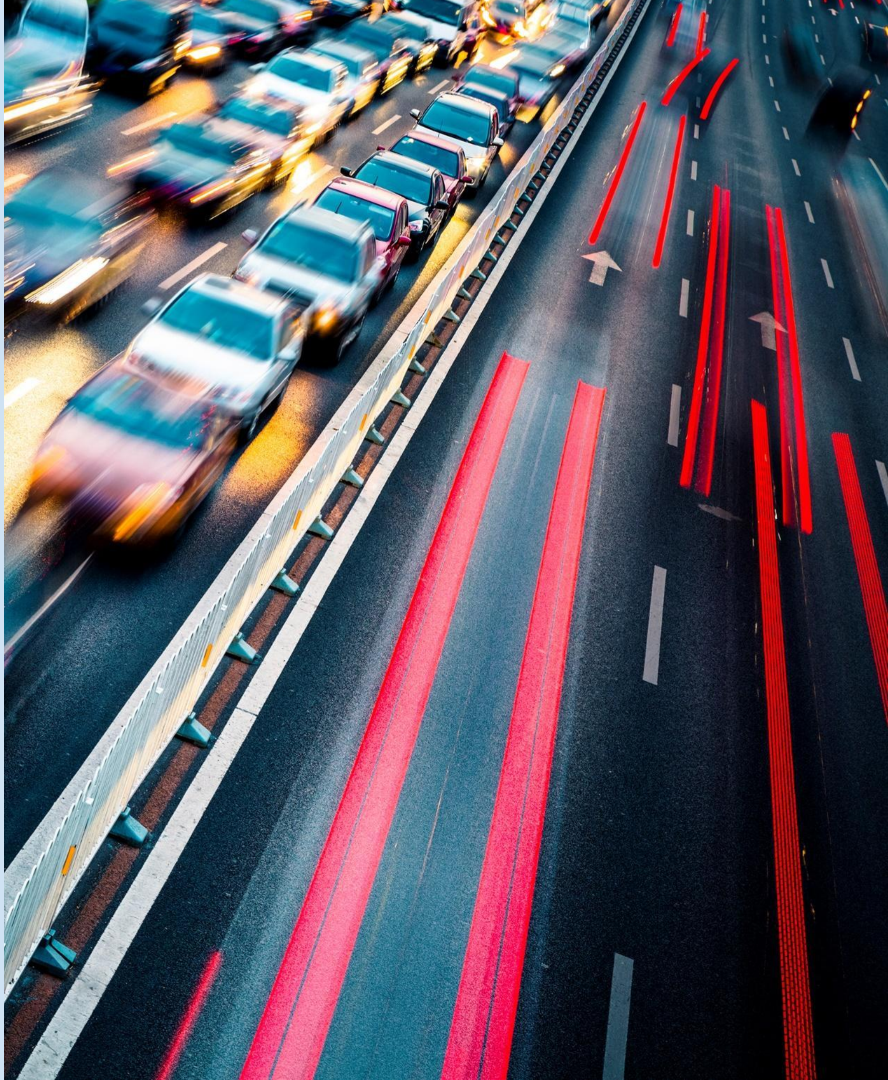
# TRAFFIC ACCIDENTS IN THE UK 2021:

*Investigating traffic accident seriousness in the UK and the variables that are more likely to lead to a cra collision*

Ingrid Ionita, Clarissa Lo, Michelle Obonyano & Ayomide Olarewaju



# Task distribution

| NAME | ROLE |
|---|---|
| Ingrid Ionita | Scrum master, Main data cleaner, Main analyst |
| Clarissa Lo | Lead visualisation, Main analyst |
| Ayomide Olarewaju | Lead data cleaner, Lead machine learning |
| Michelle Obonyano | Main analyst, Main visualisation |

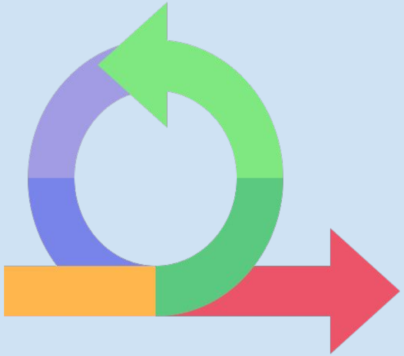
# What were our challenges?

**Communication issues:**

- Time zone differences
- Personal responsibilities outside of the CFGdegree (childcare, university, work)

**Difficulty on deciding on a project topic**

# How did we overcome them?



Agile approach

- Daily scrum meetings
- Ensuring scrum master met with everyone
- Scrum master representing absent team members
- Listening to opinions to include everyone’s voice
- Trusted each other

# How did we make it work for us?

| Trello board | Google Drive | Slack |
| --- | --- | --- |
| Trello | | slack |
| Organise tasks | Organise documents | Communicate |

**DISCUSS**
- Discuss with the team the project topic, debate the pros and cons of all suggestions. Select ONE topic.

**REVIEW**
- Review the topic of 'traffic accidents' and select an appropriate dataset. Decide on the project aims.

**CLEAN**
- Clean the three datasets (accident, casualty, vehicle) and merge them together using pandas.

**ANALYSE**
- Using the project aims as guidance, dissect the cleaned data and visualise it using matplotlib, folium, geopy and seaborn.

**REPORT**
- Using the findings from the previous step, we write a report on the discoveries and whether they confirm current research and discuss limitations.

# Our project: traffic accidents

## Why did we choose the topic of traffic accidents?

There are approximately

**150,000**

people caught in a traffic accident per year.

## Our project aims are:

To discover the circumstances in which traffic accidents are more likely to happen

To offer recommendations to the UK government in reducing the number of traffic accidents.

# Objectives

01 **Are certain drivers or casualties more likely to get involved in a severe car accident?**

- *These drivers and casualties would be categorised by their age and gender.*

02 **What dates are more likely to have a higher number of traffic accidents and cause more severe accidents?**

- *Can this be linked to environmental factors such as the weather and the light conditions?*

03 **What areas in the UK are more likely to have more severe traffic accidents?**

- *This can be from the road type, junction location, county.*

04 **Extension question: can machine learning be used to predict traffic accidents?**

# Data sources

Our sources are from the UK government!

## Road Safety Data

**Published by:** Department for Transport
**Last updated:** 15 October 2022
**Topic:** Transport
**Licence:** Open Government Licence

**Summary**

Road Safety Statistics releases and guidance about the data collection.

Data download tool for bespoke breakdowns of our data.

STATS19 R package developed independently of DfT, offering an alternative way to access this data for those familiar with the R language

View full summary

### Data links

| Link to the data | Format | File added | Data preview |
|---|---|---|---|
| Road Safety Data - Casualty Adjustment Lookup 2021 | CSV | 15 October 2022 | Preview |
| Road Safety Data - Collision Adjustment Lookup 2021 | CSV | 15 October 2022 | Preview |
| Road Safety Data - E-Scooter 2021 | CSV | 15 October 2022 | Preview |
| Road Safety Data - Casualties 1979 - 2021 | CSV | 15 October 2022 | Preview |
| Road Safety Data - Vehicles 1979 - 2021 | CSV | 15 October 2022 | Preview |
| Road Safety Data - Accidents 1979 - 2021 | CSV | 15 October 2022 | Preview |
| Road Safety Data - Casualties 2021 | CSV | 15 October 2022 | Preview |
| Road Safety Data - Vehicles 2021 | CSV | 15 October 2022 | Preview |
| Road Safety Data - Accidents 2021 | CSV | 15 October 2022 | Preview |
| Road Safety Data - Accidents 2021 - Provisional Mid Year Unvalidated Data | CSV | 25 November 2021 | Preview |
| Road Safety Data - Vehicles 2021 - Provisional Mid Year Unvalidated Data | CSV | 25 November 2021 | Preview |
| Road Safety Data - Casualties 2021 - Provisional Mid Year Unvalidated Data | CSV | 25 November 2021 | Preview |
| Road Safety - E-Scooter 2021 - Provisional Mid Year Unvalidated Data | CSV | 25 November 2021 | Preview |

# Data cleaning

Replacing missing /out of range data represented by (-1) with mode and mean while columns with more than 40% were dropped. This was done to prevent our data from being skewed.

**REMOVING DULPICATES**

```
n_duplicates =df.drop(labels=["accident_index"], axis=1).duplicated().sum()
print(f"You might have {n_duplicates} duplicates in your database.")
```

```
You might have 0 duplicates in your database.
```

**DETECTING COLUMNS WITH MISSING VALUES**

```
#checking how many NaN values each column contains.

missing_val= df.isnull().sum().sort_values(ascending=False)
percent_missing = ((missing_val/df.isnull().count())*100).sort_values(ascending=False)
missing_df = pd.concat([missing_val,percent_missing], axis=1, keys=['Total', '%'],sort=False)
missing_df[missing_df['Total']>=1]
```

| | Total | % |
|---|---|---|
| location_easting_osgr | 39 | 0.025087 |
| location_northing_osgr | 39 | 0.025087 |
| longitude | 39 | 0.025087 |
| latitude | 39 | 0.025087 |

# Drivers and casualties in a traffic accident

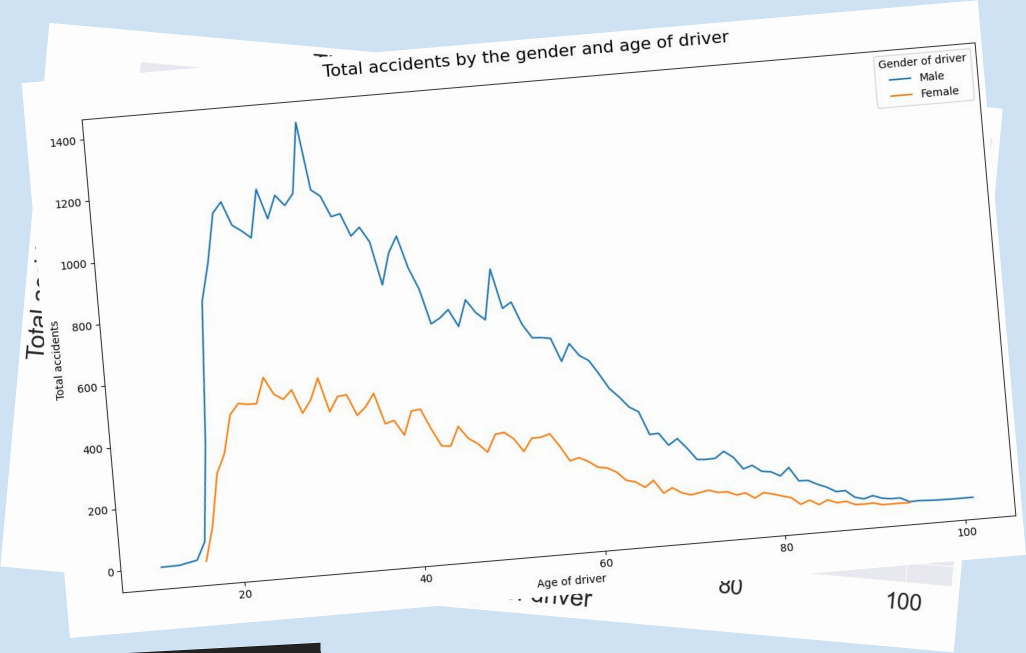
## Pivot table:

```
PIVOT_TBL_1b= GEN_AGE_AF.pivot_table(
    index = 'age_of_casualty',
    columns="sex_of_casualty",
    aggfunc = "count")['casualty_severity']

PIVOT_TBL_1b
```

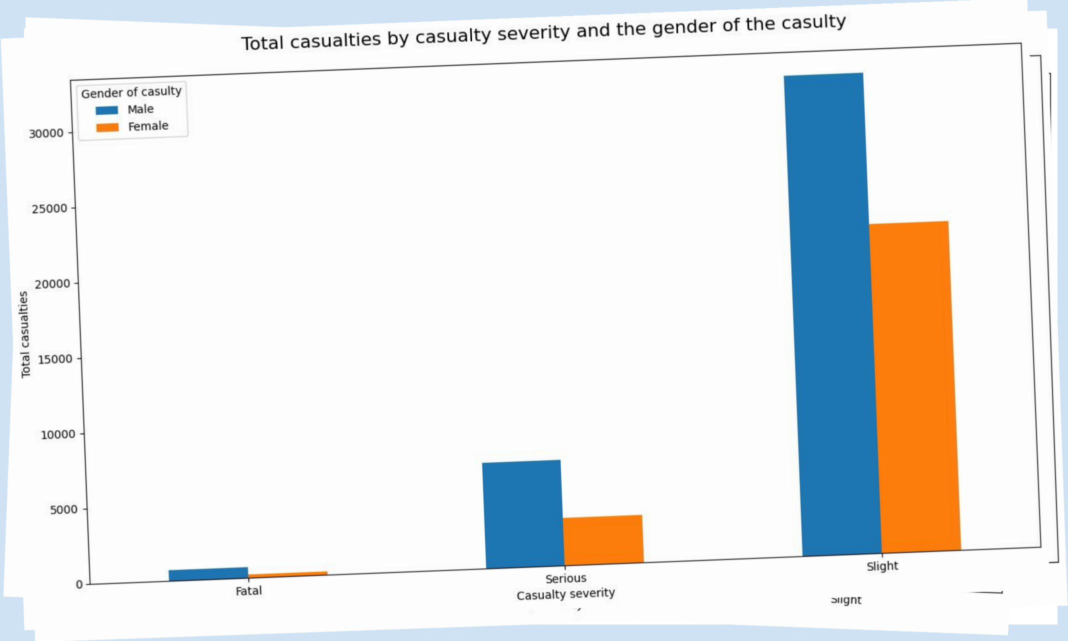
## Line chart:

```
# lines
PIVOT_TBL_1b.plot(kind="line", figsize=(15,8))

# x-axis
plt.xlabel('Age of casualty')

# y-axis
plt.ylabel('Total casualties')
```

```
# other elements of the plot
plt.title('Total casualties by the gender and age of casualty', pad=20, fontsize=16)
plt.legend(labels=["Male", "Female"], title="Gender of casualty", loc="upper right")
plt.show()
```



# Drivers and casualties in a traffic accident




## Pivot table:

```
PIVOT_TBL_1e = GEN_AGE_AF.pivot_table(
    index = 'casualty_severity',
    columns="sex_of_casualty",
    aggfunc = "count")['age_of_casualty']

PIVOT_TBL_1e
```

## Line chart:

```
# bars
PIVOT_TBL_1e.plot(kind="bar", figsize=(15,8))

# x-axis
plt.xlabel('Casualty severity')
plt.xticks(range(0,3),labels=(severity),rotation ='horizontal')

# y-axis
plt.ylabel('Total casualties')
```

```
# other elements
plt.title('Total casualties by casualty severity and the gender of the casulty',  pad=20, fontsize=16)
plt.legend(title="Gender of casulty", labels=["Male", "Female"], loc="upper left")
plt.show()
```

# Traffic accidents and the time

- Could be linked to fatigue related to work hours
- Wednesday, Thursday and Friday have the most traffic accidents
- Weather and light conditions variables explored, but no interesting findings resulted from it


```
## pivot table of week day and hour count ##

# make a new dataframe for variables required for the pivot table
DAY_HOUR_MONTH_DF = DF[['day_of_week','casualty_severity'
```

```
## count the number of accidents by accident severity and weather conditions ##

# make a new data frame with variables required
WTHR_LIGHT = DF[['hour','accident_severity', 'weather_conditions', 'light_conditions']]

# make a list of the labels for each weather condition
wthr_labels = ["Fine no high winds", "Raining no high winds", "Snowing no high winds", "Fine with high winds", "Raining with high winds", "Snow

# pivot table with accident severity as index and weather conditions as columns
PIVOT_TBL_2c = WTHR_LIGHT.pivot_table(
  index = 'accident_severity',
  columns= 'weather_conditions')['hour']
```

```
## plot the number of accidents by accident severity and weather conditions ##

# bar
PIVOT_TBL_2c.plot(kind="bar", figsize=(15,8))

#x-axis
plt.xlabel('Accident severity')
plt.xticks(range(0,3),labels=(severity),rotation ='horizontal')

#y-axis
plt.ylabel('Hour of day')
plt.yticks(range(0,24,5), rotation ='horizontal')

#other elements
plt.title('Weather conditions and the hour of the day against accident severity', pad=20, fontsize=20)
plt.legend(title="Weather conditions", title_fontsize='16', labels = wthr_labels, fontsize='16', loc="upper right", bbox_to_anchor=(1.25, 1))
```

```
elements of the plot
plt.title('The total accidents by the hour of each week day', pad=20, fontsize=20)

plt.legend(labels=days, title="Days of the week", loc="upper left")
```

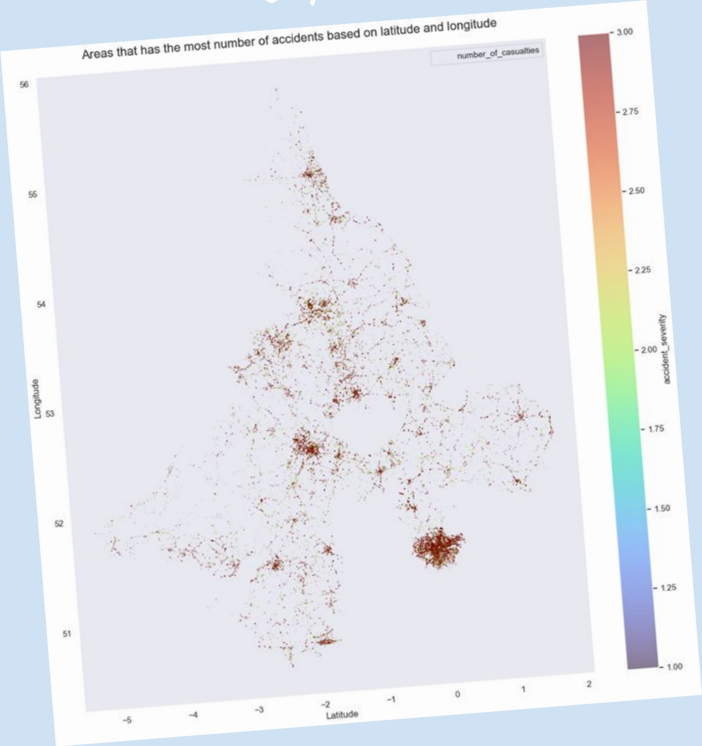
# Traffic accidents and the location

1. The darker area on the graph and where its showing on the x and y axis which is -1,+1 and 51,52

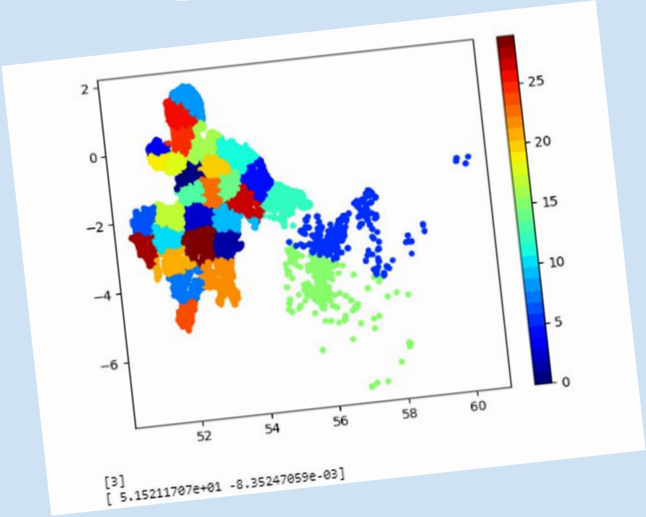
2. The figures with exponents of Ten [ 5.15211707e+01 -8.35247059e-03 ] multiplied by the required tens to get the actual longitude and latitude 51.5211707, and longitude -0.00835247 which turns out to be london

3. Junction 0-9 has high number of accident severity but higher number of accident severity with added location 10

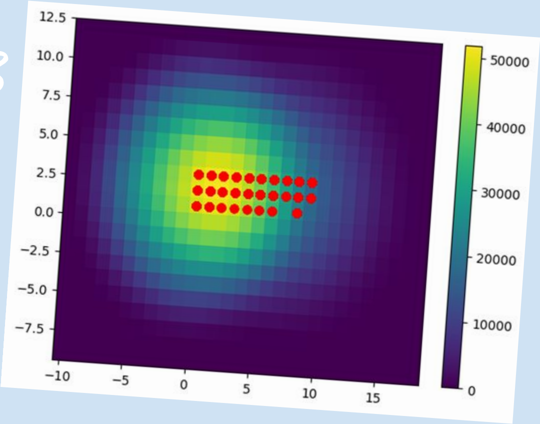
01




02



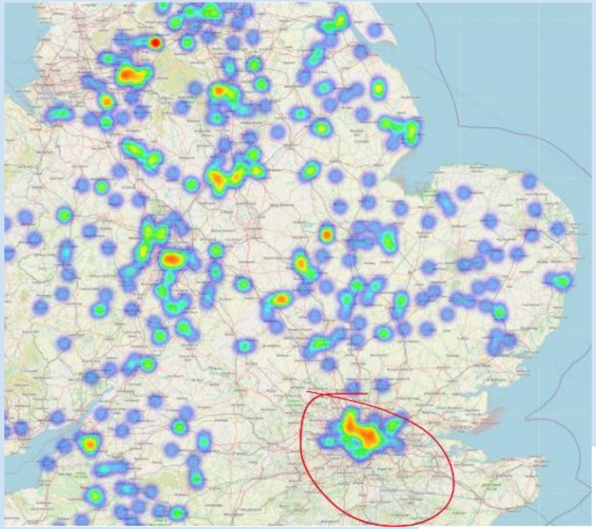

03

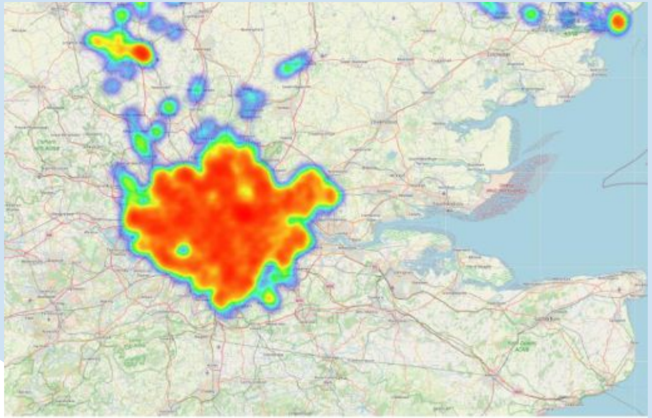


# Nominatim API

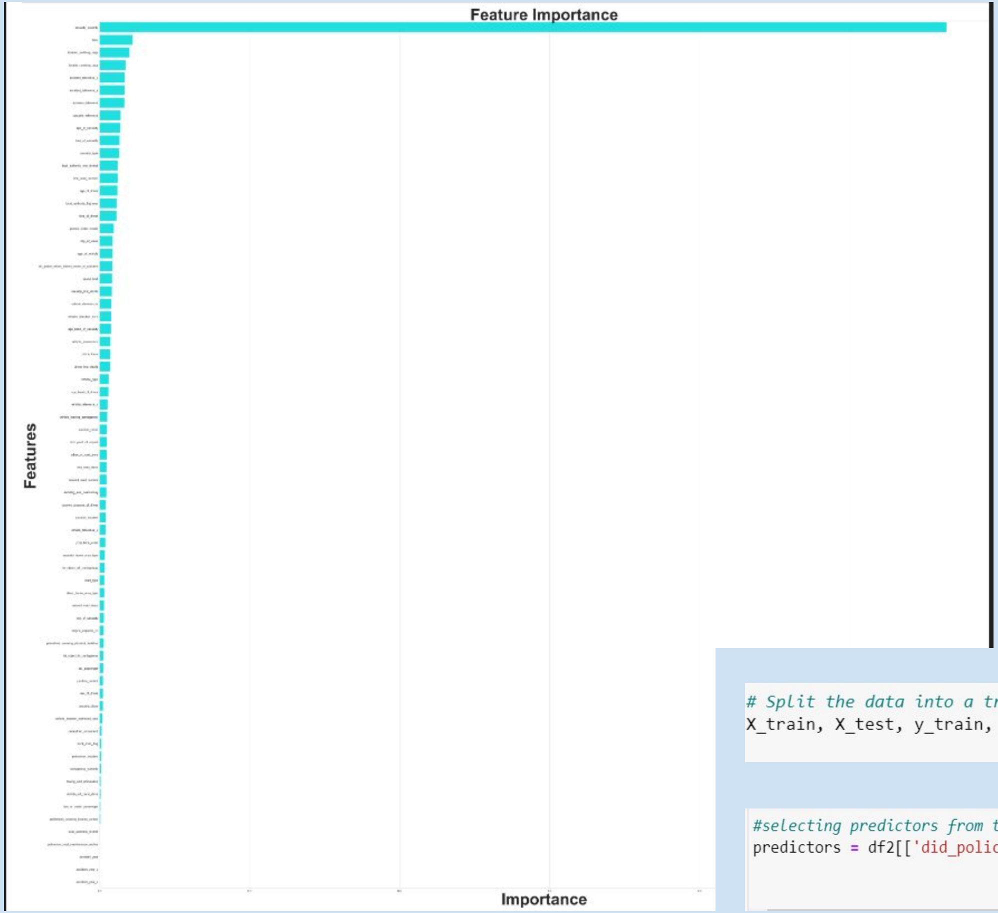
- Nominatim's API was used to produce heat maps
- Many errors in the process
- Marker map and heatmap not working initially because too many API recalls
- Group effort solved the problem

```
# Getting rid of the other values, fatal and serious, to only keep the fatal accidents.
dv3 = [1, 2]
SLIGHT = DF[DF.accident_severity.isin(dv3) ==  False]

# Creating a new map variable for the serious accidents.
SLIGHT_UK = folium.Map(location = [54.76999101318324, -2.8478385244334445], zoom_start = 6)

# Using the Lambda function to combine the latitude and longitude into one column.
slight_latlon = SLIGHT.apply(lambda row: (str(row.latitude),str(row.longitude)),axis=1)

#Plotting the latitude and longitude on the map.
HeatMap(slight_latlon).add_to(SLIGHT_UK)

# Calling the map to see the visualisation.
SLIGHT_UK
```





# Machine learning




- Feature selection from our 69 columns using random forest but observed no correlation
- Choose specific predictors
- Train_test_split : 80/20 used
- Experimented with 4 algorithms : Random forest, Decision Tree, Logistic Regression and K-NN
- Evaluation metrics was Accuracy & confusion matrix performance metrics
- Result

```python
# Split the data into a training and test set.
X_train, X_test, y_train, y_test = train_test_split(predictors.values,
                                                    df2['accident_severity'].values,test_size=0.20, random_state=99)
```

```python
#selecting predictors from the above features
predictors = df2[['did_police_officer_attend_scene_of_accident' , 'age_of_driver' ,'vehicle_type', 'age_of_vehicle',
                  'engine_capacity_cc','day_of_week' , 'road_type', 'casualty_severity',
                  'sex_of_driver' ,'speed_limit','pedestrian_location','junction_control','urban_or_rural_area']]
```

# Machine learning

- With a 98% accuracy rate, the balanced dataset of the Random Forest model is the best classifier for predicting accidents.

Unbalanced dataset

```
2    120493
1     31981
0      2944
Name: accident_severity, dtype: int64
```

Balanced dataset

```
2    120493
1    120493
0    120493
dtype: int64
```

**UNBALANCED DATASET**

| MODELS | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Random Forest | 96.4 | 96.4 | 96.4 | 96.4 |
| Decision Tree | 93.8 | 94.0 | 93.8 | 93.8 |
| K-NN | 94.2 | 94.3 | 94.2 | 93.7 |
| Logistic Regression | 84.5 | 83.0 | 85.0 | 83.0 |

**BALANCED (SMOTE) DATASET**

| MODELS | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Random Forest | 98.0 | 98.0 | 98.0 | 98.0 |
| Decision Tree | 96.8 | 96.8 | 96.8 | 96.8 |
| K-NN | 80.4 | 80.2 | 80.4 | 80.0 |
| Logistic Regression | 93.0 | 93.0 | 93.0 | 93.0 |

# Conclusion

Our findings:

- Men are more likely to be in a car accident at all level of severities
- Age?
- Wednesday, Thursday and Friday have the most number of traffic accidents
- Summer and spring months ( May - August) have a surge in traffic accidents
- London has the highest number of accidents
- Junctions seem to be the most dangerous for traffic accidents
- Machine learning is a good tool for predicting and ultimately avoiding road traffic accident severity.

Based on these we recommended the following:

- Traffic congestion in the urban areas should be reduced
- Speed and highway cameras should be installed to monitor vehicles exceeding speed limit
- Educate people on how to drive safely.
- Implement proper traffic management services and Machine Learning in making predictions on road traffic accidents.

Thank you!