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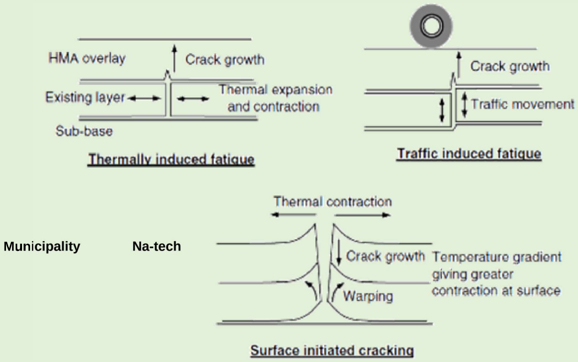

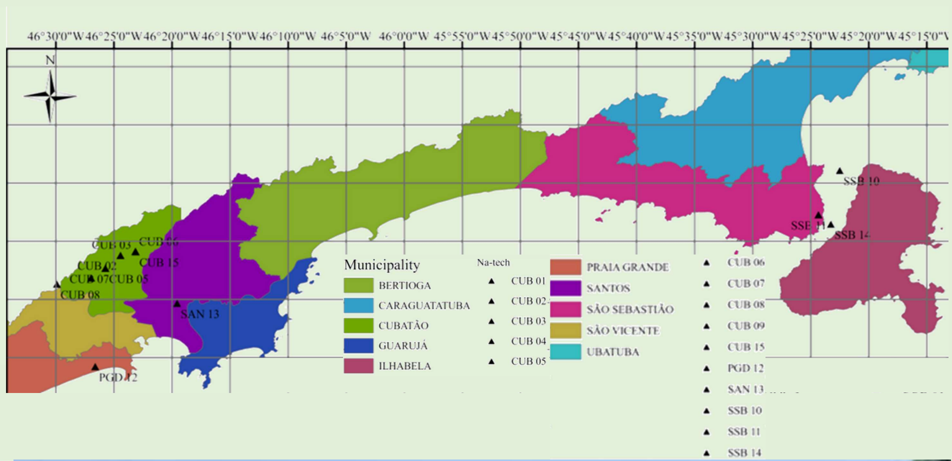

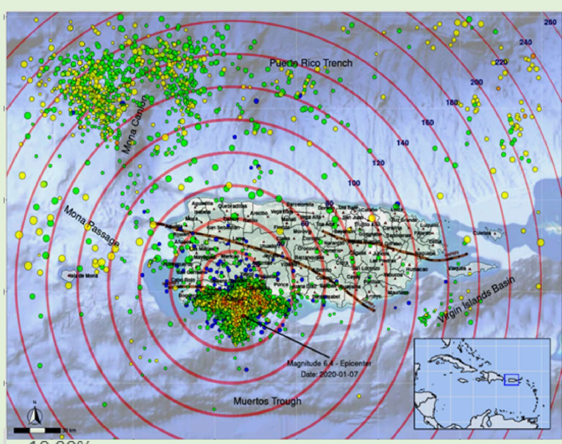

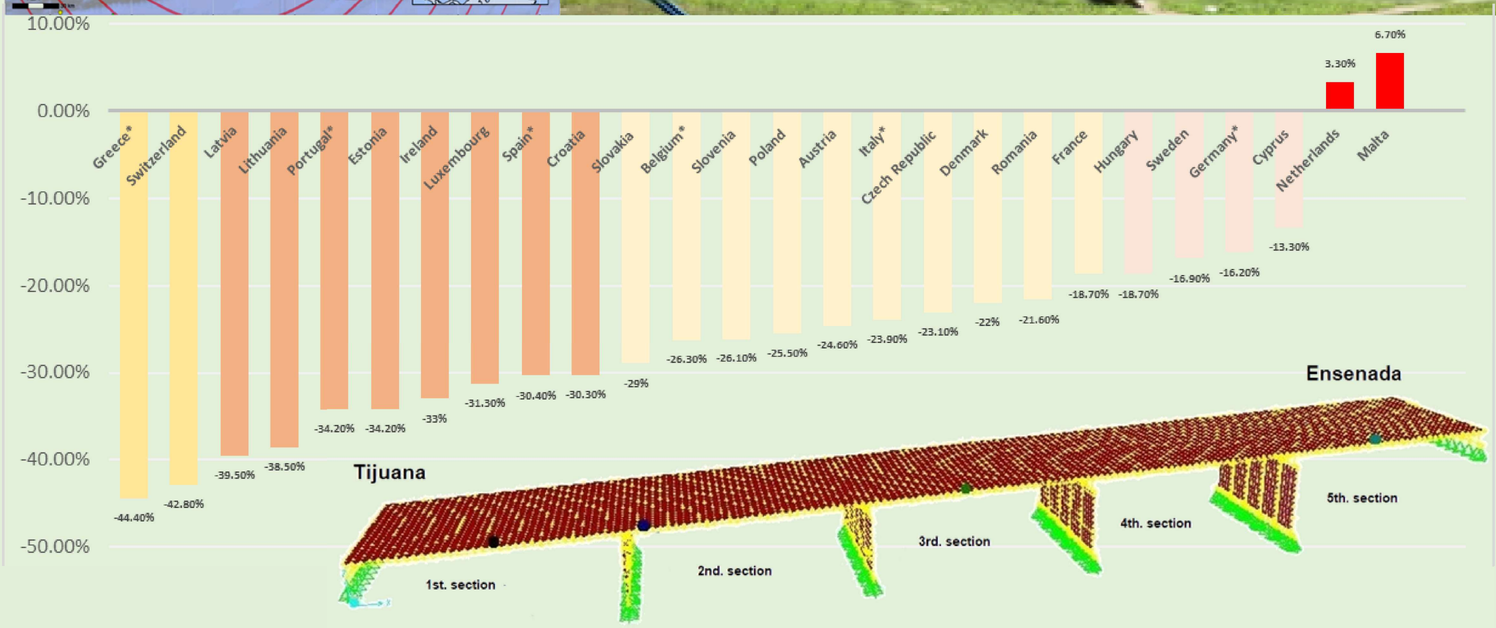

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TRAFFIC CRASH INJURIES OCCURRENCE VARIETIES ACROSS BARCELONA DISTRICTS[1]

Ahmad Aiash[2], **Francesc Robusté**[3]

ABSTRACT: Barcelona (Spain) had a total population of 1,636,762 in 2019 that are distributed on 10 districts across the city. These districts have different characteristics in size and population density. As a result, this can lead to different traffic crashes injuries occurrences and numbers in these areas. Therefore, this study is attempting to determine the conditional probabilities for each district in order to identify the district that has highest number of injuries compared to other areas. A Bayesian network approach is utilized to analyze the dataset and identify the high-risk district alongside analyzing the varieties of traffic crashes during four-year intervals. The results have shown that the district that has the highest population, highest usage of private transport mode, and highest density of passenger cars per km^2 (compared to all other districts), has the highest risk of having all types of injuries resulting from traffic crashes. For the temporal factor represented by the four years interval, traffic crashes occurrences varied from district to district based on the level of injury.

Keywords: Barcelona, districts, injuries, traffic crashes, Bayesian network

RESUMEN: Barcelona (España) tenía una población total de 1.636.762 en 2019 que se distribuyen en 10 distritos de la ciudad. Estos distritos tienen diferentes características en tamaño y densidad de población. Como resultado, esto puede conducir a diferentes ocurrencias y números de lesiones por choques de tránsito en estas áreas. Por lo tanto, este estudio intenta determinar las probabilidades condicionales de cada distrito para identificar el distrito que tiene el mayor número de lesiones en comparación con otras áreas. Se utiliza un enfoque de red bayesiana para analizar el conjunto de datos e identificar el distrito de alto riesgo junto con el análisis de las variedades de choques de tráfico durante intervalos de cuatro años. Los resultados han demostrado que el distrito que tiene la mayor población, el mayor uso del vehículo privado, y la mayor densidad de vehículos por km^2 (en comparación con todos los demás distritos), tiene el mayor riesgo de sufrir todo tipo de lesiones derivadas de choques de tráfico. Para el factor temporal representado por el intervalo de cuatro años, las ocurrencias de choques de tránsito variaron de un distrito a otro según el nivel de lesión.

Palabras claves: Barcelona, distritos, lesiones, choques de tráfico, red Bayesiana

INTRODUCTION

European countries have a plan that is updated from time to time in order to achieve less traffic crashes injuries with more focusing on fatalities and severe injuries. Fig. 1 portrays the change of road fatalities in some European countries by comparing the data between 2010 and 2019 based on a *14th Road Safety Performance Index Report (2020)*. The negative percentages in the figure are referring to a decrease in road fatalities in the designated countries and vice versa. The report showed that the reduction difference for the total number of road deaths in EU27 between 2019 and 2010 is 7,023 deaths. Greece has the highest decreasing percentage with -44.4%, while Malta had the highest increasing percentage of 6.7%. For Spain, the percentage of road fatalities was 30.4% reduced by comparing the two years 2010 and 2019. However, the medium-term target was halving the number of deaths, but as shown, the progress of lessening the number in some countries is stagnated.

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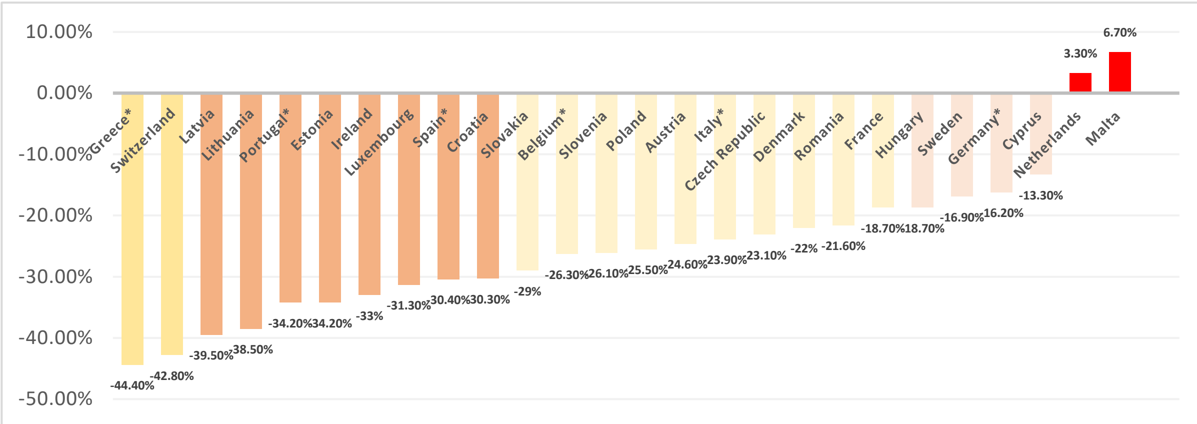

Figure 1: Relative change in road deaths 2010-2019 in Europe (Provisional data for 2019 for some indicated countries based on the provided report).

Therefore, many studies have attempted to examine traffic crashes from different perspectives to thoroughly detect and mitigate the risk factors that may impact the level of injury resulted from traffic crashes. In Barcelona, Spain, a recently published study (Aiash & Robusté, 2021a) has examined several risk factors. This study applied two models: a binary *probit* model and *chi-square* automatic interaction (CHAID) tree. The total traffic crashes that are examined are 47,153 crashes with including five potential risk factors. The findings showed that elderly and males injured-prone were more likely to have severe or fatal injuries compared to other categories. For the user type, pedestrians and drivers have shown similar trend in having severe of fatal injuries. For the temporal factors, weekends, afternoon, and night timing all are considered as a risk timing due to the likelihood of having severe or fatal injuries compared to other timings. Another recently published study (Aiash & Robusté, 2021b) have conducted an analysis for two other factors that can contribute traffic injuries. These two factors are both temporal factors including the working hours timing period and the season of the year. A Bayesian network is employed for this reason to conduct the analysis process and identify their potential impact of traffic injuries. The results showed that both summer season and working hours timing period were more likely to have higher number of reported injuries.

Bayesian network is one of the utilized approach models to analyze and predict traffic crash data. A study (Alkheder *et al*., 2020) has employed several data mining techniques to predict and detect the risk factors and their consequential impact. The study found that Bayesian network was accurately predicted the crash data better than CHAID tree and linear support vector machine. The results showed that males drivers, front seat passengers, and elderly drivers were all at higher risk of having severe or fatal injuries compare to other groups. The importance of using the seat belt in case of traffic crash was also asserted. The types of crashes and road classifications were found to have an impact on injuries resulted from traffic crashes. A side from the accurate prediction that Bayesian network can provide, a study (Zhao & Deng, 2015) has deployed the Bayesian network to make inference on crash types at urban intersections. The findings revealed that bicycle and electric bikes were more likely to be involved in frontal collision at urban intersections crashes than small cars and heavy vehicles, whereas, heavy vehicle was more likely to be involved in side collision compared to light vehicles.

Space-temporal factors can have a potential impact on traffic crash injuries. Several research studies are conducted to examine this impact. A study (Wang *et al*., 2013) have employed a Bayesian network approach to analyze the spatiotemporal effect of traffic congestion. Fatal and severe injuries were found to be more associated with the increase in traffic congestion. Another research (Jia *et al*., 2018) found that residential density and bank and hospitals point of interests have an impact on traffic crashes. Consistently, mixed use development, urban residential, single-family residential, multi-family residential, business and, office district all are found to have strong correlations with traffic analysis zones level crashes (Pulugurtha *et al*., 2013).

METHODOLOGY

Barcelona districts

Barcelona has a total population of 1,636,762 inhabitants in 2019 that are distributed on 10 districts across Barcelona. These districts are *Ciutat Vella, Eixample, Sants-Montjuïc, Les Corts, Sarrià-Sant Gervasi, Gràcia, Horta-Guinardó, Nou Barris, Sant Andreu,* and *Sant Martí,* as shown in Fig. 2. Fig. 3 is depicting the road network across Barcelona city with red lines based on (Ajuntament de Barcelona, 2022). Each of these districts is assigned to a different number based on the database source. Table 1 is presenting the detailed population in each district. The highest number of population and density per ha is found in *Eixample,* while the lowest population and density per ha is found in *Les Corts* and *Sarrià-Sant Gervasi,* respectively. This data is gathered from the City Hall of Barcelona database (Ajuntament de Barcelona*, 2019a).*

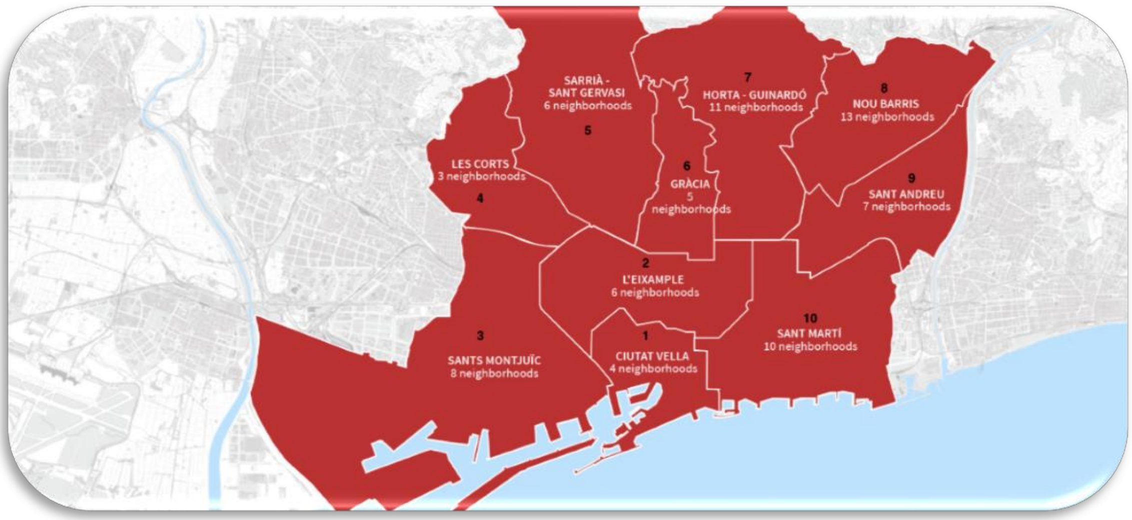

Figure 2: Barcelona districts' location and boundaries.
https://www.barcelona.cat/en/living-in-bcn/living-neighbourhood

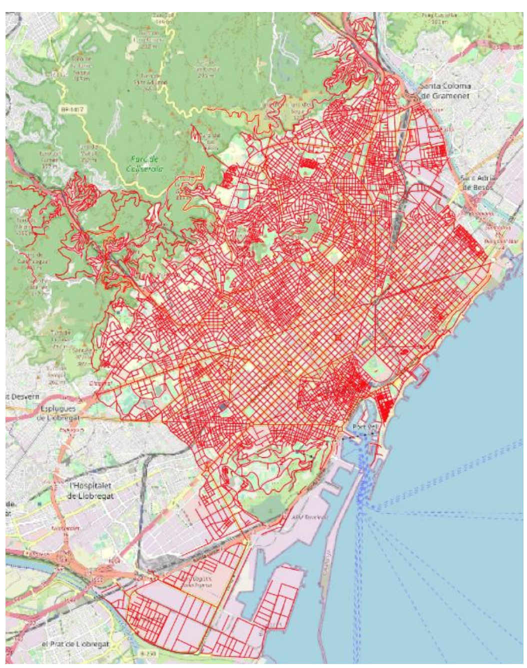

Figure 3: Road network in Barcelona city.

Table 1: Barcelona Districts population and size.

District	Population	Size in (ha)	Density (inhabitants/ha)
1. Ciutat Vella	103,429	412.1	251
2. Eixample	**265,910**	746.4	**356**
3. Sants-Montjuïc	184,091	2,267.6	81
4. Les Corts	81,974	601.1	136
5. Sarrià-Sant Gervasi	149,260	1,991.6	75
6. Gràcia	121,798	422.4	288
7. Horta-Guinardó	171,495	1,191.9	144
8. Nou Barris	170,669	805.1	212
9. Sant Andreu	149,821	658.9	227
10. Sant Martí	238,315	1,038.6	229

A recently published Statistical Yearbook of the City of Barcelona (Ajuntament de Barcelona, 2021) has included the indicators and vehicle stats across the different districts of Barcelona. Table 2 is presenting passenger car distributions across Barcelona districts. It can be noticed that *Eixample* has the highest number of passenger cars with having the highest density of passenger cars per $\mathbf{km^2}$. Table 3 is showing the number of registered vehicles in Barcelona districts in 2020. Similar to previously noticed statistics, *Eixample* has the highest number of all types of registered vehicles except for registered mopeds and trucks. Consistently, table 4 is presenting the usage of different modes of transport in Barcelona districts in 2020. It can be also noticed that *Eixample* has the highest usage of both on foot and bicycle mode of transport and private transport mode, while Sant Marti has the highest usage of public transport compared to other districts.

Table 2: Density Indicators of passenger cars in 2020.

District	Passenger car	Surface (km^2)	Passenger car / km^2
Ciutat Vella	17,679	4.2	4,204
Eixample	**77,912**	**7.5**	**10,438**
Sants-Montjuïc	49,494	22.9	2,163
Les Carts	31,393	6.0	5,223
Sarria-Sant Gervasi	59,474	19.9	2,986
Gracia	33,709	4.2	7,980
Horta-Guinardó	49,751	11.9	4,174
Nou Barris	45,792	8.1	5,684
Sant Andreu	44,922	6.6	6,815
Sant Martí	68,992	10.4	6,610

Table 3: Vehicles registered by typology and district in 2020.

District	Passenger cars	Motorcycles	Mopeds	Vans	Trucks	Other vehicles
Ciutat Vella	624	554	1,135	92	33	27
Eixample	**3,227**	**2,194**	1,171	**236**	52	**190**
Sants-Montjuic	1,962	1,054	310	184	**53**	112
Les Carts	1,369	700	36	33	12	11
Sarria-Sant Gervasi	2,363	1,846	101	75	22	60
Gracia	1,278	1,002	103	53	10	17
Horta-Guinard6	1,887	1,307	104	126	27	26
Nou Barris	1,645	826	78	114	25	34
Sant Andreu	2,018	822	56	142	25	34
Sant Marti	2,652	1,358	**2,583**	200	29	58

Table 4: Transport type usage by district in 2020.

District	Total	By foot & Bicycle	Private transport	Public transport
Ciutat Vella	333,300	253,308	25,329	54,662
Eixample	**802,039**	**544,185**	**147,750**	110,104
Sants-Montjuïc	500,419	294,860	97,666	107,894
Les Corts	264,350	176,951	53,956	33,444
Sarria-Sant Gervasi	455,135	259,254	136,183	59,699
Gracia	380,898	250,154	68,424	62,320
Horta-Guinardó	490,973	271,132	108,942	110,899
Nou Barris	526,307	294,752	108,715	122,840
Sant Andreu	460,405	289,878	88,952	81,574
Sant Martí	713,044	435,258	137,993	**139,793**

Bayesian network

In this study, a Bayesian network is employed to analyze the utilized data that is gathered from *The City Hall of Barcelona* (Barcelona's City Hall Open Data Service, 2019b). Tree Augmented Naïve Bayes technique is used through the IBM Watson Studio platform that is developed based on *Bayesian Network Classifiers* (Friedman *et al*., 1997). Two predictors are analyzed including all districts of Barcelona and a range of years that extended from 2016 to 2019. The dependent variable is the level of injury which consists of slight injury and severe or fatal injury. The total number of utilized crashes in this study is 47,081. The undefined areas or values are eliminated from the final utilized data. The conditional probabilities are determined as shown in the following equation and similar to a previously mentioned and conducted study (Aiash & Robusté, 2021b). More details about the applied model can be found at IBM report (2016):

$$Pr\left(Y_i|X_1 = x_1^j, X_2 = x_2^j, \dots, X_n = x_n^j\right) = \frac{Pr(Y_i)\left(X_1 = x_1^j, X_2 = x_2^j, \dots, X_n = x_n^j|Y_i\right)}{Pr\left(X_1 = x_1^j, X_2 = x_2^j, \dots, X_n = x_n^j\right)} \quad (1)$$

$$\propto Pr\ (Y_i)\prod_{k=1}^{n} Pr\left(X_k = x_k^j|\pi_k^j, Y_i\right)$$

d is the data set. the case that is classified to which it belongs to i^{th} target category is d_j. The target Y_i is level of injury including two categories: slight injury and severe or fatal injury. The independent variable is x. The number of independent variables which is two in this study is n. As a result, $d_j = \left(x_1^j, x_2^j, \dots, x_n^j\right)$. Non-redundant parameters number is K. The parent set of the independent variables alongside the dependent variable is π_k, it maybe empty for Tree Augmented Naïve Bayes. The conditional probability is $Pr\left(X_k = x_k^j\middle|\pi_k^j, Y_i\right)$ related to the developed two nodes.

RESULTS AND DISCUSSIONS

Figure 4 is showing the structure of the applied TAN model. It consists of three nodes starting with the injury level which is the dependent variable followed by district and year nodes. District node is including the ten different aforementioned districts in Barcelona, while the year node is including 4 years which they are 2016, 2017, 2018, and 2019. Based on the applied model, district as an independent variable is more important than year variable in predicting the utilized data. The prediction accuracy for the applied model is found to be for the training and testing is 98.01% and 98%, respectively.

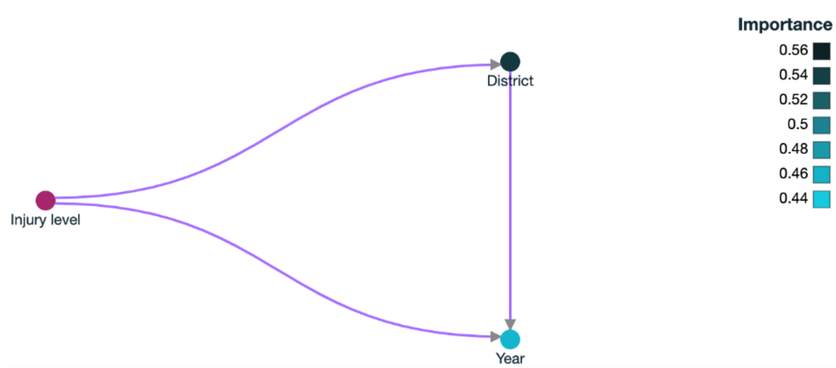

Figure 4: Structure of the applied TAN model.

Table 5 and Table 6 are showing the determined conditional probabilities for both nodes of the independent variables. Table 5 is presenting the probabilities for the districts. As shown, *Eixample* has the highest probabilities compared to all other districts which indicate that both slight, severe, and fatal injuries are more likely to happen in this district. *Sant Martí* is following *Eixample* in having the highest probabilities, followed by *Sants-Montjuïc* and *Sarrià-Sant Gervasi.* It is worth mentioning that the differences between the last mentioned three districts is slightly low and training and testing sample should be considered as these results are representing 70 % of the utilized dataset, while the testing set represents 30%.

Table 5: Calculated conditional probabilities for districts.

Parents	Probability										
Injury level	Ciutat Vella	Eixample	Gràcia	Sants-Montjuïc	Sarrià-Sant Gervasi	Horta-Guinardó	Les Corts	Sant Martí	Sant Andreu	Nou Barris	Total
Slight Injuries	0.051	**0.304**	0.046	0.111	0.107	0.07	0.073	0.125	0.062	0.051	32,482
Severe or fatal injuries	0.048	**0.273**	0.026	0.102	0.108	0.064	0.092	0.145	0.067	0.076	660

Table 6 is depicting the calculated conditional probabilities for different years with having two parents based on the applied model which they are the district and the dependent variable which is the level of injury. For *Ciutat Vella* as a parent node, all types of injuries have higher probabilities in 2018 compared to all other years. While for ***Eixample*****,** slight injuries are higher in 2016, and severe or fatal injuries are higher in 2018 compared to other years. *Gràcia* has the highest probabilities in 2017 for all types of injuries. Slight injuries are higher in 2019 while severe and fatal injuries are higher in 2016 in *Sants-Montjuïc* district. *Sarrià-Sant Gervasi* has higher number of slight injuries in 2018, however, severe or fatal injuries are found to be high at three different years 2016, 2017 and 2018. For *Horta-Guinardó*, 2016 has the highest number of slight injuries and 2019 has the highest number of severe or fatal injuries. *Les Corts* has the highest number of slight injuries in 2016 and the highest number of severe or fatal injuries in 2017. In 2019, the highest number slight injuries is identified in *Sant Martí,* while in 2017, the highest number of severe or fatal injuries is identified at the same district. For *Sant Andreu,* 2019 has the highest probabilities for all types of injuries. *Nou Barris* has its highest number of slight injuries during 2018 and its highest number of severe or fatal injuries during 2016.

Table 6: Calculated conditional probabilities for years.

Parents		Probability				
District	Injury level	2016	2017	2018	2019	Total
Ciutat Vella	Slight Injuries	0.225	0.253	**0.259**	0.262	1,655
Ciutat Vella	Severe or fatal injuries	0.25	0.188	**0.344**	0.219	32
Eixample	Slight Injuries	**0.262**	0.239	0.245	0.254	9,862
Eixample	Severe or fatal injuries	0.233	0.222	**0.306**	0.239	180
Gràcia	Slight Injuries	0.249	**0.257**	0.250	0.244	1,487
Gràcia	Severe or fatal injuries	0.118	**0.471**	0.118	0.294	17
Sants-Montjuïc	Slight Injuries	0.258	0.238	0.242	**0.262**	3,591

Sants-Montjuïc	Severe or fatal injuries	**0.328**	0.239	0.224	0.209	67
Sarrià-Sant Gervasi	Slight Injuries	0.241	0.246	**0.267**	0.247	3,479
Sarrià-Sant Gervasi	Severe or fatal injuries	**0.254**	**0.254**	**0.254**	0.239	71
Horta-Guinardó	Slight Injuries	**0.273**	0.240	0.256	0.231	2,283
Horta-Guinardó	Severe or fatal injuries	0.167	0.214	0.262	**0.357**	42
Les Corts	Slight Injuries	**0.256**	0.252	0.253	0.238	2,386
Les Corts	Severe or fatal injuries	0.295	**0.328**	0.197	0.180	61
Sant Martí	Slight Injuries	0.255	0.255	0.232	**0.258**	4,076
Sant Martí	Severe or fatal injuries	0.167	**0.365**	0.302	0.167	96
Sant Andreu	Slight Injuries	0.254	0.224	0.260	**0.262**	2,005
Sant Andreu	Severe or fatal injuries	0.205	0.182	0.250	**0.364**	44
Nou Barris	Slight Injuries	0.252	0.258	**0.262**	0.229	1,658
Nou Barris	Severe or fatal injuries	**0.360**	0.220	0.220	0.200	50

CONCLUSIONS

Traffic crashes intensity or occurrence can vary greatly from region to region or from district to district. Therefore, this spatial influence on traffic crashes can also impact the level of injury and its types. In Barcelona, 10 different districts with different populations and size that are distributed across the city. Consequently, this study is attempting to classify these districts according to traffic crashes and their resulted injuries whether it is a slight injury, severe, or fatal injury. A Bayesian network represented by TAN technique is employed in order to analyze the utilized data that consists of 47,081 traffic crashes that resulted into different level of injuries during four years interval including 2016, 2017, 2018, and 2019.

The results have shown that *Eixample* has the highest probabilities of having all types of injuries compared to all other districts. This could be a result of a combination of factors that can lead to this status. One of these factors is, the fact that, *Eixample* has the highest density per hectare and population compared to all other districts; street traffic is also high on the grid streets designed by Civil Engineer Ildefons Cerdà. Additionaly, *Eixample* has the highest figures related to owned passenger cars, motorcycles and vans, highest usage of private transport mode, and the highest density of passenger cars per $\mathbf{km^2}$compared to all other districts. For the temporal factor represented by years, the number of injuries vary significantly from district to district during different years as there is no one single year that has the highest number of injuries for all districts. For the future work, an extensive analysis can be carried out related to traffic crashes in *Eixample* in order to identify risk factors. These risk factors can include spatiotemporal factors, average daily traffic, person characteristics who was involved in the crash, type of the crash, and the transport mode that led to the crash.

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