | 20.3% | 2 | 1.0% | 5.1% | 22.7% | 31 | 19.6% | 2 | 1.5% | 7.6% | 32.6% |
| Shelby | 116 | 9.7% | 9 | 0.7% | 7.4% | 20.2% | 228 | 19.0% | 7 | 0.6% | 3.2% | 17.4% | 221 | 18.5% | 6 | 0.5% | 2.6% | 13.4% |
| Sherman | 9 | 4.8% | 0 | 0.2% | 4.0% | 5.9% | 35 | 18.8% | 1 | 0.3% | 1.5% | 8.6% | 50 | 26.9% | 2 | 0.8% | 3.0% | 24.6% |
| Smith | 648 | 4.0% | 34 | 0.2% | 5.2% | 10.6% | 1742 | 10.7% | 58 | 0.4% | 3.4% | 18.5% | 2920 | 18.0% | 45 | 0.3% | 1.5% | 14.1% |
| Somervell | 29 | 7.2% | 4 | 1.1% | 15.0% | 29.0% | 109 | 27.0% | 6 | 1.5% | 5.7% | 41.2% | 152 | 37.6% | 5 | 1.1% | 3.0% | 30.5% |
| Starr | 112 | 5.7% | 6 | 0.3% | 5.8% | 16.2% | 240 | 12.3% | 9 | 0.5% | 3.8% | 23.0% | 372 | 19.0% | 7 | 0.4% | 1.8% | 17.1% |
| Stephens | 31 | 9.4% | 3 | 0.8% | 8.6% | 29.9% | 62 | 18.8% | 4 | 1.2% | 6.4% | 44.7% | 85 | 25.8% | 1 | 0.3% | 1.3% | 12.3% |
| Sterling | 5 | 5.3% | 0 | 0.1% | 1.2% | 0.9% | 27 | 28.4% | 3 | 2.7% | 9.3% | 39.4% | 7 | 7.4% | 0 | 0.2% | 2.6% | 2.8% |
| Stonewall | 6 | 8.3% | 3 | 4.2% | 50.4% | 53.5% | 10 | 13.9% | 0 | 0.2% | 1.2% | 2.1% | 13 | 18.1% | 0 | 0.6% | 3.1% | 7.2% |
| Sutton | 20 | 4.8% | 1 | 0.3% | 6.2% | 6.2% | 106 | 25.7% | 6 | 1.6% | 6.1% | 32.5% | 59 | 14.3% | 1 | 0.2% | 1.7% | 5.2% |
| Swisher | 18 | 6.3% | 3 | 0.9% | 14.6% | 28.2% | 80 | 27.9% | 2 | 0.7% | 2.4% | 21.0% | 35 | 12.2% | 1 | 0.2% | 1.9% | 7.0% |
| Tarrant | 4888 | 5.6% | 203 | 0.2% | 4.2% | 12.4% | 3226 | 3.7% | 130 | 0.1% | 4.0% | 7.9% | 22277 | 25.6% | 350 | 0.4% | 1.6% | 21.3% |
| Taylor | 421 | 3.9% | 23 | 0.2% | 5.4% | 11.3% | 815 | 7.5% | 23 | 0.2% | 2.9% | 11.5% | 1119 | 10.4% | 18 | 0.2% | 1.6% | 8.7% |
| Terrell | 6 | 10.9% | 1 | 2.2% | 20.6% | 41.1% | 10 | 18.2% | 1 | 2.2% | 12.0% | 39.8% | 9 | 16.4% | 1 | 1.9% | 11.9% | 35.6% |
| Terry | 44 | 8.1% | 4 | 0.7% | 8.3% | 24.2% | 95 | 17.6% | 3 | 0.5% | 2.9% | 18.0% | 174 | 32.2% | 5 | 0.9% | 2.7% | 31.0% |
| Throckmorton | 6 | 7.2% | 0 | 0.2% | 2.7% | 15.2% | 25 | 30.1% | 0 | 0.3% | 1.0% | 23.6% | 8 | 9.6% | 0 | 0.3% | 3.1% | 23.5% |

| | Crashes with Alcohol Drunk Drivers | | | | | | Speed Involved Crashes | | | | | | Distracted Diver Crashes | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| COUNTY | # of all crashes with Alcohol drunk driver Total | (2)-Accidents with Alc / all accidents | Alc FOS Total | (5)_FOS of accidents with Alc / all accidents | (4)_FOS of accidents with Alc / all accidents with Alc | (1)_FOS of accidents with Alc / FOS of all accidents | # of all speed involved crashes Total | (2)-Accidents with Spd / all accidents | Spd inv cr FOS Total | (5)_FOS of accidents with Spd / all accidents | (4)_FOS of accidents with Spd / all accidents with Spd | (1)_FOS of accidents with Spd / FOS of all accidents | # of all crashes with Dist D Total | (2)-Accidents with Dist / all accidents | Dist inv cra FOS Total | (5)_FOS of accidents with Dist / all accidents | (4)_FOS of accidents with Dist / all accidents with Dist | (1)_FOS of accidents with Dist / FOS of all accidents |
| Titus | 97 | 4.1% | 7 | 0.3% | 6.9% | 13.6% | 210 | 8.8% | 9 | 0.4% | 4.5% | 19.0% | 434 | 18.3% | 7 | 0.3% | 1.6% | 14.2% |
| Tom Green | 249 | 3.5% | 17 | 0.2% | 6.9% | 13.4% | 392 | 5.5% | 22 | 0.3% | 5.5% | 16.9% | 1051 | 14.6% | 20 | 0.3% | 1.9% | 15.4% |
| Travis | 4590 | 9.3% | 179 | 0.4% | 3.9% | 15.9% | 2917 | 5.9% | 107 | 0.2% | 3.7% | 9.5% | 13734 | 27.8% | 263 | 0.5% | 1.9% | 23.3% |
| Trinity | 47 | 12.2% | 5 | 1.2% | 10.2% | 25.1% | 47 | 12.2% | 3 | 0.9% | 7.0% | 17.2% | 50 | 13.0% | 2 | 0.5% | 3.6% | 9.5% |
| Tyler | 52 | 8.9% | 4 | 0.7% | 8.0% | 13.8% | 179 | 30.7% | 7 | 1.2% | 3.9% | 23.0% | 69 | 11.8% | 5 | 0.9% | 7.8% | 17.7% |
| Upshur | 110 | 6.9% | 6 | 0.4% | 5.5% | 13.3% | 149 | 9.4% | 7 | 0.5% | 4.9% | 16.2% | 409 | 25.8% | 9 | 0.6% | 2.2% | 19.8% |
| Upton | 20 | 9.0% | 4 | 1.6% | 18.0% | 21.5% | 36 | 16.3% | 5 | 2.2% | 13.4% | 28.7% | 56 | 25.3% | 2 | 0.9% | 3.4% | 11.5% |
| Uvalde | 93 | 6.6% | 7 | 0.5% | 7.8% | 22.9% | 105 | 7.5% | 4 | 0.3% | 3.8% | 12.6% | 516 | 36.8% | 8 | 0.6% | 1.5% | 25.1% |
| Val Verde | 145 | 6.3% | 8 | 0.3% | 5.2% | 17.6% | 137 | 6.0% | 4 | 0.2% | 3.2% | 10.3% | 827 | 36.2% | 13 | 0.6% | 1.6% | 31.0% |
| Van Zandt | 213 | 8.5% | 14 | 0.6% | 6.7% | 17.6% | 486 | 19.4% | 18 | 0.7% | 3.7% | 22.2% | 504 | 20.1% | 14 | 0.6% | 2.8% | 17.4% |
| Victoria | 204 | 6.8% | 21 | 0.7% | 10.1% | 22.3% | 196 | 6.5% | 12 | 0.4% | 6.0% | 12.7% | 237 | 7.9% | 6 | 0.2% | 2.5% | 6.3% |
| Walker | 236 | 5.5% | 18 | 0.4% | 7.6% | 21.0% | 643 | 15.0% | 19 | 0.5% | 3.0% | 22.9% | 276 | 6.5% | 8 | 0.2% | 2.8% | 9.1% |
| Waller | 145 | 7.7% | 7 | 0.4% | 4.9% | 11.3% | 266 | 14.1% | 13 | 0.7% | 5.0% | 20.9% | 467 | 24.7% | 8 | 0.4% | 1.8% | 13.4% |
| Ward | 64 | 7.8% | 9 | 1.1% | 14.5% | 23.9% | 102 | 12.5% | 4 | 0.5% | 3.8% | 10.0% | 227 | 27.7% | 5 | 0.6% | 2.1% | 12.0% |
| Washington | 152 | 6.2% | 10 | 0.4% | 6.7% | 18.6% | 299 | 12.2% | 8 | 0.3% | 2.8% | 15.5% | 355 | 14.5% | 8 | 0.3% | 2.2% | 14.5% |
| Webb | 421 | 2.5% | 18 | 0.1% | 4.3% | 7.0% | 205 | 1.2% | 8 | 0.0% | 3.9% | 3.2% | 1260 | 7.4% | 22 | 0.1% | 1.8% | 8.8% |
| Wharton | 175 | 8.7% | 9 | 0.5% | 5.3% | 18.0% | 369 | 18.4% | 11 | 0.5% | 2.9% | 20.6% | 280 | 14.0% | 8 | 0.4% | 2.8% | 15.2% |
| Wheeler | 31 | 8.7% | 5 | 1.4% | 15.5% | 31.1% | 53 | 14.8% | 3 | 0.8% | 5.7% | 19.4% | 70 | 19.6% | 3 | 0.9% | 4.8% | 21.8% |
| Wichita | 367 | 5.3% | 17 | 0.2% | 4.5% | 16.2% | 480 | 6.9% | 12 | 0.2% | 2.6% | 12.3% | 3060 | 43.9% | 34 | 0.5% | 1.1% | 33.6% |
| Wilbarger | 36 | 4.2% | 2 | 0.3% | 6.9% | 10.4% | 120 | 14.1% | 5 | 0.6% | 4.2% | 21.3% | 172 | 20.1% | 4 | 0.4% | 2.2% | 15.5% |
| Willacy | 54 | 13.0% | 2 | 0.5% | 3.7% | 17.8% | 124 | 29.8% | 2 | 0.6% | 2.0% | 21.8% | 47 | 11.3% | 3 | 0.7% | 6.0% | 25.3% |
| Williamson | 936 | 5.9% | 55 | 0.3% | 5.9% | 17.0% | 729 | 4.6% | 29 | 0.2% | 4.0% | 8.9% | 4451 | 27.9% | 73 | 0.5% | 1.7% | 22.6% |
| Wilson | 118 | 6.2% | 9 | 0.5% | 7.7% | 16.9% | 285 | 15.1% | 12 | 0.6% | 4.1% | 21.4% | 527 | 27.9% | 8 | 0.4% | 1.6% | 15.6% |
| Winkler | 35 | 8.2% | 4 | 0.8% | 10.2% | 17.9% | 57 | 13.3% | 2 | 0.4% | 3.2% | 9.1% | 138 | 32.3% | 3 | 0.8% | 2.5% | 17.1% |
| Wise | 163 | 6.2% | 10 | 0.4% | 6.0% | 13.0% | 431 | 16.3% | 16 | 0.6% | 3.6% | 20.7% | 456 | 17.3% | 7 | 0.3% | 1.5% | 9.3% |
| Wood | 109 | 7.3% | 8 | 0.6% | 7.7% | 14.3% | 290 | 19.4% | 15 | 1.0% | 5.3% | 26.1% | 283 | 18.9% | 8 | 0.5% | 2.9% | 13.8% |
| Yoakum | 18 | 5.5% | 2 | 0.8% | 13.8% | 22.9% | 45 | 13.8% | 2 | 0.5% | 4.0% | 16.5% | 26 | 8.0% | 2 | 0.5% | 6.1% | 14.6% |
| Young | 30 | 4.0% | 3 | 0.4% | 9.3% | 17.6% | 85 | 11.5% | 3 | 0.4% | 3.6% | 19.3% | 266 | 35.8% | 3 | 0.4% | 1.1% | 18.3% |
| Zapata | 21 | 6.0% | 1 | 0.4% | 6.3% | 16.7% | 13 | 3.7% | 2 | 0.6% | 17.2% | 28.3% | 80 | 23.0% | 1 | 0.2% | 1.0% | 9.8% |
| Zavala | 13 | 9.8% | 2 | 1.2% | 12.2% | 12.5% | 14 | 2.3% | 3 | 1.9% | 18.5% | 20.4% | 26 | 19.5% | 2 | 1.1% | 5.8% | 11.8% |

## Appendix C: Obtained Three Coordinates (Ratios) of the Counties

| COUNTY | Percent of FOS of crashes with the 3 driver-related factors from all crashes multiplied by 1000 | | |
|---|---|---|---|
| | **Alcohol related ratio** | **Speeding related ratio** | **Distraction related ratio** |
| Anderson | 3.8 | 5.9 | 4.6 |
| Andrews | 17.8 | 9.3 | 5.1 |
| Angelina | 2.3 | 2.4 | 2.3 |
| Aransas | 3.2 | 4.0 | 5.9 |
| Archer | 9.1 | 6.6 | 1.4 |
| Armstrong | 6.2 | 13.6 | 8.2 |
| Atascosa | 3.7 | 3.2 | 5.2 |
| Austin | 3.9 | 7.7 | 4.1 |
| Bailey | 8.4 | 5.9 | 6.1 |
| Bandera | 11.9 | 15.2 | 6.1 |
| Bastrop | 5.2 | 3.9 | 7.8 |
| Baylor | 21.7 | 22.5 | 12.7 |
| Bee | 4.6 | 2.6 | 5.5 |
| Bell | 2.9 | 3.5 | 3.0 |
| Bexar | 2.0 | 1.3 | 7.1 |
| Blanco | 16.9 | 17.8 | 9.6 |
| Borden | 0.2 | 39.2 | 4.2 |
| Bosque | 9.9 | 14.2 | 5.6 |
| Bowie | 2.7 | 2.9 | 3.2 |
| Brazoria | 3.4 | 2.5 | 3.7 |
| Brazos | 2.2 | 1.6 | 2.8 |
| Brewster | 8.1 | 1.7 | 16.8 |
| Briscoe | 0.5 | 5.3 | 8.8 |
| Brooks | 2.3 | 7.3 | 5.6 |
| Brown | 3.1 | 3.5 | 2.8 |
| Burleson | 5.2 | 4.8 | 4.0 |
| Burnet | 8.0 | 8.8 | 6.8 |
| Caldwell | 5.7 | 5.8 | 4.2 |
| Calhoun | 5.1 | 2.8 | 6.2 |
| Callahan | 4.1 | 6.5 | 4.0 |
| Cameron | 2.2 | 1.5 | 1.0 |
| Camp | 5.6 | 7.5 | 3.9 |
| Carson | 2.8 | 4.2 | 18.8 |

| COUNTY | Percent of FOS of crashes with the 3 driver-related factors from all crashes multiplied by 1000 | | |
|---|---|---|---|
| | **Alcohol related ratio** | **Speeding related ratio** | **Distraction related ratio** |
| Cass | 6.7 | 9.8 | 6.2 |
| Castro | 9.1 | 7.6 | 2.5 |
| Chambers | 4.6 | 3.5 | 3.0 |
| Cherokee | 5.9 | 6.1 | 4.2 |
| Childress | 7.1 | 8.6 | 3.5 |
| Clay | 7.2 | 9.3 | 2.6 |
| Cochran | 2.6 | 1.3 | 5.2 |
| Coke | 39.5 | 6.0 | 25.0 |
| Coleman | 5.6 | 2.9 | 6.2 |
| Collin | 2.1 | 1.6 | 3.9 |
| Collingsworth | 60.9 | 21.2 | 21.4 |
| Colorado | 3.9 | 8.9 | 3.6 |
| Comal | 3.9 | 4.1 | 4.5 |
| Comanche | 4.2 | 6.7 | 5.6 |
| Concho | 9.7 | 5.0 | 2.7 |
| Cooke | 9.6 | 9.7 | 8.6 |
| Coryell | 4.0 | 3.0 | 2.8 |
| Cottle | 0.0 | 4.2 | 31.0 |
| Crane | 12.0 | 10.9 | 3.1 |
| Crockett | 5.4 | 9.9 | 7.8 |
| Crosby | 20.6 | 8.9 | 10.7 |
| Culberson | 2.9 | 20.3 | 10.1 |
| Dallam | 0.7 | 3.8 | 2.4 |
| Dallas | 2.6 | 2.2 | 2.3 |
| Dawson | 5.9 | 4.2 | 6.7 |
| Deaf Smith | 3.7 | 1.7 | 3.1 |
| Delta | 6.9 | 2.3 | 3.3 |
| Denton | 1.8 | 1.7 | 2.9 |
| Dewitt | 3.1 | 4.3 | 5.3 |
| Dickens | 3.0 | 2.8 | 1.5 |
| Dimmit | 5.5 | 12.1 | 8.0 |
| Donley | 1.2 | 14.1 | 6.9 |
| Duval | 3.4 | 4.3 | 11.5 |

| COUNTY | Percent of FOS of crashes with the 3 driver-related factors from all crashes multiplied by 1000 | | |
|---|---|---|---|
| | **Alcohol related ratio** | **Speeding related ratio** | **Distraction related ratio** |
| Eastland | 6.9 | 12.6 | 6.4 |
| Ector | 6.7 | 3.5 | 3.1 |
| Edwards | 9.0 | 22.8 | 4.0 |
| Ellis | 4.2 | 5.0 | 8.3 |
| El Paso | 2.2 | 0.9 | 2.7 |
| Erath | 5.1 | 7.2 | 8.7 |
| Falls | 9.3 | 6.6 | 5.0 |
| Fannin | 4.7 | 5.7 | 9.1 |
| Fayette | 8.6 | 7.4 | 9.3 |
| Fisher | 9.1 | 20.5 | 7.0 |
| Floyd | 0.8 | 0.5 | 4.1 |
| Foard | 1.4 | 1.9 | 43.6 |
| Fort Bend | 2.2 | 1.6 | 2.6 |
| Franklin | 19.0 | 10.5 | 1.8 |
| Freestone | 1.5 | 3.1 | 5.3 |
| Frio | 9.3 | 10.8 | 14.0 |
| Gaines | 8.9 | 8.1 | 11.4 |
| Galveston | 2.4 | 1.8 | 4.4 |
| Garza | 1.5 | 8.8 | 7.2 |
| Gillespie | 3.1 | 5.8 | 7.3 |
| Glasscock | 3.7 | 8.5 | 8.5 |
| Goliad | 4.8 | 8.6 | 11.0 |
| Gonzales | 5.8 | 9.6 | 7.8 |
| Gray | 3.9 | 4.0 | 1.3 |
| Grayson | 6.7 | 6.1 | 9.4 |
| Gregg | 2.7 | 3.1 | 4.4 |
| Grimes | 4.7 | 4.5 | 5.4 |
| Guadalupe | 2.7 | 2.8 | 4.5 |
| Hale | 4.4 | 5.6 | 3.7 |
| Hall | 6.3 | 6.9 | 8.6 |
| Hamilton | 8.3 | 16.0 | 14.7 |
| Hansford | 20.9 | 11.8 | 13.0 |
| Hardeman | 7.4 | 9.1 | 14.1 |

| COUNTY | Percent of FOS of crashes with the 3 driver-related factors from all crashes multiplied by 1000 | | |
|---|---|---|---|
| | **Alcohol related ratio** | **Speeding related ratio** | **Distraction related ratio** |
| Hardin | 5.2 | 5.1 | 4.5 |
| Harris | 1.8 | 1.0 | 1.6 |
| Harrison | 6.0 | 6.2 | 3.9 |
| Hartley | 4.1 | 8.8 | 8.1 |
| Haskell | 13.8 | 19.5 | 18.4 |
| Hays | 3.9 | 4.3 | 3.9 |
| Hemphill | 1.0 | 2.0 | 6.2 |
| Henderson | 5.9 | 5.2 | 6.5 |
| Hidalgo | 2.3 | 2.0 | 1.3 |
| Hill | 4.9 | 6.2 | 9.5 |
| Hockley | 4.5 | 5.3 | 7.2 |
| Hood | 2.2 | 4.4 | 1.4 |
| Hopkins | 3.3 | 6.4 | 2.9 |
| Houston | 5.4 | 7.0 | 5.6 |
| Howard | 2.0 | 4.0 | 1.7 |
| Hudspeth | 14.0 | 18.4 | 12.1 |
| Hunt | 4.3 | 3.7 | 6.1 |
| Hutchinson | 9.3 | 5.4 | 8.3 |
| Irion | 11.2 | 8.2 | 15.8 |
| Jack | 2.2 | 3.2 | 2.8 |
| Jackson | 10.7 | 6.9 | 7.7 |
| Jasper | 3.4 | 6.4 | 4.2 |
| Jeff Davis | 2.1 | 24.0 | 3.1 |
| Jefferson | 1.5 | 0.9 | 1.9 |
| Jim Hogg | 6.8 | 7.4 | 11.2 |
| Jim Wells | 3.0 | 3.2 | 1.4 |
| Johnson | 3.9 | 4.5 | 4.9 |
| Jones | 12.0 | 10.2 | 8.6 |
| Karnes | 5.9 | 5.8 | 8.7 |
| Kaufman | 4.6 | 3.7 | 4.1 |
| Kendall | 5.0 | 6.8 | 4.1 |
| Kenedy | 0.8 | 7.1 | 8.4 |
| Kent | 7.5 | 9.3 | 2.5 |

| COUNTY | Percent of FOS of crashes with the 3 driver-related factors from all crashes multiplied by 1000 | | |
|---|---|---|---|
| | **Alcohol related ratio** | **Speeding related ratio** | **Distraction related ratio** |
| Kerr | 5.2 | 6.4 | 8.0 |
| Kimble | 3.8 | 4.6 | 8.0 |
| King | 0.4 | 14.2 | 0.9 |
| Kinney | 10.7 | 10.6 | 12.2 |
| Kleberg | 2.9 | 3.3 | 3.2 |
| Knox | 26.8 | 17.9 | 2.7 |
| Lamar | 3.1 | 3.2 | 4.2 |
| Lamb | 10.1 | 7.2 | 3.9 |
| Lampasas | 0.8 | 5.1 | 4.3 |
| Lasalle | 6.9 | 10.5 | 20.5 |
| Lavaca | 6.5 | 5.0 | 7.1 |
| Lee | 6.4 | 10.9 | 5.1 |
| Leon | 5.7 | 7.6 | 7.2 |
| Liberty | 4.8 | 4.6 | 3.7 |
| Limestone | 6.4 | 5.4 | 4.7 |
| Lipscomb | 8.2 | 5.3 | 2.1 |
| Live Oak | 2.7 | 5.5 | 11.1 |
| Llano | 7.8 | 10.5 | 4.6 |
| Loving | 18.0 | 4.3 | 2.7 |
| Lubbock | 2.6 | 2.1 | 1.9 |
| Lynn | 8.2 | 13.5 | 8.8 |
| Madison | 6.9 | 3.9 | 12.4 |
| Marion | 11.3 | 10.4 | 5.1 |
| Martin | 3.1 | 8.9 | 6.9 |
| Mason | 6.6 | 5.1 | 18.7 |
| Matagorda | 7.9 | 7.3 | 4.2 |
| Maverick | 1.3 | 0.9 | 5.9 |
| McCulloch | 7.3 | 8.0 | 5.0 |
| McLennan | 3.2 | 2.7 | 3.0 |
| McMullen | 4.3 | 2.4 | 5.4 |
| Medina | 3.6 | 5.8 | 5.1 |
| Menard | 2.2 | 14.2 | 1.4 |
| Midland | 4.3 | 2.5 | 3.3 |

| COUNTY | Percent of FOS of crashes with the 3 driver-related factors from all crashes multiplied by 1000 | | |
|---|---|---|---|
| | **Alcohol related ratio** | **Speeding related ratio** | **Distraction related ratio** |
| Milam | 4.0 | 5.7 | 4.6 |
| Mills | 4.6 | 8.9 | 11.9 |
| Mitchell | 11.0 | 7.4 | 6.6 |
| Montague | 6.9 | 9.3 | 6.7 |
| Montgomery | 3.1 | 2.7 | 2.7 |
| Moore | 7.6 | 4.8 | 1.1 |
| Morris | 6.7 | 13.7 | 8.6 |
| Motley | 11.4 | 2.8 | 3.9 |
| Nacogdoches | 5.0 | 4.7 | 1.8 |
| Navarro | 3.3 | 2.8 | 4.6 |
| Newton | 7.5 | 7.5 | 1.3 |
| Nolan | 4.6 | 8.8 | 4.1 |
| Nueces | 3.7 | 1.5 | 2.4 |
| Ochiltree | 4.0 | 6.4 | 8.3 |
| Oldham | 3.3 | 13.3 | 3.3 |
| Orange | 3.2 | 3.4 | 2.7 |
| Palo Pinto | 5.0 | 5.8 | 4.3 |
| Panola | 5.9 | 9.5 | 3.6 |
| Parker | 2.2 | 3.7 | 3.8 |
| Parmer | 3.5 | 7.3 | 2.3 |
| Pecos | 4.3 | 6.4 | 5.5 |
| Polk | 6.9 | 4.7 | 4.3 |
| Potter | 3.4 | 2.5 | 1.6 |
| Presidio | 2.2 | 11.0 | 8.5 |
| Rains | 5.8 | 8.6 | 8.4 |
| Randall | 3.4 | 2.5 | 2.0 |
| Reagan | 3.6 | 13.9 | 5.2 |
| Real | 19.9 | 40.7 | 13.4 |
| Red River | 14.9 | 8.5 | 2.3 |
| Reeves | 7.2 | 9.0 | 9.5 |
| Refugio | 5.9 | 10.1 | 5.2 |
| Roberts | 10.4 | 14.2 | 10.3 |
| Robertson | 7.6 | 6.0 | 4.9 |

| COUNTY | Percent of FOS of crashes with the 3 driver-related factors from all crashes multiplied by 1000 | | |
|---|---|---|---|
| | **Alcohol related ratio** | **Speeding related ratio** | **Distraction related ratio** |
| Rockwall | 2.3 | 0.9 | 4.2 |
| Runnels | 12.6 | 6.6 | 2.3 |
| Rusk | 5.5 | 6.7 | 5.2 |
| Sabine | 16.9 | 19.2 | 7.3 |
| San Augustine | 16.3 | 12.4 | 7.9 |
| San Jacinto | 9.9 | 12.4 | 3.6 |
| San Patricio | 4.6 | 5.0 | 4.8 |
| San Saba | 19.7 | 12.1 | 20.0 |
| Schleicher | 16.2 | 19.0 | 3.7 |
| Scurry | 6.3 | 6.5 | 5.0 |
| Shackelford | 9.6 | 10.3 | 14.8 |
| Shelby | 7.2 | 6.2 | 4.8 |
| Sherman | 1.9 | 2.9 | 8.2 |
| Smith | 2.1 | 3.6 | 2.7 |
| Somervell | 10.8 | 15.4 | 11.4 |
| Starr | 3.3 | 4.7 | 3.5 |
| Stephens | 8.1 | 12.1 | 3.3 |
| Sterling | 0.6 | 26.6 | 1.9 |
| Stonewall | 42.0 | 1.7 | 5.6 |
| Sutton | 3.0 | 15.6 | 2.5 |
| Swisher | 9.2 | 6.8 | 2.3 |
| Tarrant | 2.3 | 1.5 | 4.0 |
| Taylor | 2.1 | 2.2 | 1.6 |
| Terrell | 22.5 | 21.8 | 19.5 |
| Terry | 6.7 | 5.0 | 8.6 |
| Throckmorton | 1.9 | 3.0 | 3.0 |
| Titus | 2.8 | 3.9 | 2.9 |
| Tom Green | 2.4 | 3.0 | 2.8 |
| Travis | 3.6 | 2.2 | 5.3 |
| Trinity | 12.4 | 8.5 | 4.7 |
| Tyler | 7.2 | 12.0 | 9.2 |
| Upshur | 3.8 | 4.6 | 5.7 |
| Upton | 16.3 | 21.9 | 8.7 |

| COUNTY | Percent of FOS of crashes with the 3 driver-related factors from all crashes multiplied by 1000 | | |
|---|---|---|---|
| | **Alcohol related ratio** | **Speeding related ratio** | **Distraction related ratio** |
| Uvalde | 5.2 | 2.9 | 5.7 |
| Val Verde | 3.3 | 1.9 | 5.8 |
| Van Zandt | 5.7 | 7.1 | 5.6 |
| Victoria | 6.9 | 3.9 | 1.9 |
| Walker | 4.2 | 4.5 | 1.8 |
| Waller | 3.8 | 7.0 | 4.5 |
| Ward | 11.3 | 4.7 | 5.7 |
| Washington | 4.1 | 3.4 | 3.2 |
| Webb | 1.1 | 0.5 | 1.3 |
| Wharton | 4.6 | 5.3 | 3.9 |
| Wheeler | 13.5 | 8.4 | 9.5 |
| Wichita | 2.4 | 1.8 | 4.9 |
| Wilbarger | 2.9 | 6.0 | 4.3 |
| Willacy | 4.8 | 5.9 | 6.8 |
| Williamson | 3.5 | 1.8 | 4.6 |
| Wilson | 4.8 | 6.1 | 4.5 |
| Winkler | 8.3 | 4.2 | 8.0 |
| Wise | 3.7 | 5.9 | 2.6 |
| Wood | 5.6 | 10.2 | 5.4 |
| Yoakum | 7.6 | 5.5 | 4.8 |
| Young | 3.8 | 4.1 | 3.9 |
| Zapata | 3.8 | 6.4 | 2.2 |
| Zavala | 11.9 | 19.5 | 11.3 |

## Appendix D: Codes of the algorithms written in Python

```python
#insert module for defining the dataset
from sklearn import datasets, cluster
#insert the module for creating arrays
import numpy as np
#insert the modules to print
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
#insert the module for opening and writing on an excel file
import xlrd
#insert the module which contains the silhouette calculator function
from sklearn.metrics import silhouette_score
#insert the module which contains the k-means algorithm function
from sklearn.cluster import KMeans
# note: I deliberately chose a random seed that ends up
# labeling the clusters with the same numbering convention
# as the original y values
# np.random.seed(2)

# Load data
file_location="E:/EMU/4th semester (Thesis)/CLUSTERING/DATA/summary (input).xlsx"
#assign an identifier (name) to the opened excel file
workbook=xlrd.open_workbook(file_location)
#open the first sheet of the opened excel file and assign it the name "sheet"
sheet=workbook.sheet_by_index(0)
#Load the data in columns 44,45 and 46 and rows  3 to 256 in the excel file
#and assign names to each serie
alcdata=[sheet.cell_value(r,44)for r in range(2,256)]
spddata=[sheet.cell_value(r,45)for r in range(2,256)]
disdata=[sheet.cell_value(r,46)for r in range(2,256)]
# integrated3coordinates=inco (create an empty list)
inco=[]
# create an empty list
tg=[]
for i in range(0,254):
#add the 3 coordinates of the counties to inco and create the coordinates set
    inco.insert(i,[alcdata[i],spddata[i],disdata[i]])
#determine the primary(optional) clusters each county belongs to (guess)
#and in this way create the target list named tg
for i in range(0,64):
    tg.insert(i,0)
for i in range(64,128):
    tg.insert(i,1)
for i in range(128,192):
    tg.insert(i,2)
for i in range(192,254):
    tg.insert(i,3)
#convert inco and trg from list to matrix and assign them the names m and trg
#respectively
m=np.array(inco)
trg=np.array(tg)

#texasdata=tdata (create a dictionary in which the keys are target and data (string)
#and values are trg and m )
tdata = {'target_names':['severe', 'high', 'medium','low'], 'target': trg , 'data':m}
# replace the previous values of the iris dataset with the values of the dictionary,
#such that the first components (x) are the coordinates and the second components are
# the assigned clusters
X_iris = tdata['data']
y_iris = tdata['target']
# assign values 2 to 50 one by one to k (cluster number) and run k-means algorithm
#for each case
for n_cluster in range(2, 50):
    kmeans = KMeans(n_clusters=n_cluster).fit(X_iris)
    label = kmeans.labels_
# calculate silhouette coefficient for each case of k
    sil_coeff = silhouette_score(X_iris, label, metric='euclidean')
    print("For n_clusters={}, The Silhouette Coefficient is {}".format(n_cluster, sil_coeff))
```

Figure D- 1: Silhouette Code in Python

```python
import numpy as np
from scipy.cluster.vq import kmeans,vq
from scipy.spatial.distance import cdist
from sklearn import datasets, cluster
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import xlrd
import decimal
# Load data
file_location="E:/EMU/4th semester (Thesis)/CLUSTERING/DATA/summary (input).xlsx"
#assign an identifier (name) to the opened excel file
workbook=xlrd.open_workbook(file_location)
#open the first sheet of the opened excel file and assign it the name "sheet"
sheet=workbook.sheet_by_index(0)
#Load the data in columns 44,45 and 46 and rows  3 to 256 in the excel file
#and assign names to each serie
alcdata=[sheet.cell_value(r,44)for r in range(2,256)]
spddata=[sheet.cell_value(r,45)for r in range(2,256)]
disdata=[sheet.cell_value(r,46)for r in range(2,256)]
# integrated3coordinates=inco (create an empty list)
inco=[]
# create an empty list
tg=[]
#add the 3 coordinates of the counties to inco and create the coordinates set
for i in range(0,254):
    inco.insert(i,[alcdata[i],spddata[i],disdata[i]])
for i in range(0,64):
    tg.insert(i,0)
for i in range(64,128):
    tg.insert(i,1)
for i in range(128,192):
    tg.insert(i,2)
for i in range(192,254):
    tg.insert(i,3)
#convert inco and trg from list to matrix and assign them the names m and
#trg respectively
m=np.array(inco)
trg=np.array(tg)
#selection of the range of k values to be tested
K = range(1,50)
#scipy.cluster.vq.kmeans
#apply the kmeans function on the data (m) 50 times, for k=1,2,3,...,50
KM = [kmeans(m,k) for k in K]
#assign the name "centroids" to the set of produced centroids of the clusters for each k
centroids = [cent for (cent,var) in KM]   # cluster centroids
#avgWithinSS = [var for (cent,var) in KM] # mean within-cluster sum of squares
# alternative: scipy.cluster.vq.vq
#Z = [vq(X,cent) for cent in centroids]
#avgWithinSS = [sum(dist)/X.shape[0] for (cIdx,dist) in Z]
# alternative: scipy.spatial.distance.cdist
#obtain distance between each data in per cluster and the centroid of that cluster
#for each value of k
D_k = [cdist(m, cent, 'euclidean') for cent in centroids]
#return the minimun sum of square
cIdx = [np.argmin(D,axis=1) for D in D_k]
dist = [np.min(D,axis=1) for D in D_k]
#obtain the average within-cluster sum of square corresponding to each value
#of k (number of clusters)
avgWithinSS = [sum(d)/m.shape[0] for d in dist]
##### plot ###
kIdx = 4
# elbow curve
fig = plt.figure()
ax = fig.add_subplot(111)
#draw curve of average within-cluster sum of square corresponding to each value of k
ax.plot(K, avgWithinSS, 'b*-')
# mark the optimum point with a red color circle
ax.plot(K[kIdx], avgWithinSS[kIdx], marker='o', markersize=12,
    markeredgewidth=2, markeredgecolor='r', markerfacecolor='None')
plt.grid(True)
plt.xlabel('Number of clusters')
plt.ylabel('Average within-cluster sum of squares')
plt.title('Elbow for KMeans clustering')
```

Figure D- 2: Elbow Method Code in Python

```python
# drawing the scatter plot
fig = plt.figure()
ax = fig.add_subplot(111)
#ax.scatter(X[:,2],X[:,1], s=30, c=cIdx[k])
clr = ['b','g','r','c','m','y','k']
for i in range(K[kIdx]):
    ind = (cIdx[kIdx]==i)
    ax.scatter(m[ind,2],m[ind,1], s=30, c=clr[i], label='Cluster %d'%i)
plt.xlabel('Alcohol used')
plt.ylabel('Speeding')
plt.legend()
plt.show()
```

Figure D- 3 (Continued): Elbow Method Code in Python

```python
#insert module for defining the dataset
from sklearn import datasets, cluster
#insert the module for creating arrays
import numpy as np
#insert the modules to print
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
#insert the module for opening and writing on an excel file
import xlrd
# load data
file_location="E:/EMU/4th semester (Thesis)/CLUSTERING/DATA/summary (input).xlsx"
#assign an identifier (name) to the opened excel file
workbook=xlrd.open_workbook(file_location)
#open the first sheet of the opened excel file and assign it the name "sheet"
sheet=workbook.sheet_by_index(0)
#load the data in columns 44,45 and 46 and rows  3 to 256 in the excel file
#and assign names to each serie
alcdata=[sheet.cell_value(r,44)for r in range(2,256)]
spddata=[sheet.cell_value(r,45)for r in range(2,256)]
disdata=[sheet.cell_value(r,46)for r in range(2,256)]
# integrated3coordinates=inco (create an empty list)
inco=[]
# create an empty list
tg=[]
for i in range(0,254):
#add the 3 coordinates of the counties to inco and create the coordinates set
    inco.insert(i,[alcdata[i],spddata[i],disdata[i]])
#determine the primary(optional) clusters each county belongs to (guess)
#and in this way create the target list named tg
for i in range(0,64):
    tg.insert(i,0)
for i in range(64,128):
    tg.insert(i,1)
for i in range(128,192):
    tg.insert(i,2)
for i in range(192,254):
```

Figure D- 4: K-means Algorithm Code in Python

```python
    tg.insert(i,3)
#convert inco and trg from list to matrix and assign them the names m and trg respectively
m=np.array(inco)
trg=np.array(tg)
#texasdata=tdata (create a dictionary in which the keys are target and data (string)
# and values are trg and m )
tdata = {'target_names':['severe', 'high', 'medium','low'], 'target': trg , 'data':m}
# replace the previous values of the iris dataset with the values of the dictionary,
#such that the first
# components (x) are the coordinates and the second components are the assigned clusters
X_iris = tdata['data']
y_iris = tdata['target']
# call the function of kmeans clustering and determine the values for each parameter and
# assign it the name k_means
# (n_clusters:The number of clusters to form as well as the number of centroids to generate)
# (max_iter: Maximum number of iterations of the k-means algorithm for a single run)
# (n_init: Number of time the k-means algorithm will be run with different centroid seeds.
#The final results will be the best output of n_init consecutive runs in terms of inertia.
# (init : Method for initialization. k-means++' : selects initial cluster centers for k-mean
# clustering in a smart way to speed up convergence.\
#'random': choose k observations (rows) at random from data for the initial centroids.)
# (precompute_distances: Precompute distances)
# (tol: Relative tolerance with regards to inertia to declare convergence)
# (random_state: The generator used to initialize the centers. If an integer is given, it
#fixes the seed)
# (copy_x: When pre-computing distances it is more numerically accurate to center the data first.
# If copy_x is True, then the original data is not modified. If False, the original data is
#modified, and put back before the function returns, but small numerical differences may be
#introduced by subtracting and then adding the data mean.)
k_means = cluster.KMeans(n_clusters=4 , init='k-means++' , n_init=100 , max_iter=500 ,
                         precompute_distances='auto',tol=0.001 , random_state=None , copy_x=True)
#apply the defined k_means function on the new dataset of this study
k_means.fit(X_iris)
labels = k_means.labels_
print "-"*120
```

Figure D-3 (Continued): K-means Algorithm Code in Python

```
# plot the clusters in color
# create a figure object in dimentions 15 and 15 inch (width and height)
fig = plt.figure(1, figsize=(15,15))
#give the option of adding a new figure to the before defined figure
plt.clf()
#add a 3D coordinate axises system and adjusting the distances between the subplots and
#determine dimentions
ax = Axes3D(fig, rect=[0, 0, 1, 1], elev=8, azim=200)
plt.cla()
#loading the clustered data on the axises and assign different colors to each cluster
ax.scatter(X_iris[:, 0], X_iris[:, 1], X_iris[:, 2],c=labels.astype(np.float))
ax.w_xaxis.set_ticklabels([])
ax.w_yaxis.set_ticklabels([])
ax.w_zaxis.set_ticklabels([])
#set the titles of each axis
ax.set_xlabel('Alcohol drunk drivers')
ax.set_ylabel('Speeding involved crashes')
ax.set_zlabel('Distracted driver crashes')
plt.show()
print "-"*120
#assign the name "lbl" to the set of counties cluster number
lbl=k_means.labels_
print("lable of each county, respectively:",lbl)
print "*"*150
# define the list of counties (name of each county)
counties=[sheet.cell_value(r,0)for r in range(2,256)]
# assign each county its corresponding cluster
d=dict(zip(counties,lbl))
#separate the created clusters from each other
c0,c1,c2,c3=[],[],[],[]
for item in d:
    if d[item]==0:
        c0.append(item)
    elif d[item]==1:
        c1.append(item)
    elif d[item]==2:
        c2.append(item)
    else:
        c3.append(item)


countiescoords=dict(zip(counties,inco))
#print countiescoords
#print the clusters and counties in each of them
print "*"*150
print ("cluster0=",c0)
print ("# of counties in C0=", len(c0))
print "-"*120
print ("cluster1=",c1)
print ("# ofcounties in C1=", len(c1))
print "-"*120
print ("cluster2=",c2)
print ("# of counties in C2=", len(c2))
print "-"*120
print ("cluster3=",c3)
print ("# of counties in C3=", len(c3))
print "-"*120
#print the centroids of the clusters
print ("Cluster Centers are:",k_means.cluster_centers_)
print "-"*120

#example of prediction
k_means.predict([45,12,20])
```
Figure D-3 (Continued): K-means Algorithm Code in Python

```
from sklearn import datasets, cluster
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

# note: I deliberately chose a random seed that ends up
# labeling the clusters with the same numbering convention
# as the original y values
np.random.seed(2)
# load data
iris = datasets.load_iris()
X_iris = iris.data
y_iris = iris.target
# do the clustering
k_means = cluster.KMeans(n_clusters=3)
k_means.fit(X_iris)
labels = k_means.labels_
# check how many of the samples were correctly labeled
correct_labels = sum(y_iris == labels)
# plot the clusters in color
fig = plt.figure(1, figsize=(8, 8))
plt.clf()
ax = Axes3D(fig, rect=[0, 0, 1, 1], elev=8, azim=200)
plt.cla()
ax.scatter(X_iris[:, 3], X_iris[:, 0], X_iris[:, 2], c=labels.astype(np.float))
ax.w_xaxis.set_ticklabels([])
ax.w_yaxis.set_ticklabels([])
ax.w_zaxis.set_ticklabels([])
ax.set_xlabel('Petal width')
ax.set_ylabel('Sepal length')
ax.set_zlabel('Petal length')
plt.show()
```

Figure D-4: K-means Code on Iris dataset

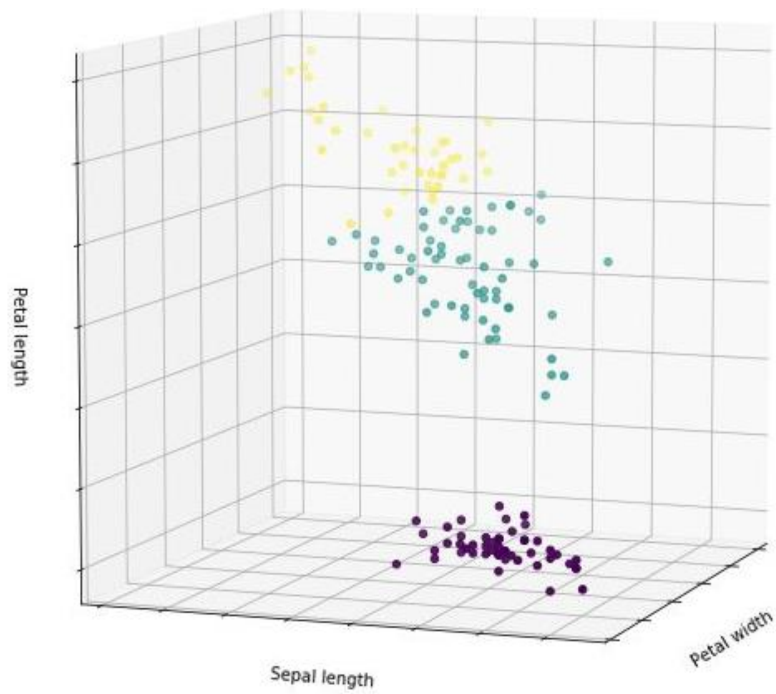


Figure D-5: Output of K-means Algorithm on Iris Dataset

[1] Fatality Rate – The number of fatalities per 100,000,000 vehicle miles traveled.

[2] Driving Under the Influence (DUI) Alcohol – Driver BAC Result > 0.00 or Contributing Factor of "Had Been Drinking" or "Under the Influence of Alcohol". This only includes alcohol involvement, not drugs.

BAC – Blood Alcohol Concentration.

[3] Speed Involved Crash – A crash in which at least one driver had a reported Contributing Factor of "Unsafe Speed" or "Speeding – (Over Limit)".

[4] Distracted Driving – Crashes with Contributing Factor of "Distraction in Vehicle", "Driver Inattention" or "Cellular/Mobile Phone Use".

[5] Fatal Crash – Any injury crash that results in one or more fatal injuries.

Fatal Injury (Fatality) – Any injury sustained in a motor vehicle traffic crash that results in death within thirty days of the motor vehicle traffic crash.

[6] Incapacitating Crash – A crash in which the most severe injury sustained was an incapacitating injury.

Incapacitating Injury – Any injury, other than a fatal injury, which prevents the injured person from walking, driving or normally continuing the activities he was capable of performing before the injury occurred.

[7] Non-Incapacitating Crash – A crash in which the most severe injury sustained was a non-incapacitating injury.

Non-Incapacitating Injury - Any injury, other than a fatal or an incapacitating injury, which is evident to observers at the scene of the crash in which the injury occurred.

[8] Possible Injury – Any injury reported or claimed which is not a fatal, incapacitating or non-incapacitating injury.

Possible Injury Crash – A crash in which the most severe injury sustained was a possible injury.

[9] Non-Injury Crash – Any motor vehicle crash other than an injury crash. A non-injury crash is also called a property damage only crash.

[10] Iris flower data set or Fisher's Iris data set – It is a multivariate data set which consists of 50 samples from each of three species of Iris (Iris setosa, Iris virginica and Iris versicolor). Four features were measured from each sample: the length and the width of the sepals and petals, in centimeters. Based on the combination of these four features, Fisher developed a linear discriminant model to distinguish the species from each other. Based on Fisher's linear discriminant model, this data set became a typical test case for many statistical classification techniques in machine learning such as support vector machines.