Haladó adatelemzési módszerek - Accidents in France

Júlia Jankó, Péter Mészáros, Anna Gergály

March 2024

Contents

1 Introduction **1**

2 Description of files **2**
2.1 Places . . . 2
2.2 Characteristics . . . 2
2.3 Vehicle . . . 2
2.4 Users . . . 2

3 Data preparation and visualisation **2**
3.1 Places . . . 3
3.2 Characteristics . . . 4
3.3 Vehicle . . . 4
3.4 Users . . . 4
3.5 Merging the dataset . . . 8
3.6 Visualization on map . . . 8

4 Model construction **9**
4.1 Choosing a model and preparing the data . . . 9
4.2 Working with Bayesian Networks and pgmpy . . . 10
4.3 Inference method . . . 10

1 Introduction

The dataset we selected for our project details the accidents that have happened on the roads of France from 2005 to 2016. The dataset contains in-depth information about the vehicles, people and road involved in the accident as well as the weather and other driving conditions. Our goal with this project is to gain insight into what factors play a significant role in roadside accidents and their severity; aiming to be able to predict accident chances and consequences.

We downloaded the dataset from Kaggle where it has been already aggregated for the years 2005-2016, however the data is originally from an official french government website, where it is stored by year. The data is organized into 5 .csv files, one of which contains holiday dates, the other four containing data pertaining to the accidents: characteristics, places, users and vehicles.

2 Description of files

2.1 Places

Contains data about the place the accident took place, the road quality and other characteristics. There is a lot categorical data describing road type, condition, accident situation, road curvature, traffic type, terrain and infrastructure. These are fairly well filled out and have only a few category options; they are very well usable.

There are a few unknown fields in this file, dealing with a PR value and the french road numbering system, which we do not have further information about.

Out of the remaining fields only three can be considered 'continuous', these all deal with width of the road in some way: number of lanes, width in meters, central width. Sadly these columns have a lot of bad data: values above even 90 for number of lanes and 800 meter wide roads, along with a large number of zero values.

2.2 Characteristics

Contains the characteristics of the accident. A lot of categorical columns can be found in this .csv file, represented in numerical coding. This file also holds information about the the time of the accident, in separate columns for day, month and year.

There are a few problematic columns in this file, mostly dealing with spacial data. Address is very specific, down to the street name and as such hard to extrapolate from. There are also problems with missing data, both for the address and the long-lat columns have about 230 000 rows filled out correctly out of the 900 000.

2.3 Vehicle

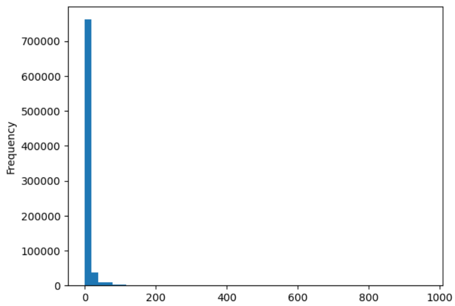
Contains the properties of the vehicles. Flow direction and Occupants columns have a very high 92%-99% null ratio. Flow direction's only gives information about the numbering of the postal address numbers. Occupants is only filled out when public transportation is involved in the accident.

2.4 Users

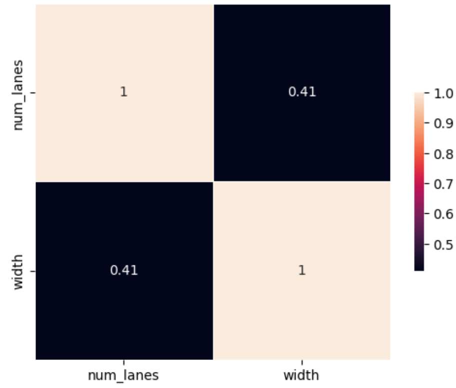
Contains information about the users (people involved in the accident). Birth year, user type (e.g. driver, passenger, pedestrian), severity are essential information and are almost never missing. Severity could serve as a main goal of the data analysis, extremities (death and no injury) are the most common. Birth may be useful when considering the driver. There is additional information about pedestrians, their location, action and whether they were accompanied at the time of the accident. Safety equipment is also noted and when used together with the severity of the accident, could reveal useful insights. The type of trip is missing in 29% of cases. Seat in the vehicle is also described, but between 2004 and 2008 it was not recorded.

3 Data preparation and visualisation

Because many variables are categorical, we could not use correlation to measure their pairwise association, instead, we used Cramer's V for this purpose.

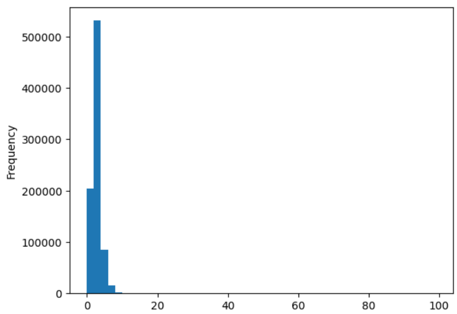


(a) The distribution of central width

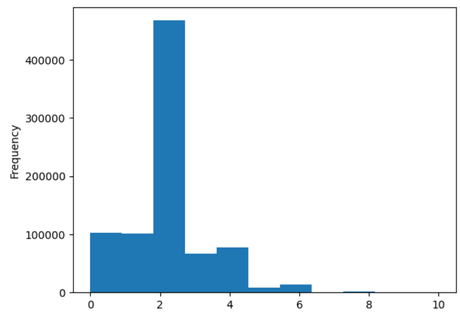


(b) Correlation of width and number of lanes

Figure 1: Width and central width



(a) The distribution of lane numbers before data cleansing



(b) ...and after

Figure 2: Data cleansing on number of lanes

3.1 Places

We have removed quite a few columns while preparing this file. The road numbering system is very opaque and seems unusable for both that reason and because the available data is fairly sparse: v1 and v2 are missing for more than half of rows and road number is 0 for more than half of them.

We also removed the columns relating to a so-called 'pr value' (pr and pr distance) as the site contained no information regarding the meaning of this field and a large percentage of the data was missing. There were several columns concerning the width of the road (number of lanes, width, central width) of which the latter two were removed.

Central width had an overwhelming majority of 0 values1a, while width contained very outlandish values ranging from -81 to 999 meters and had a fairly high correlation with number of lanes1b. The number of lanes was mostly correct, but contained way too large values: up to 99, so these were removed.1

Missing values in each column have been filled with either the other/not applicable value (0 in most cases) or with the most common/most likely value for the field (2 lanes for traffic, normal road conditions).

The values in this file are almost exclusively categorical and so the used correlation metric was Cramer's V (Figure 3).

3.2 Characteristics

The lighting column values were renumbered from 1 to 5 in a way that now 1 means there was more lighting and 5 means no lighting instead of a random numbering of the categories. The address column contained a lot of missing values and it was sadly not really useful. The most common street address was "AUTOROUTE A1" with 2816 rows which was very little out of the 839.985 rows so we removed it.

Longitude, latitude and GPS columns were removed because department and municipality columns provided enough information to visualise the data and not too detailed for later work. Most other columns contained very few null values and these were filled with the most common values.

There were quite a few correlations in the characteristics file (Figure 4). The most obvious is the holiday column and the date. Holiday is an added column based on the holiday.csv file. This column has a 1 if it's a holiday and a 0 if it's not so it is understandable why it correlates with the time.

Another strong correlation is the Time-Lighting columns. While the time contains the time of day, lighting contains if it's a full day, twilight or dawn, night with or without public lighting. With this information it makes sense that these correlate so notably. Localisation describes if accident took place in more urban or rural areas, so it is expected that it correlates with the value of lighting, because public lighting is more common in built-in areas.

3.3 Vehicle

This data contained very few missing values. For fix obstacles and mobile obstacles columns, null values were filled with the majority value (0) also signaling that there was likely no obstacle if the field was not filled out. For the shock and maneuver columns they were also filled with the most common value, since the few hundred missing values should not be significant compared to the 1.4 million rows of complete data. The flow direction column had 1.3 million missing values, therefore it was removed.

When investigating the correlation of the vehicle's properties, there weren't any strong correlations (Figure 5). Only a mild correlation between fix obstacle and mobile obstacle, probably because it is uncommon to have both in an accident. The other correlation is between maneuver and shock, which might be because maneuver could highly influence where the car was damaged.

3.4 Users

In this case, not much data was missing, most columns were almost completely filled out. Seat was missing in four years (between 2005 and 2008), in that case it was filled with 0 to indicate that it is unknown. User type, severity and sex were not missing. Trip was not given in just a couple of cases (about 300). Severity variable was reordered to become a scale which reflects the severity of the accident (1 meaning no harm, 4 meaning death). Safety equipment was not given in about 2% of cases, it was filled with the unknown category. Safety equipment consists of two digits, the first one referring to the existence of a safety equipment (and type of safety equipment), the second one referring to whether it was used or not (or could not be determined), these were separated into two columns.

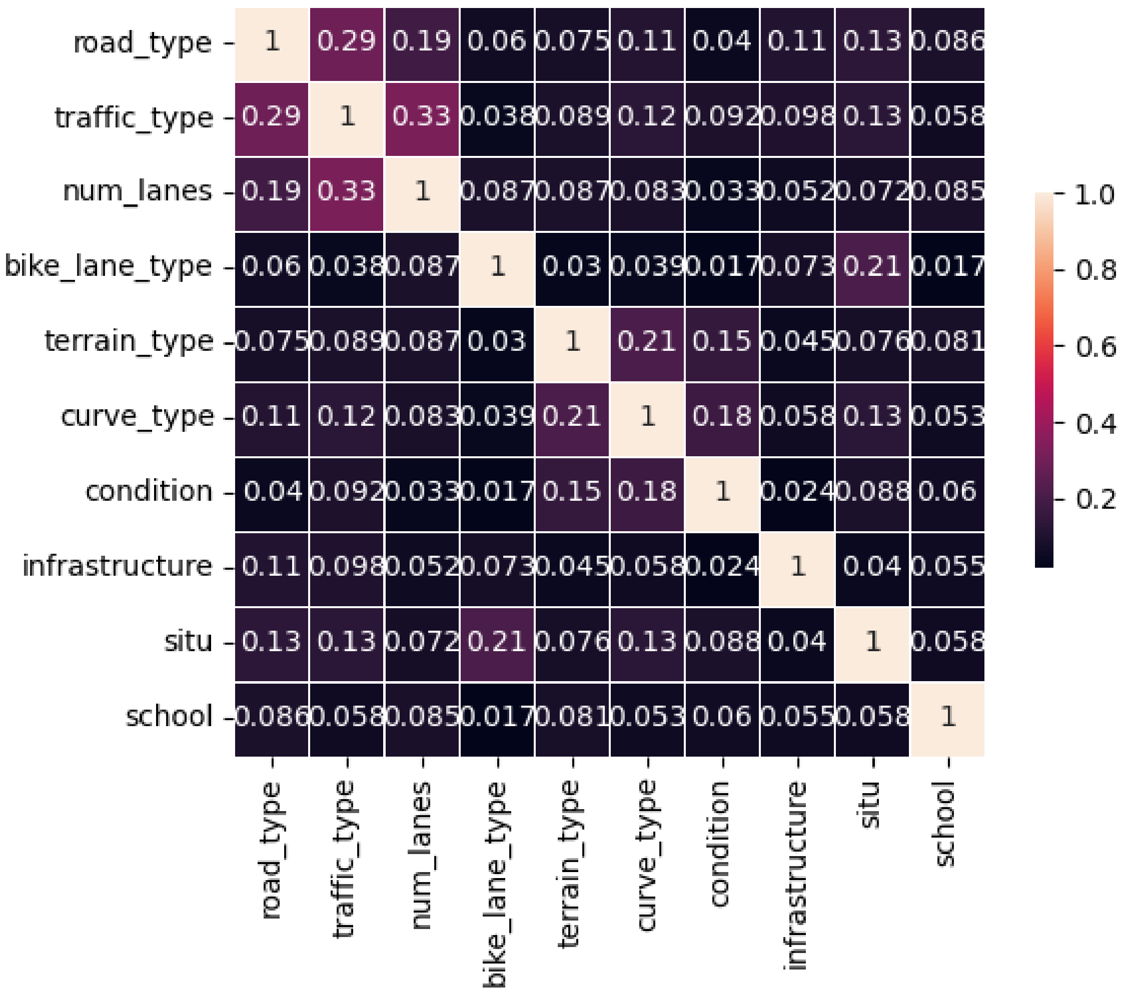


Figure 3: Correlation via Cramer's V in the fields of the places file

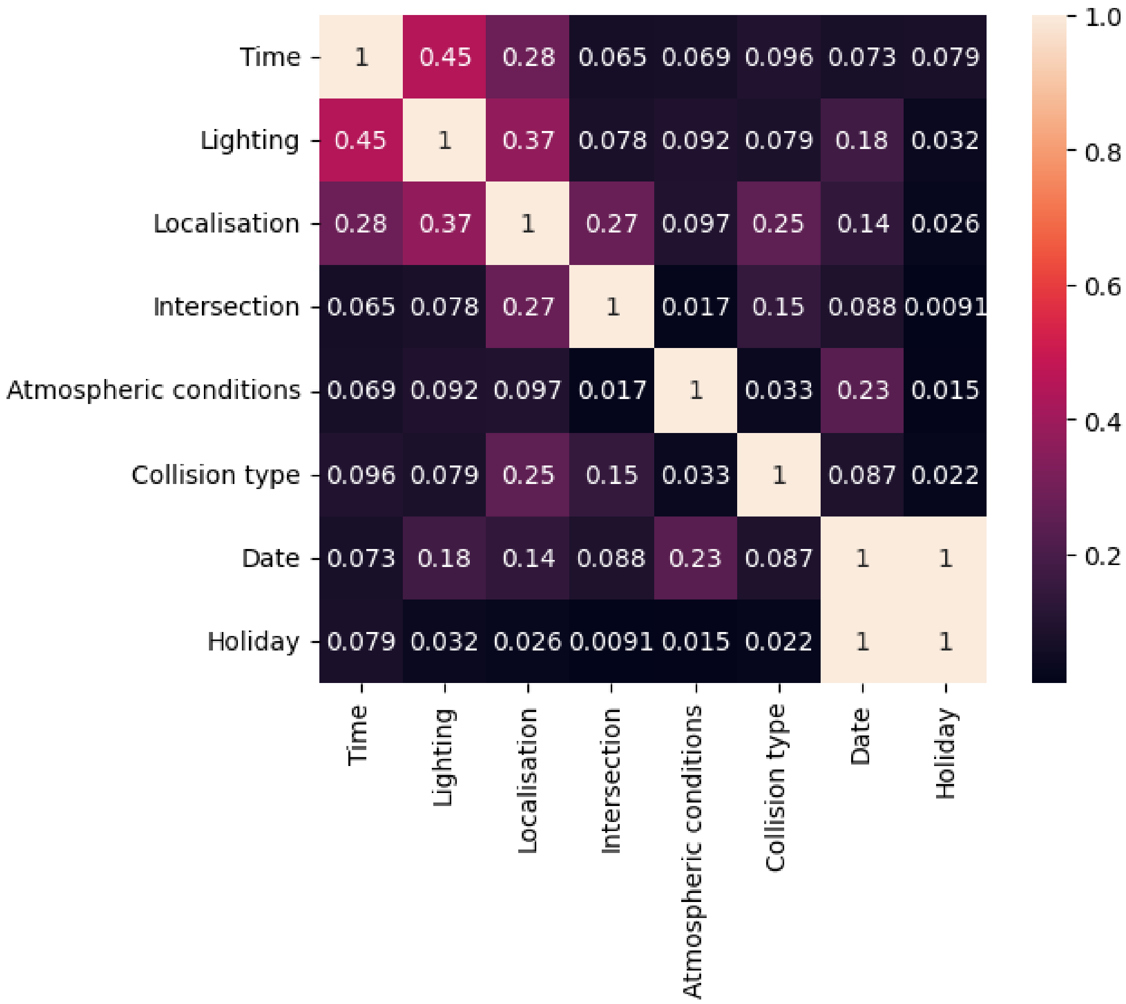


Figure 4: Correlation via Cramer's V in the fields of the characteristics file

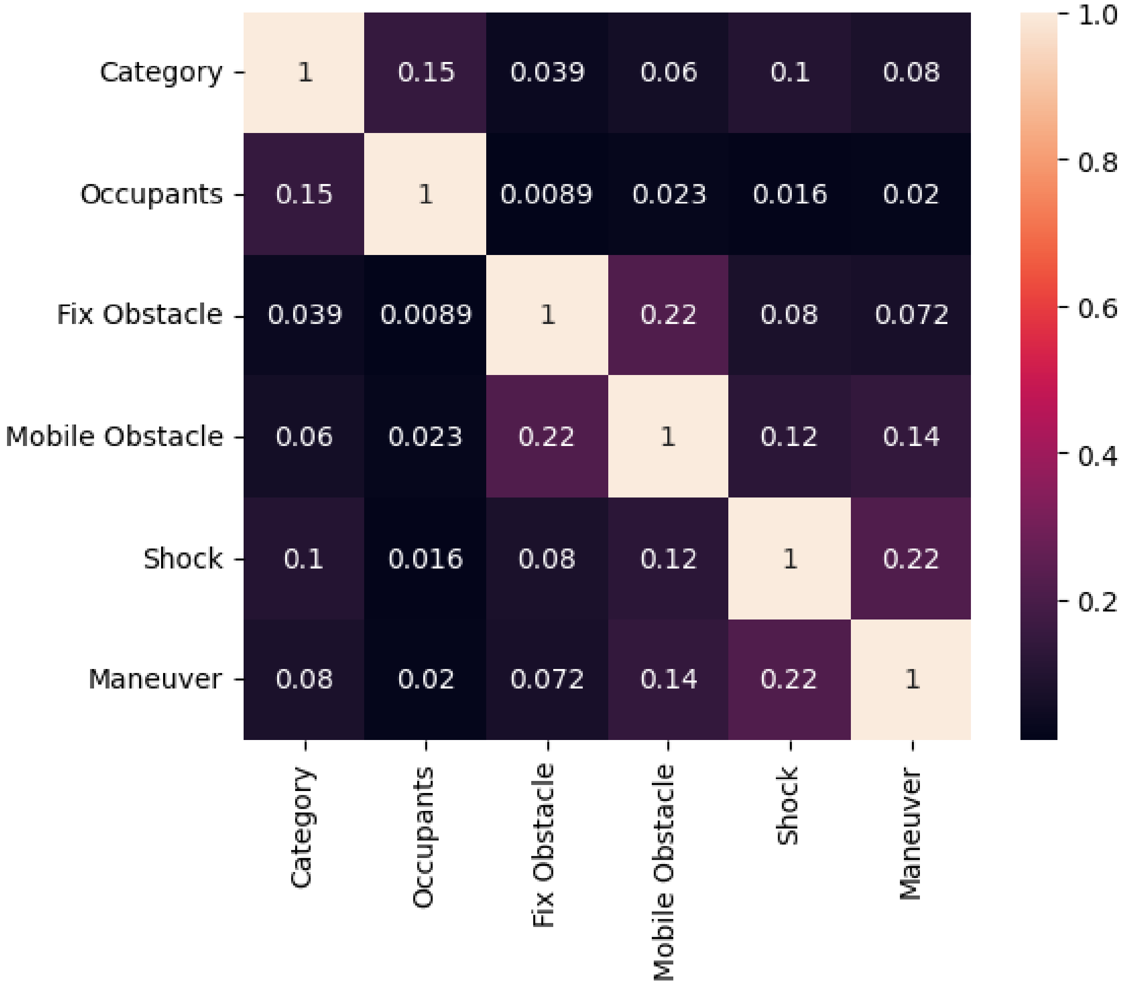
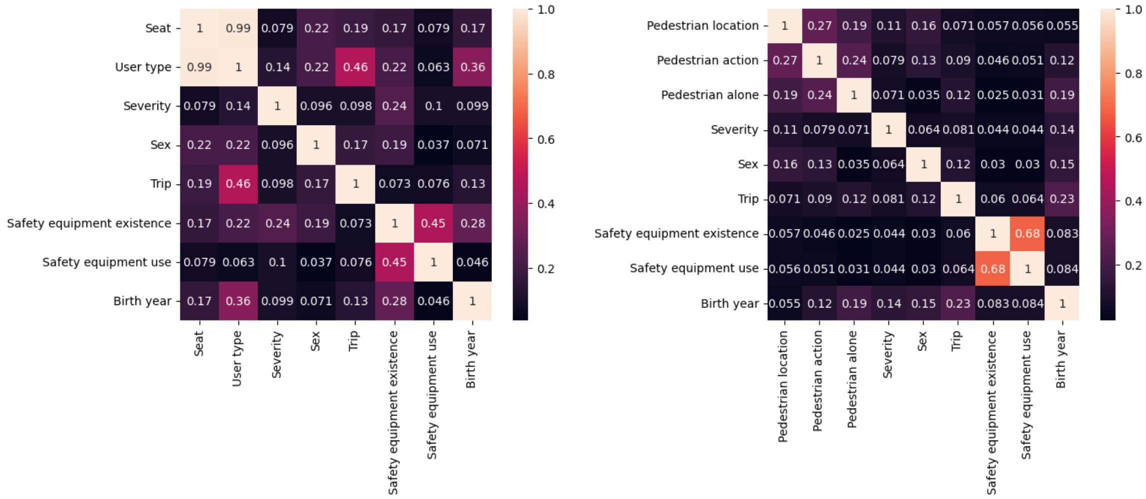


Figure 5: Correlation via Cramer's V in the fields of the vehicles file



(a) Not pedestrians (i.e. drivers and passengers)

(b) Pedestrians

Figure 6: Association of the user columns depending on user type

The association of the variables can be seen on Figure 6. Separating pedestrians and non-pedestrians (i.e. drivers and passengers) is necessary, because pedestrians have additional variables (location, action and whether they were alone) and some variables are not applicable to them (e.g. seat in the vehicle). Another reason for making the distinction, is that an accident can have different outcomes whether one is in a vehicle (and therefore 'protected' in a sense) or not.

The seat and user type have a high association because in a sense seat further refines the type of user, more precisely the seat of the passenger. In more than 99.9% of cases the driver was in the front left seat (which is expected, because people drive on the right in France). High association is also between safety equipment existence and use, but that could also be due to the missing values (i.e. both variables being 0).

Figure 7 shows the distribution of trip and user types in age intervals with a 10 year step. Younger and very old people tend to be passengers, 30-50 year old people are mostly drivers. The most common trip type was "Walking-leisure", although in many cases the data is not known.

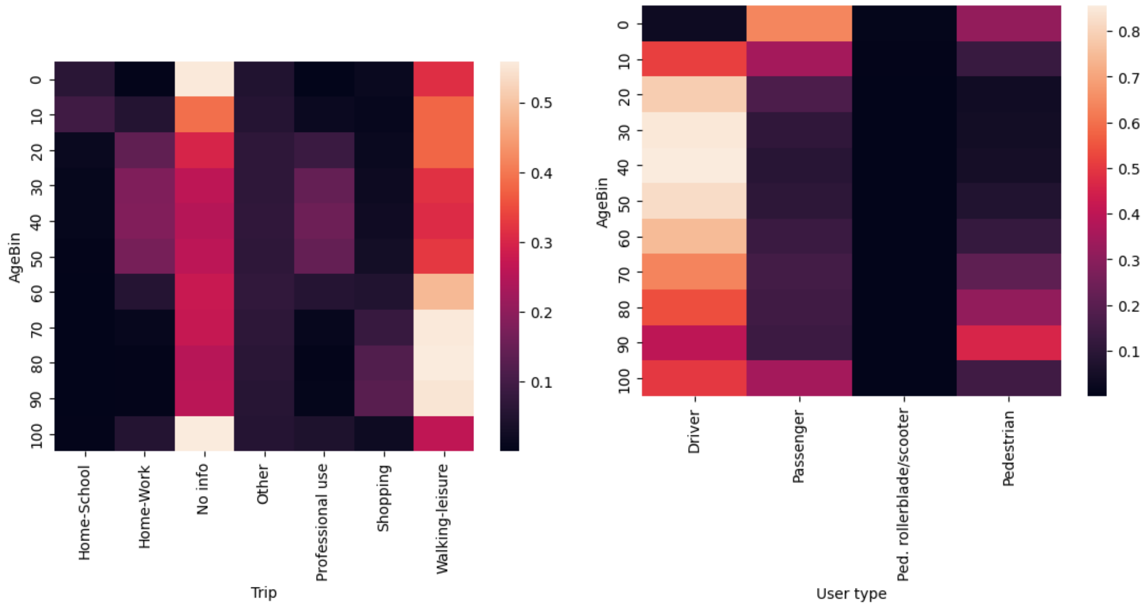
3.5 Merging the dataset

To be able to effectively train a model, we concluded that we should merge our data into one big dataset. In order to do this we have to make as many rows as many vehicles took part in the accident, because each vehicle contains at least one person the vehicle rows all had to be expanded.

This process yielded 1.876.005 rows; each row contains the characteristics of the accident they took part in, the properties of the place and vehicle they were in and the person's attributes.

3.6 Visualization on map

We have made two visualizations on a map, using the department codes of the injuries, see Figure **??**. (Departments refer to geographical regions/administrative units). Some regions around Paris had no data, but that could be due to department changes along the years. The average severity of



(a) Trip

(b) User type

Figure 7: Trip and user type category popularities in age intervals. AgeBin refers to age intervals by 10 years, e.g. 0-10, 10-20, etc.

injuries vary a bit by department, areas with fewer accidents had higher average severity.

4 Model construction

4.1 Choosing a model and preparing the data

Our chosen model for working with this data was a Bayesian network. This is beneficial for both explainability and querying, which are important in our use-case. The goal is to train a model that can give insight into causality and the interconnectedness of the factors involved in predicting accident outcomes and we want to be able to query the model with a limited number of these factors available.

To make our data compatible with such a network first we deleted the columns used only as database keys and we worked on creating categorical columns with hopefully a low cardinality. To achieve this we quantized our continuous variables, by for example creating age brackets from the date of the accident and the birthyear of the involved persons. Most of the data was already categorical, but we still needed to make changes in some cases because of high cardinality. One of these cases was the department (administrative region) value, where there were in total 101 different values, which needed to be grouped together to create larger geographical units.

This way we ended up with around 35 columns for each datapoint, each with under 10 different values, this was however still subject to change while actually fitting our model, as described in the next chapter.

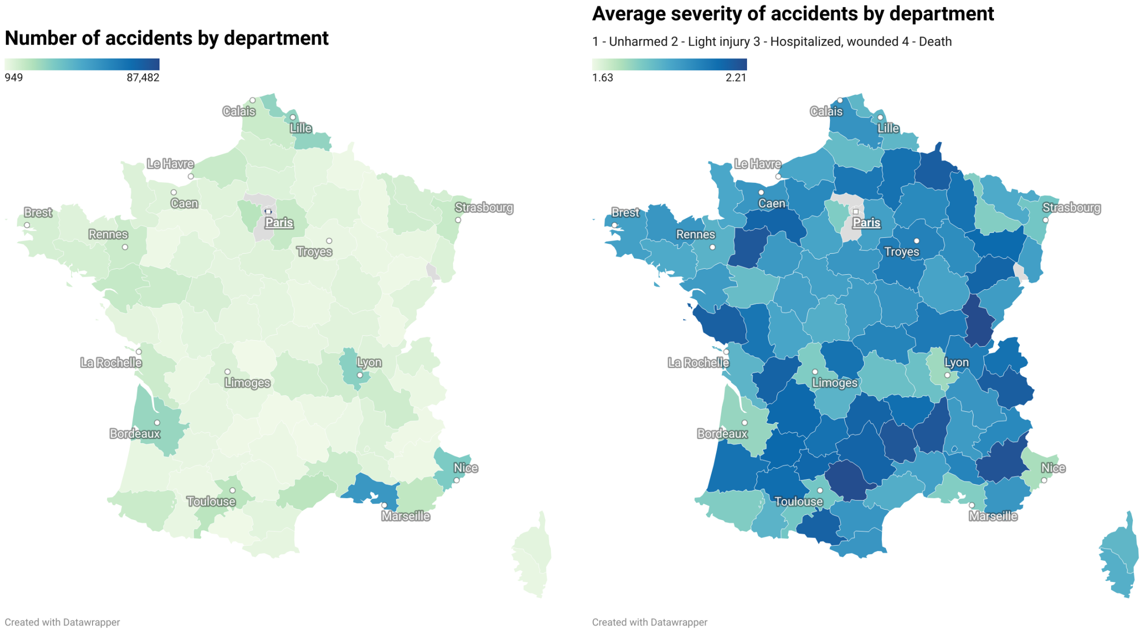


Figure 8: Visualizations by departments.

4.2 Working with Bayesian Networks and pgmpy

To create and fit a Bayesian network from just the available datapoints is a very hard task, so we decided to use pgmpy python library which has a couple algorithms implemented for each related task.

To get to a sampleable complete network from the data, we needed to run both structure learning and parameter estimation. Structure learning estimates the shape of the network's graph. Initially we planned to use the min-max hill climb algorithm for this task, but with the large amount of columns in our data, the runtime of this algorithm seemed unfeasable. To deal with this problem we switched to a hill climb algorithm and restricted the maximum in-degree.

To estimate the parameters in the resulting network we used the maximum likelihood estimator included in the library. This process was much faster than the structure learning phase and did not impact our runtime significantly.

4.3 Inference method

For using the resulting model for inference we first used Gibbs-sampling, but at this failed because of high memory demands.