UK Road Traffic Collision

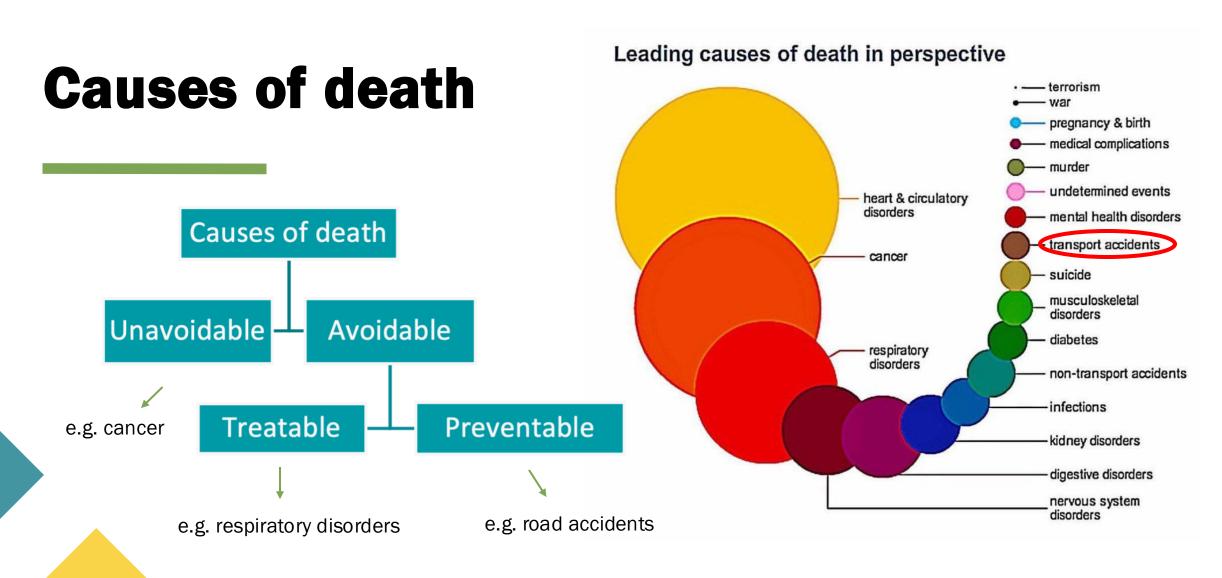
Nonparametric Statistics project





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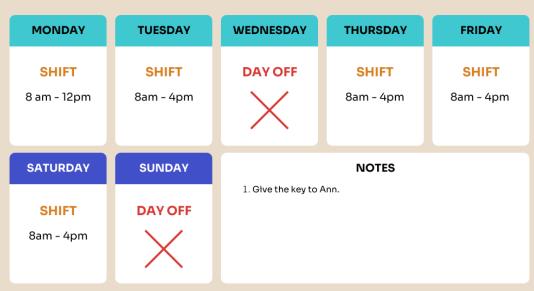


According to the latest data published by the WHO in 2020, deaths from road accidents is the 30^{th} cause of death (0.42% of total deaths).

Stakeholders

Understanding the potential number of accidents that may occur in a specific area and in a specific time slot provides support for the planning of **police** and **first aid** services.

Employee Work Schedule







Dataset

Collision data

For each **collision** we know:

- Date and time;
- Geographical location (latitude and longitude);
- Local authority district;
- Road type and conditions;
- Weather conditions.

Vehicle data

For every **vehicle** involved in each accident we have:

- Vehicle type and propulsion;
- Vehicle manoeuvre;
- Vehicle age;
- Point of impact;
- Position in carriageway;
- Age and sex of the driver.

Casualty data

For every **casualty** of each vehicle we know:

- Casualty severity (slight, serious, fatal);
- Age band and sex;
- Casualty class (driver/rider, passenger, pedestrian, ...)
- Position on the road in pedestrian case.

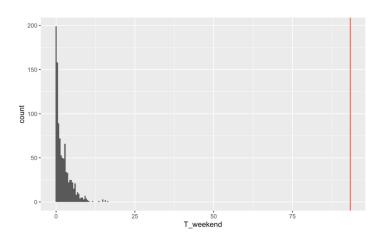
We used **official** data from the UK's **Department of Transport**, we decided to focus on the years from **2005** to **2022**.

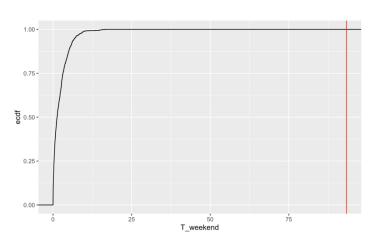
Nonparametric Tests and ANOVA

Significance of number of casualties, light condition and weekend class on casualty severity

casualty_severity ~ number_of_casualties + light_conditions + weekend

The results of permutational suggest that all the covariates are significant, with p-value of zero.





Accident severity

GAM for the severity of an accident

We employed 2 **GAM** models to analyse the accident **severities**:

- 1) We started by analysing the **3 categories** of severities, **slight, serious and fatal**, with an ordered categorical family with the identity link function: $g_1(y) = y$.
- 2) Then we reduced the response to **2** categories: **slight and serious-fatal**. The same semiparametric model for the covariates was maintained, and the link function was changed: $g_2(y) = \log(y)$.

```
\begin{split} g_j(accident\ severity_i) \sim number\ of\ casualties_i\ +\ weekend_i \\ &+ light\ conditions_i\ +\ f_1(time_i) \\ &+ f_2(number\ of\ vehicles_i)\ +\ f_3(speed\ limit_i) \\ i = 1, \dots, \quad j = 1, 2, \quad f_1, f_2, f_3\ are\ cubic\ splines, in\ addition\ f_1 is\ periodic \end{split}
```

Due to imbalanced of the data towards the class "slight severity", we kept the second model.

Results

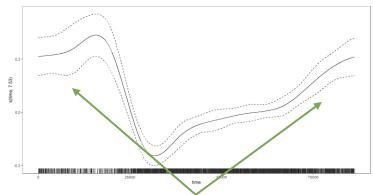
Parametric coefficients

Parametric coefficients	binary model
Intercept	-1.506703
number of casualties	0.207505
weekend	0.072481
Dummy for light conditions: "Darkness -	0.107128
no lights"	
Dummy for light conditions: "Daylight"	0.002283

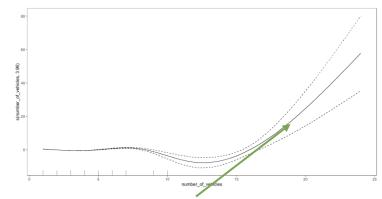
Comments:

- Positive influence on the severity of collisions by all the parametric coefficients;
- Coefficient of the dummy variable Daylight is positive, but it was the only coefficient that did not show statistical significance in the parametric test conducted by the model.

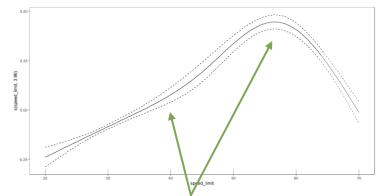
Splines



Increase during night-time and early morning hours



Clearly increasing as the alongside the number of vehicles



speed limit increases severity until ~60mph (further investigations are warranted)

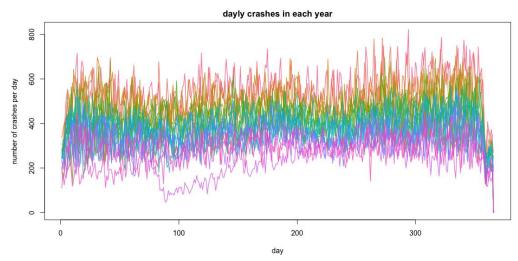
Functional data

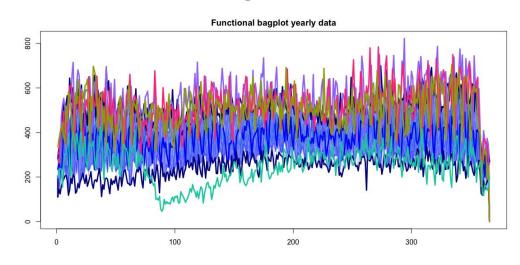
We model the **number** of **crashes** as **functional** data, focusing on **4** different **time horizons**: year, month, week, day.

Yearly data

We found:

- A clear **outlier** in the year 2020, due to the covid pandemic;
- A clear decreasing trend as the years progress despite the increase in circulating vehicle.





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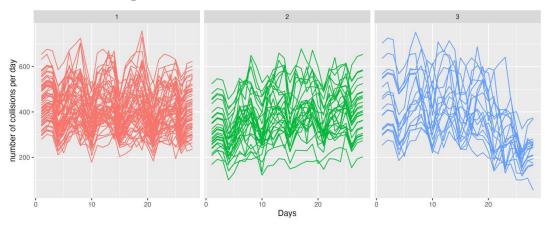
Functional data

Monthly data

When considering monthly data, we decided to **align** the data using **shift warping function** to properly capture the weekly pattern in the data.

Functional clustering using k-means

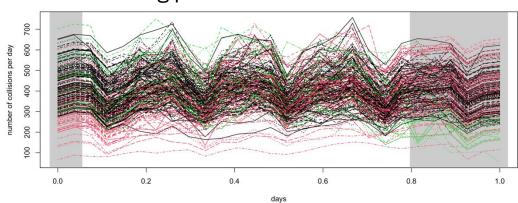
We found **3 clusters**: one containing predominantly the months of **January** and **April**, one containing mostly **December** and the **remaining** months were clustered together.



Permutation tests on the identified clusters

We validated the results using permutation tests:

- Global permutational ANOVA;
- Local permutational ANOVA using an intervalwise testing procedure.



Functional data

Weekly data

There were two distinct clusters:

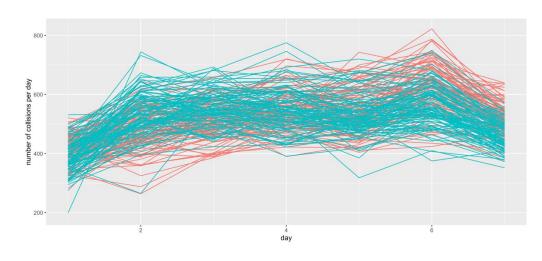
- Regular working weeks;
- Weeks belonging to a holiday period.

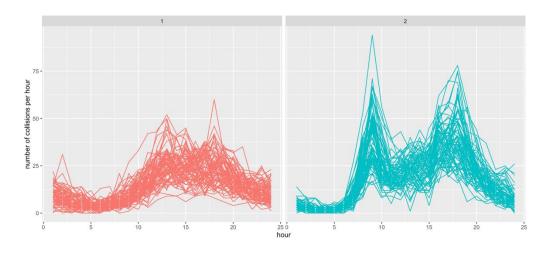
Daily data

There were two distinct clusters:

- Regular working days;
- Weekends and holidays.

The significance of the clusters was validate using a **global permutation** 2 population test for the difference in distribution. From a **local** permutation test the distribution was different **on the whole time span**.



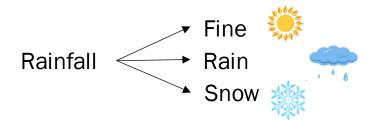


Robust GAM

Robust GAM for the average number of accidents per day

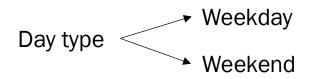
We considered data spanning from 2005 to **2021**. Considering the restrictions on normal vehicular movement during the **COVID** period, we decided to employ a **robust method**.

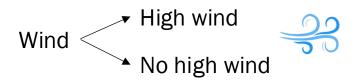
Average n^o of collisions \sim day type + wind + rainfall + f_1 (day of the year)



Day of the year: 1, ..., 365 modelled using **natural cubic splines**

Year: 2005, ..., 2021

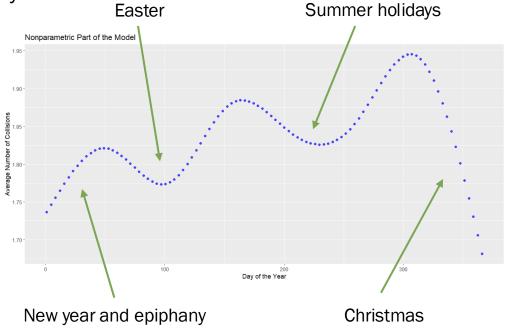




Results

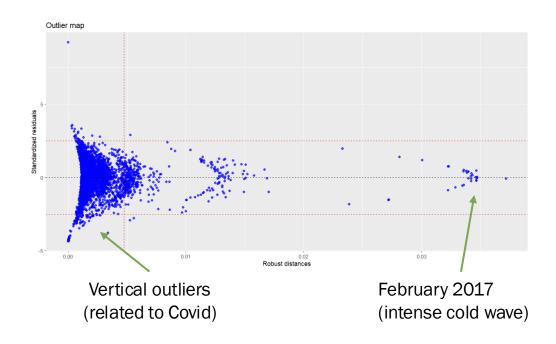
Day of the year

The nonparametric part of the model is able to correctly **capture** the **nonlinear behaviour** of the number of crashes in the **different periods** of the year.



Outlier map

The most recent **vertical outlier** corresponds to the observation on March 24, 2020. The full **lockdown** was officially declared on March 23, 2020, by Prime Minister Boris Johnson.



Conformal prediction

Prediction bands for the daily number of accidents

We decided to produce conformal prediction bands following a split conformal approach for each district.

The predictions were built from the output of a GAM built independently for each district.

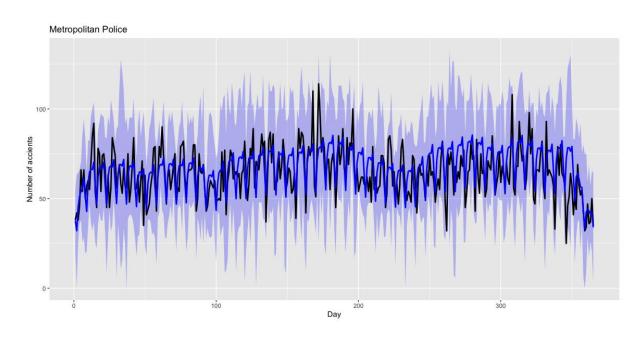
The prediction bands were obtained by:

$$C_{n,1-\alpha}^s := \{ y \in \mathcal{Y}(\mathcal{T}) : y(t) \in [g_{\mathcal{I}_1}(t) \pm k^s s_{\mathcal{I}_1}(t)] \forall t \in \mathcal{T} \}$$

where:

$$s_{\mathcal{I}_1}(t) = \frac{\max_{j \in \mathcal{H}_2} \left| y_j(t) - g_{\mathcal{I}_1}(t) \right|}{\int_{\mathcal{T}} \max_{j \in \mathcal{H}_2} \left| y_j(t) - g_{\mathcal{I}_1}(t) \right| dt}$$

$$\mathcal{H}_2 := \{ j \in \mathcal{I}_2 : \sup_{t \in \mathcal{T}} \left| y_j(t) - g_{\mathcal{I}_1}(t) \right| \le k \}$$

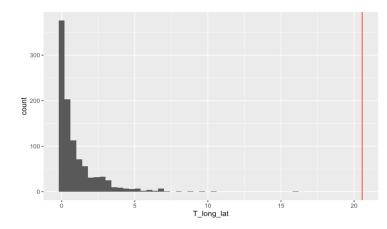


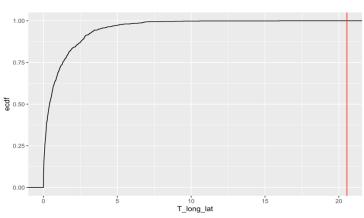
Nonparametric Tests and ANOVA

Significance of latitude and longitude on the number of crashes

In order to test the significance of the geolocation we used a two-way Permutational ANOVA with interactions:

- The **interaction** have a **significant** impact on the number of crashes. This suggests that geographic location is an important factor in traffic accidents.
- The p-value of the test: H_0 : interaction_{i,j} = 0 vs H_1 : interaction_{i,j} \neq 0 is equal to zero, hence the main effect are significant as well
- Permutational ANOVA was used because the data do not follow the Gaussian distribution.

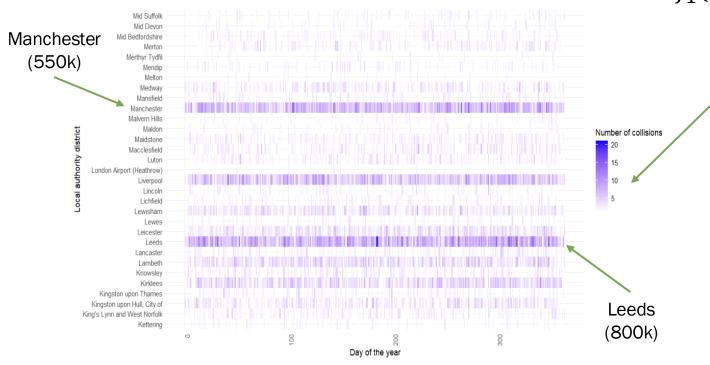




N° of daily collisions per district

GAM model with mixed effects

 $\log(mean \ n^{\circ} \ of \ collisions_{i}) \sim day \ type_{i} + wind_{i} + rainfall_{i} + year_{i} \\ + f_{1}(day \ of \ the \ year_{i}) + b_{i}$



Heatmap of the number of collision for 30 districts during the year 2005. Random intercept for the local authority district used to capture the difference in the population across the country.

POLICE

Year: 2005, ..., 2019

Results

Day of the year

We decided not to consider Covid years.

Year: 2005, ..., 2019

The nonparametric part of the model is analogous to the one shown in the robust model.

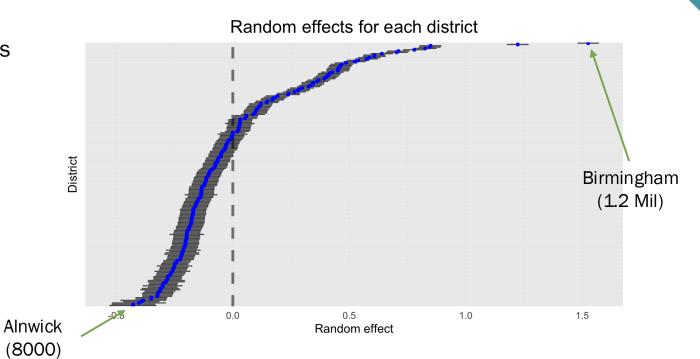
Rain fall

In Birmingham the 1st of Feb 2019 the predicted mean number of crashes are:

Rainfall	Mean n° of collisions
Fine	6,78
Rain	6,43
Snow	6,20

Random effects

The random intercept correctly accounts for the **population differences** of the districts.



Including spatial information

GAM model using latitude and longitude

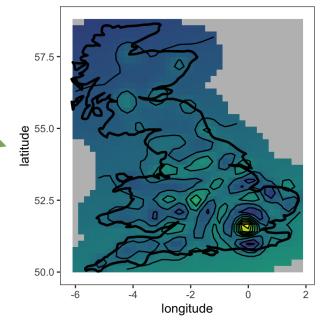
We decided to include in the model the **latitude** and **longitude** components to better model the spatial distribution of the data.

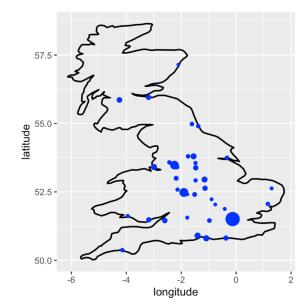
We are capturing the distribution of the **population** on the territory with the added non parametric term.

 $\log(mean\ n^{\circ}\ of\ collisions) \sim day\ type\ +$ wind + rainfall + year + $f_1(day\ of\ the\ year)$ + $f_2(\ longitude, latitude)$

The spatial part was modelled using a **Gaussian Process** with covariance function:

$$\begin{cases} 1 - 1.5d/\rho + 0.5(d/\rho)^3 & \text{if } d < \rho \\ 0 & \text{otherwise} \end{cases}$$

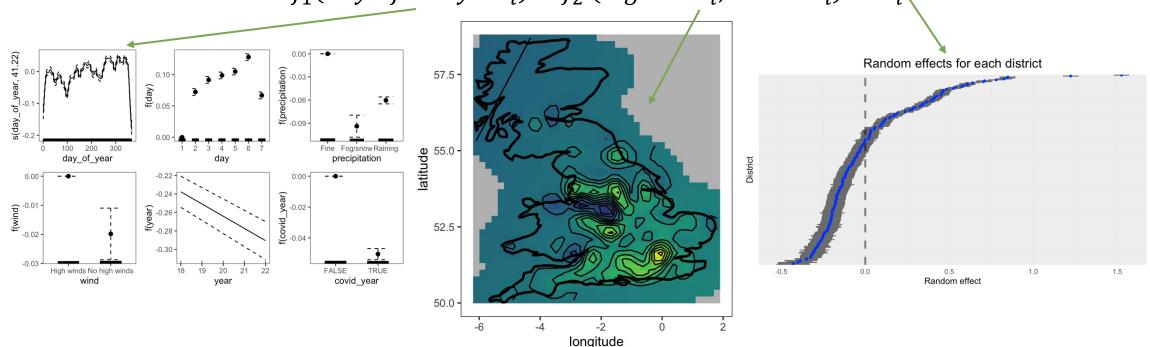




Combining both approaches

The complete GAM model

 $\log(mean \ n^{\circ} \ of \ collisions_{i}) \sim day \ type_{i} + wind_{i} + rainfall_{i} + year_{i} + covid \ year_{i} + f_{1}(day \ of \ the \ year_{i}) + f_{2}(logitude_{i}, latitude_{i}) + b_{i}$



Thank you for the attention!

References:

- 1.UK Department for Transport. Road safety data, from https://www.data.gov.uk/dataset/cb7ae6f0-4be6-4935-9277-47e5ce24a11f/road-safety-data
- 2. J. Diquigiovanni, M. Fontana, and S. Vantini. The importance of being a band: Finite-sample exact distribution-free prediction sets for functional data, 2021.
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- 4. A. Pini, S. Vantini, B. M. Colosimo, and M. Grasso. Domain-Selective Functional Analysis of Variance for Supervised Statistical Profile Monitoring of Signal Data. Journal of the Royal Statistical Society Series C: Applied Statistics, 67(1):55–81, 2017.
- 5. L. M. Sangalli, P. Secchi, S. Vantini, and V. Vitelli. k-mean alignment for curve clustering. Computational Statistics Data Analysis, 54(5):1219–1233,2010.