Crash Risk Prediction Model using Data Science

This manuscript (permalink) was automatically generated from uiceds/cee-492-term-project-fall-2022-swifties@c7b5b10 on October 29, 2022.

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Project selection and Introduction

Road accidents are responsible for a significant number of injuries reported every year. According to the World Health Organization (WHO), approximately 1.3 million people die each year as a result of road traffic crashes (as of June, 2022). In addition, road traffic crashes cost countries 3% of their gross domestic product (Safarpour et al, 2020; WHO, 2022). Consequently, understanding what influences these accidents on roads is of utmost importance. However, it is not easy to decide which exact conditions lead to these accidents. Different road, climate, vehicle and driver conditions affect the likelihood of a driver to be in a fatal/serious accident.

The ability of predicting in an accurate way the potential occurence of car crashes is a valuable contribution for road safety. In an approach frequently used in the literature, crash records' data are used for the development of crash prediction models, so that agencies can allocate investments to priority areas of the roadway network. However, given that the budget for infrastructure improvements is limited, adopting countermeasures for all facilities that crashes are potentially occuring is not financially feasible. Therefore, informing drivers about the potential safety risks is a way to proactively compensate the aforementioned limitations. Moreover, with the development of connected and autonomous vehicles, this information can be provided in a more optimized way, contributing for vehicles' route decision, as well as for real-time alerts that can lead drivers to take the necessary precautions to operate more safely (Yu et al, 2021).

Project Objective and Plan Proposal

The objective of this work is to use the Illinois Department of Transportation (IDOT) extensive crash data to be analyzed and, finally, be used for a crash risk prediction model based on main categorical data that can be real-time updated (such as the weather/lighting/pavement conditions). Ideally, it could be used by navigation systems to allert drivers to adopt more cautious behavior as soon as they enter higher-risk sections.

The plan to be carried out will follow the basic steps described as follows:

1. Read the IDOT's crash data CSV files available as an open data source.
2. Clean the data by deleting unwanted columns, handling missing data, and removing irrelevant observations.
3. Tidy the data by organizing the variables into columns and the observations into rows.
4. Analyze and visualize the data by finding correlations both analytically and graphically.
5. Model a prediction algorithm for crash risk according to categorical variables.

Description of the Data Set

IDOT has generated datasets with statewide crash locations produced by the Crash Information Section of the Illinois Department of Transportation (IDOT). The accident data has been collected througout the years usign Application Programming Interfaces (APIs) that provided streaming traffic incident data. There are about 300,000 accident records per year in these datasets, and each record contains attributes that include conditions like (among others that are not listed and described because these are not relevant for this study):

1. Time and date (day, month, year)
2. Coordinates (x,y)
3. Type of collision
4. A quantitative description of fatalities and injuries

5. Crash severity classification based on their impact on traffic
6. The road surface condition (“Dry”, “Wet”, “Snow or slush”, “Ice”, or “Sand/Dirt/Mud”)
7. Road defects (“Debris on roadway”, “Rut/Holes”, “Unkown”, or “No defects”)
8. Light conditions (rated in a scale from 1 to 9)
9. Geometric characteristics of the road section
10. Work Zone (“construction”, “maintenance”, “utility”, “unknown”, or “N/A”)
11. Possible causes of the accident.

The datasets for different years are available for downloan as a .CSV file in the IDOT’s website:

https://gis-idot.opendata.arcgis.com/search?groupIds=6d2862031a6d47c7a8c211e38e423e05

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Exploratory Data Analysis

Open-source crashes' data is publicided by the Illinois Department of Transportation (IDOT), yearly. Each year's dataset was found to have extensive crashes' reports, which include several variables to describe each crash event. Each dataset is organized with observations filled according to the IDOT Traffic Crash Report SR 1050 Instruction Manual (2019). The datasets for each year are available in .csv format by IDOT, and they contain the observations arranged in rows and the independent variables in columns. The datasets from 2017, 2018, and 2019 were included in this Exploratory Data Analysis. The datasets from 2020 and 2021 were discarded in this analysis given the COVID-19 pandemic outbreak, which altered drastically the dynamics of traffic worldwide, and of course crash-related data (Yasin, Grivna & Abu-Zidan, 2021). When it comes to the size of the datasets, each one had over 300,000 rows (944,328 in total, combined), and at least 80 columns (only the 2019 dataset included 5 extra columns, discarded).

Reading the Data

To carry out the first step, the datasets were imported to Visual Studio Code using the CSV library. The datasets were merged into a unified file, once the total numbers of columns of each of them were matched to an homegeneus number since it was noticeable that the latest dataset included additional independent variables the first two did not include. The three files were merged into a new database after this first sanity check. The final dataset integrated 80 variables (columns) and 944,328 observations (rows).

Cleaning Process

It was found that several independent variables would not provide fruitful information due to missing, unknown or incomplete data. Thus, the datasets were visually inspected to filter out irrelevant or incomplete variables. For instance, information pertaining the location (latitude & longitude, or X & Y coordinates) have not been taken into account. Columns containing codes describing the city, county or ID of the location where the crash took place have also been excluded. Columns involving duplicate information (e.g. two columns describing the same independent variable with a label and a number), and traffic structures were also removed. For few other independent variables, information that could potentially be useful was found to be significantly incomplete. That happened with, for example, the number of lanes and the type of intersection, so therefore these variables were not included on the clean dataset. Finally, additional cleaning was carried out for independent variables with a high number of description labels. For example, the "Railroad Crossing Number" variable presented several unique values taht were found not to provide handy information for the end-user. In terms of variables (columns), after filtering out the information that would not be utilized for this analysis, the number of independent variables went from 80 to 21.

When it comes to crash reports, several inconsistencies are considerably frequent. In the literature, for example, it is mentioned that "investigation of traffic safety by means of crash records is a reactive approach, where researchers need to deal with imprecise, incomplete, inconsistent, and, sometimes, inexistent records", and thats why the acquisition of historical series to provide minimal consistency to the analysis of crashes to reduce misinterpretations and misleading conclusions is crucial (Hauer & Hakkert, 1989; Chin & Quek, 1997; Farmer, 2003). This justifies the need of dedicating a considerable amount of time, after filtering the columns (variables) of interest, to the cleaning process of the rows (observations). For each column, the observations labeled as "blank", "unknown", and "other" were matter of discussion among the group on how these inconsistencies would be handled. For all variables, the "blank" observations were immediately removed from the dataset.

Analysis and Visualization

Plots

Trends

Potential Issues

Modeling plan

What we want to predict?

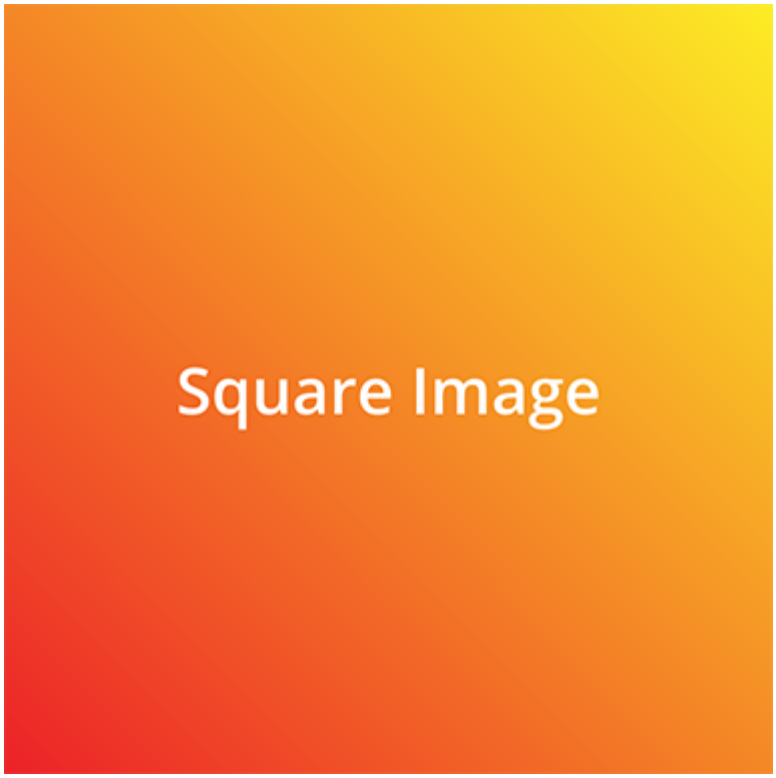

Figure 1: A square image at actual size and with a bottom caption. Loaded from the latest version of image on GitHub.

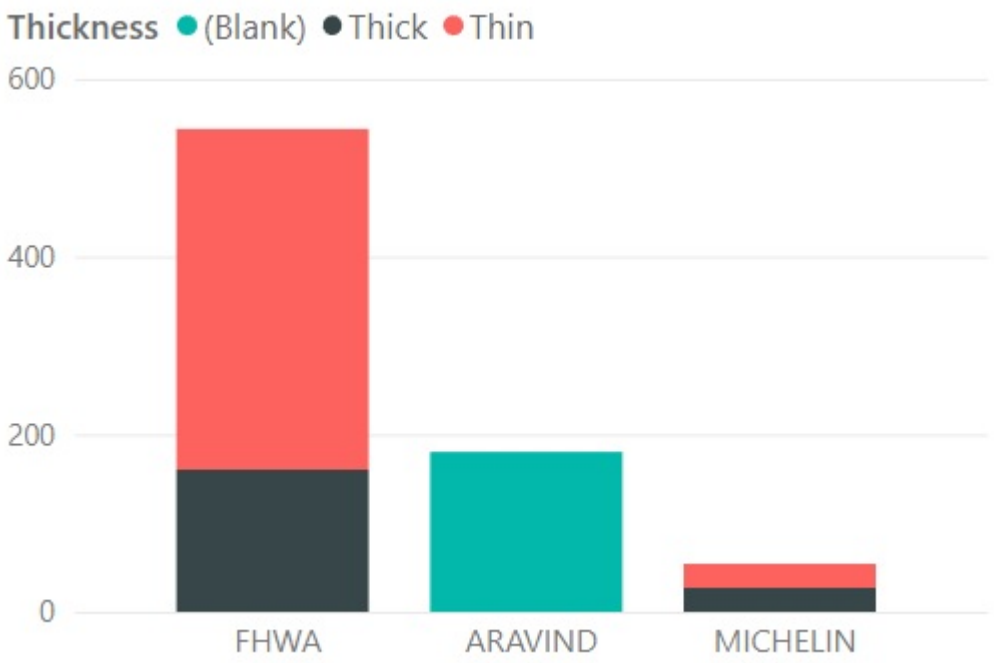

Figure 2: A random sample bar chart to test quality. Loaded from the latest version of image on GitHub.

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