Data Mining - Report

James Donohue (16024143)

Abstract

This is the abstract.
Exercise choices: classification and clustering

Contents

1 Data Choice

1.1 Data Set

The open data set used in this report is the Department for Transport's 2016 release of Road Safety Data (Department for Transport, 2017), which gives "the circumstances of personal injury road accidents … the types (including Make and Model) of vehicles involved and the consequential casualties". The data are published annually on the data.gov.uk website under a licence that permits non-commercial exploitation with attribution (The National Archives, 2017).

The source of the data is the 'STATS19' accident reporting form used by police and so the data is also referred to by this name. The STATS19 data has been recorded (with some changes in attribute semantics) since 1979 (Administrative Data Liaison Service, 2018). The Department for Transport also produces a 'STATS20' document which provides guidance on completing the form defines some of its terminology (Department for Transport, 2004).

The 2016 data set is distributed as three separate ZIP-compressed comma-separated variable (CSV) files, listed in Table 1 along with the number of data rows in each (each file also includes a single 'header' row providing metadata (Han, Kamber and Pei, 2012, p. 92) in the form of field names).

Table 1: Overview of 2016 data files

Link	Decompressed filename	Data rows
Road Safety Data - Accidents 2016	`dftRoadSafety_Accidents_2016.csv`	136621
Road Safety Data - Vehicles 2016	`Veh.csv`	252500
Road Safety Data - Casualties 2016	`Cas.csv`	181384

1.2 Attribute types

Every data row in each data file represents an object with a number of attributes that describe its features or characteristics (Han, Kamber and Pei, 2012, p. 40). The types of each attribute in the data set are summarised in Appendix A.

1.3 Coding of nominal data

Many attributes in the data set are of nominal data type (that is, representing names of things) but contain integer values. For example, an object in the *Accidents* file may have a value of *20* for the attribute `Police_Force`, but this number is not intended to be used quantitively, instead it represents a nominal value (Han, Kamber and Pei, 2012, p. 41). In this case, *20* represents the West Midlands police force.

An accompanying Excel spreadsheet `Road-Accident-Safety-Data-Guide.xls` (linked under *Addi-*

tional resources) provides lookup tables of all possible values for such 'coded' nominal types. This means such attributes have an *enumerated value domain* (OECD, 2006). The spreadsheet also explains that the special value `-1` represents "NULL or out of range values".

1.4 Data relationships

The Excel spreadsheet that accompanies the data set also explains the relations between the individual files:

> The ACC_Index field give a unique index for each accident and links to Vehicle and Casualty data. Casualties are linked to vehicles by "VEHREF".

Each of the three files therefore constitutes a relation with its own primary key (Codd, 1970), with `ACC_Index` (given as `Accident_Index` in the CSV header rows) as a unique accident identifier and `Casualty_Reference` and `Vehicle_Reference` identifying each casualty and the vehicle with which they are associated, respectively. The primary keys for each relation are shown in the simplified Entity Relationship (ER) diagram in Figure 1.

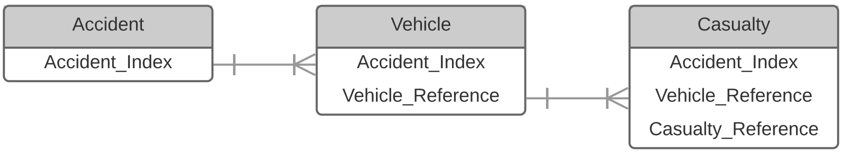


Figure 1: Simplified Entity Relationship diagram for data set

The `Number_of_Vehicles` and `Number_of_Casualties` fields in the *Accidents* file indicate the number of related rows in the other two files. For example, if `Number_of_Vehicles` is 2, there will be two rows in the *Vehicles* file with the same `Accident_Reference`, having a `Vehicle_Reference` of 1 and 2 respectively. The same applies to casualties.

1.5 Applicability of data mining techniques

1.5.1 Clustering

Cluster analysis involves "grouping objects that are similar to each other and dissimilar to the objects belonging to other clusters" (Bramer, 2016, p. 311). This technique, a form of unsupervised machine learning, might allow us to discover groups of accidents that have similar characteristics and make them the focus of further analysis. In practice this could eventually lead to recommendations about additional safety measures (for example, changes to road design or rider training) that might reduce the prevalance of such accident classes. Clustering can also be an initial process that prepares data for other kinds of data mining.

Two challenges of this data set for clustering analysis are its large number of attributes and the fact that it mainly consists of nominal attributes, since many clustering algorithms focus on numeric data and work best with a small number of attributes (Han, Kamber and Pei, 2012, p. 446–7).

1.5.2 Literature review

Hill (2005) evaluated the usefulness of several cluster analysis methods in identifying relatively homogenous groups of accidents from the STATS19 data from 1997 and 2002 for further investigation with a goal "to generate ideas for how the number of these accidents might be reduced". SPSS TwoStep, CHAID and cross-tabulation were evaluated, with the last two being the most promising. For Hill two-step cluster analysis on these data requires too much subjective intervention by the analyst and produces less 'transparent' results than the latter two methods.

Although the TwoStep algorithm (SPSS, Inc., 2001) is efficient on large datasets and supports a mixture of continuous and categorical variables, SPSS was not available for this report to compare with Hill's findings.

Castro and Kim (2015) approached identifying the factors that contribute the most to accident severity in STATS19 datasets as a classification problem, where the classifier models created were used to predict the class (severity) of the accident. WEKA was used to create a Bayesian (belief) network, a C4.5-based decision tree and a multi-layer perceptron (neural network) and the accuracy of each in classifying unseen instances was tested using crossfold validation. The results showed that the Bayesian network was the most accurate and that light conditions and road type were the most significant factors. However, extensive filtering and other preprocessing was preformed on the data.

Ehsaei and Evdorides (2011) used data mining techniques to analyse the temporal variation in contribution of road infrastructure features to accident severity over a five-year period, in response to changes in national road policies. The reserchers again used WEKA and a Bayesian network, but limited their study only to accidents in the Greater Manchester area and to road infrastructure features. Training and testing was performed using a 66%/34% split. However, rather than attempting to demonstrate the accuracy of their model, in their results they extracted the the probabilities of different road features (such as 'Junction Detail') occuring in conjunction with different severities from the classifier. This served as a way of identifying the most high-risk locations on the road network.

2 Data Analysis

As the data set contains over 70 attributes this section will focus only on selected attributes as illustrations of the process of data analysis.

2.1 `Number_of_Vehicles`

The attribute `Number_of_Vehicles` (in the *Accidents* file) represents how many vehicles were involved in each accident. It is a numeric ratio-scaled attribute (that is, has an inherent zero-point) however as a typical 'count' attribute its values are only integers. In the 2016 data set it has no missing values.

Using the *Statistics* node in KNIME we can calculate some basic statistical descriptions for this attribute. The minimum and maximum values are 1 and 16 respectively. The **mean** number of vehicles in an accident is 1.8482, however as the data are positively skewed for this attribute (skew = 1.5756) a better measure of the centrally tendency is the **median** (Han, Kamber and Pei, 2012, p. 46). Here we can say that the median accident involved 2 vehicles. The **mode** is also 2. The histogram in Figure 2 shows the distribution of values for this attribute. Values of 6 and above are grouped together as they account for only a very small proportion of the data.

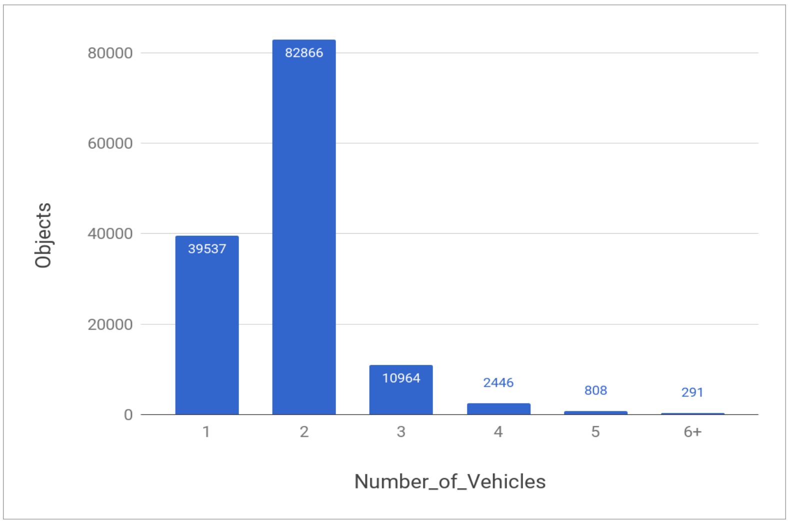


Figure 2: Histogram for `Number_of_Vehicles`

2.2 `Vehicle_Type`

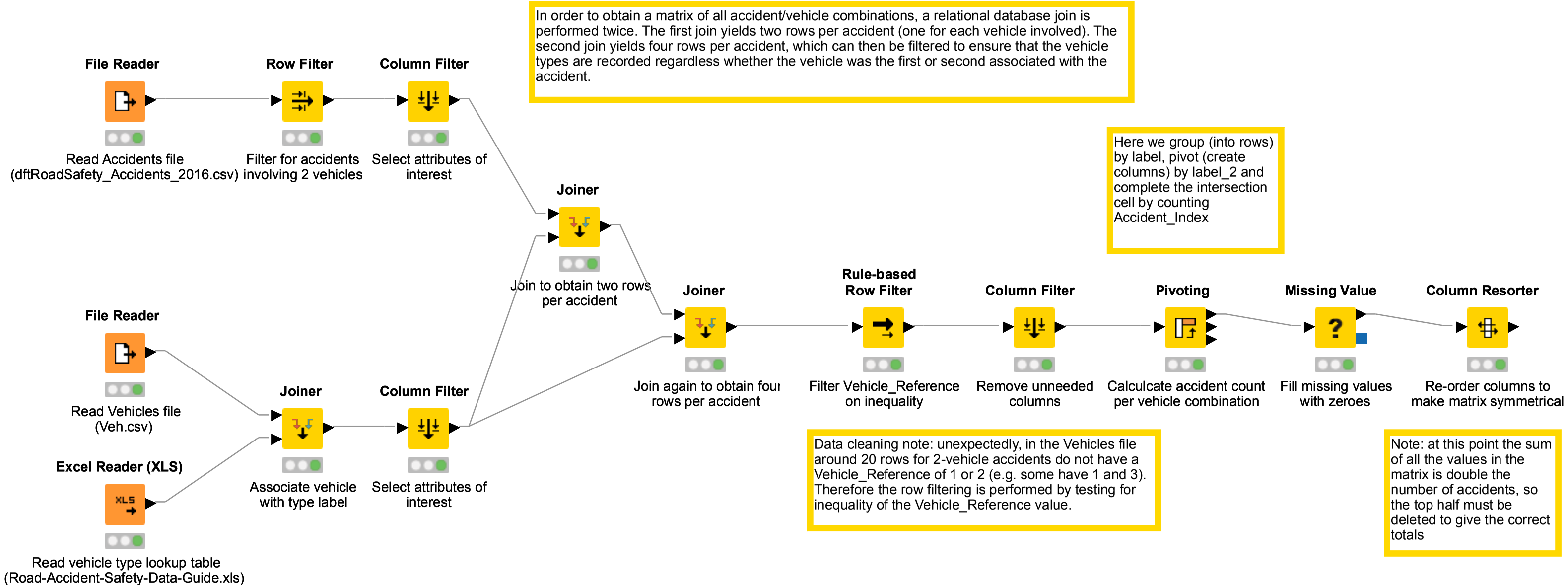
The `Vehicle_Type` attribute in the *Vehicles* file indicates the type of each vehicle involved in an acident. It is a nominal (categorical) attribute. Although represented as an integer, it does not make sense to perform mathematical operations on it so we cannot calculate the mean vehicle type (Han, Kamber and Pei, 2012, p. 78), however the mode (most commonly occuring) type is 9 (Car). The integer values correspond to values in the *Vehicle Type* sheet of Excel spreadsheet that accompanies the data.

The KNIME workflow *Vehicle type correlation matrix* produces a correlation matrix for vehicle types in accidents involving two vehicles. In the resulting table, both the rows and columns represent a given vehicle type and the intersecting cell gives the number of accidents involving that combination of vehicles. This can be further visualised as a 'heat map' such as Figure 4 in order to reveal possible patterns. Cells are highlighted in different shades of red depending on their value; the highlighting midpoint was set to the 85th percentile after some experimentation to produce the clearest differentiation between cells. Note that cells along the top diagonal need to have their values halved to avoid showing a double count; this is because of the way the Joiner and Pivoting nodes work.

2.3 `Date`

The `Date` attribute in the *Accidents* file is a string representation (with the format `MM/dd/YYYY`) of the calendar date between 1 January and 31 December 2016 that each accident occurred. It considered interval-scaled because it is measured on a scale of equal-size units (here days) but no true zero-point (Han, Kamber and Pei, 2012, p. 80).

Every date occcurs at least once in the data set. Using the *Statistics* node in KNIME we can determine that the date that occurs the most (i.e. with the most accidents) was 25 November, with 566 accidents.



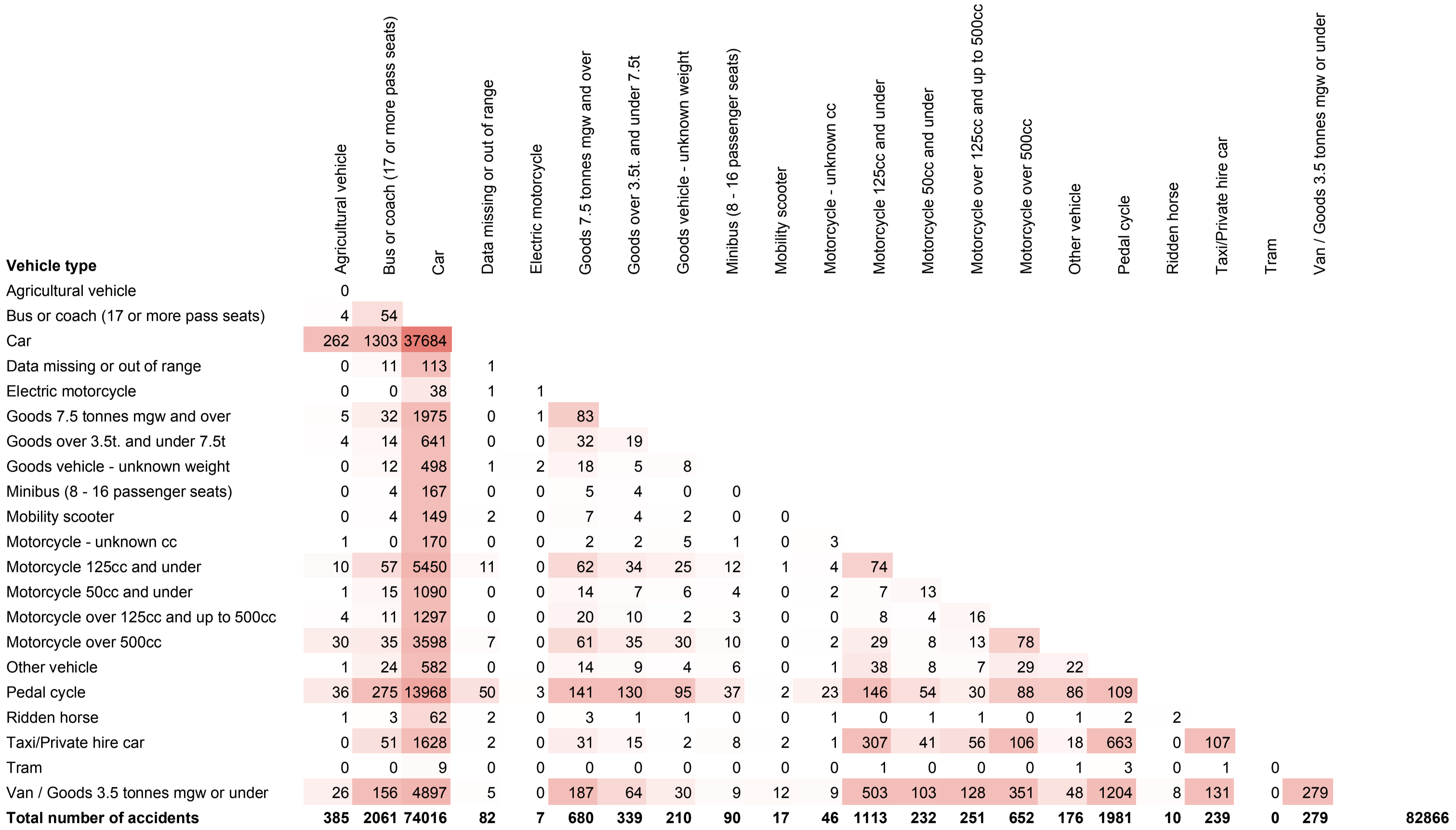
In order to obtain a matrix of all accident/vehicle combinations, a relational database join is performed twice. The first join yields two rows per accident (one for each vehicle involved). The second join yields four rows per accident, which can then be filtered to ensure that the vehicle types are recorded regardless whether the vehicle was the first or second associated with the accident.

Here we group (into rows) by label, pivot (create columns) by label_2 and complete the intersection cell by counting Accident_Index

Data cleaning note: unexpectedly, in the Vehicles file around 20 rows for 2-vehicle accidents do not have a Vehicle_Reference of 1 or 2 (e.g. some have 1 and 3). Therefore the row filtering is performed by testing for inequality of the Vehicle_Reference value.

Note: at this point the sum of all the values in the matrix is double the number of accidents, so the top half must be deleted to give the correct totals

Figure 3: Workflow for vehicle type correlation matrix



Vehicle type	Agricultural vehicle	Bus or coach (17 or more pass seats)	Car	Data missing or out of range	Electric motorcycle	Goods 7.5 tonnes mgw and over	Goods over 3.5t. and under 7.5t	Goods vehicle - unknown weight	Minibus (8 - 16 passenger seats)	Mobility scooter	Motorcycle - unknown cc	Motorcycle 125cc and under	Motorcycle 50cc and under	Motorcycle over 125cc and up to 500cc	Motorcycle over 500cc	Other vehicle	Pedal cycle	Ridden horse	Taxi/Private hire car	Tram	Van / Goods 3.5 tonnes mgw or under	
Agricultural vehicle	0																					
Bus or coach (17 or more pass seats)	4	54																				
Car	262	1303	37684																			
Data missing or out of range	0	11	113	1																		
Electric motorcycle	0	0	38	1	1																	
Goods 7.5 tonnes mgw and over	5	32	1975	0	1	83																
Goods over 3.5t. and under 7.5t	4	14	641	0	0	32	19															
Goods vehicle - unknown weight	0	12	498	1	2	18	5	8														
Minibus (8 - 16 passenger seats)	0	4	167	0	0	5	4	0	0													
Mobility scooter	0	4	149	2	0	7	4	2	0	0												
Motorcycle - unknown cc	1	0	170	0	0	2	2	5	1	0	3											
Motorcycle 125cc and under	10	57	5450	11	0	62	34	25	12	1	4	74										
Motorcycle 50cc and under	1	15	1090	0	0	14	7	6	4	0	2	7	13									
Motorcycle over 125cc and up to 500cc	4	11	1297	0	0	20	10	2	3	0	0	8	4	16								
Motorcycle over 500cc	30	35	3598	7	0	61	35	30	10	0	2	29	8	13	78							
Other vehicle	1	24	582	0	0	14	9	4	6	0	1	38	8	7	29	22						
Pedal cycle	36	275	13968	50	3	141	130	95	37	2	23	146	54	30	88	86	109					
Ridden horse	1	3	62	2	0	3	1	1	0	0	1	0	1	1	0	1	2	2				
Taxi/Private hire car	0	51	1628	2	0	31	15	2	8	2	1	307	41	56	106	18	663	0	107			
Tram	0	0	9	0	0	0	0	0	0	0	0	1	0	0	0	1	3	0	1	0		
Van / Goods 3.5 tonnes mgw or under	26	156	4897	5	0	187	64	30	9	12	9	503	103	128	351	48	1204	8	131	0	279	
Total number of accidents	**385**	**2061**	**74016**	**82**	**7**	**680**	**339**	**210**	**90**	**17**	**46**	**1113**	**232**	**251**	**652**	**176**	**1981**	**10**	**239**	**0**	**279**	**82866**

Figure 4: Heat map for `Vehicle_Type` in two-vehicle accidents

This is therefore the mode date. However least-occurring date (i.e. with the least accidents) was 25 December, with only 138, which is likely due to fewer people travelling on Christmas Day. For comparison, since 2016 was a leap year with 366 days and the *Accidents* file contains data about 136621 accidents, we can say that the mean number of accidents per day was 373.28.

Although analysis of accident numbers over the year might reveal seasonal trends, to be sound any conclusions would need to be supported by comparison with data from other years. Since reviewing multiple years' data is out of scope for this report, an alternate approach is to look for trends within the year under study. For example, we may wish to know if significantly different numbers of accidents occur at weekends. Figure 5 uses a box plot to visualise the distribution of of accidents per day of the week. Each bar represents a different day. Data points that are more than 1.5 times the inter-quartile range (IQR) are plotted separately, all of which are classified by KNIME as 'mild' outliers.

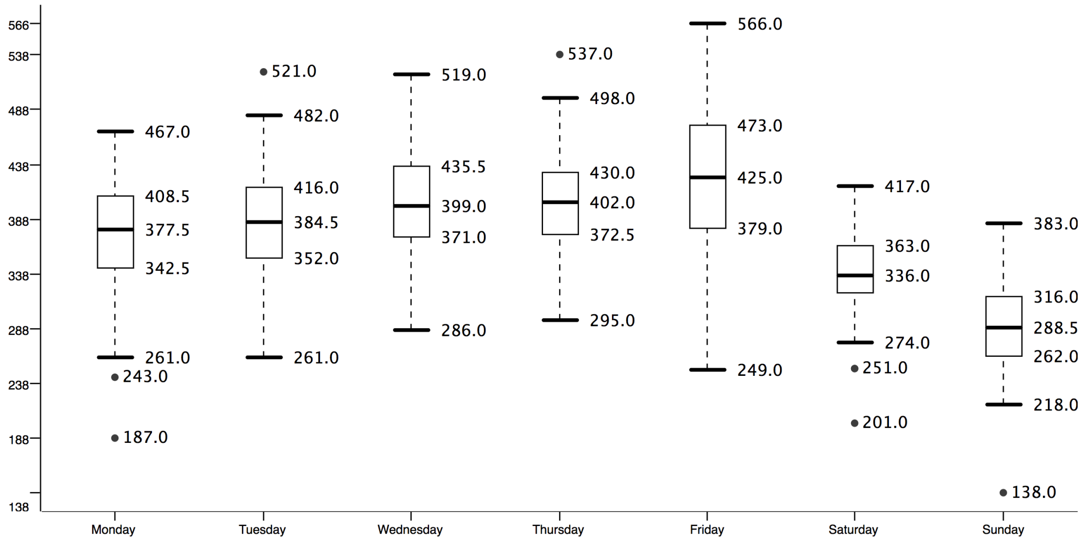


Figure 5: Box plot of accidents by day of week

From this we can see that the number of accidents increases slightly as the week progresses, and that weekends have significantly fewer accidents. It is also notable that the 'whiskers' (representing the maximum and minimum values) for Friday are much longer for other days. Table 2 confirms that Friday has a much larger standard deviation than other days of the week, meaning that it has the greatest dispersion of values.

Table 2: Distribution of accidents by day of week

Day of week	Min	Max	Mean	StdDev
Monday	187	467	370.69	57.34
Tuesday	261	521	386.62	46.42
Wednesday	286	519	401.37	47.73
Thursday	295	537	402.87	47.43
Friday	249	566	426.02	63.82
Saturday	201	417	336.19	42.73
Sunday	138	383	288.92	42.34

Note that this analysis does not allow us to conclude that weekends are somehow inherently safer - there may simply be less traffic. In order to know for sure we would need to cross-reference data about how many vehicles are on the road on each day, which is beyond the scope of this study.

2.4 Time

The Time attribute in the *Accidents* file represents the time of day that an accident occurred. Like Date, it is an interval-scaled attribute with values ranging from 00:00 (midnight) to 23:59. By extracting the hour and minute components from each time we can produce histograms that reveal patterns in the data.

Figure 6 shows the number of accidents that occur during each hour of the day, from 0 to 23, across the whole data set. This shows that the fewest accidents occur between 04:00-04:59, while there are noticeable peaks between 08:00-08:59 and 17:00-17:59. These peaks could be predicted as they correspond to the usual 'rush hours' at the start and end of the working day. Nearly 25% of accidents occurred between 8am and 9am or between 4pm and 6pm.

Similarly, Figure 7 shows the number of accidents that occur during each minute of the day, from 0 to 59, across the whole data set. It is apparent that the most frequent times are on the hour and half-past the hour, with smaller peaks every five minutes. Although this could mean that acccidents happens more frequently at these points, a more likely explanation is that the police offers reporting the accident often round their approximation of the accident time to the nearest 5- or 30-minute boundary. This 'snapping' effect implies that attempting to analyse the Date and Time attributes with a resolution of less than 5 minutes is unlikely to be successful. A comparable level of accuracy in police reporting road accident times was inferred for road accident data collected about Helsinki's Ring Road (Innamaa et al., 2014, p. 18).

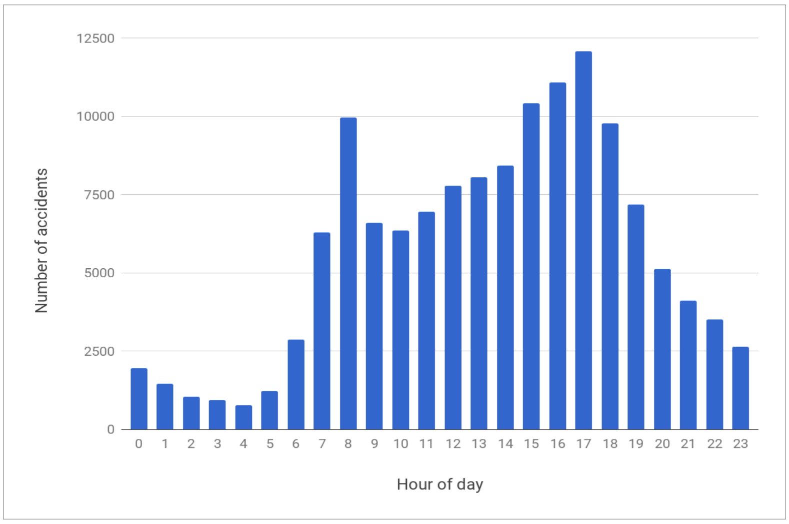


Figure 6: Histogram of number of accidents occuring during each hour of day

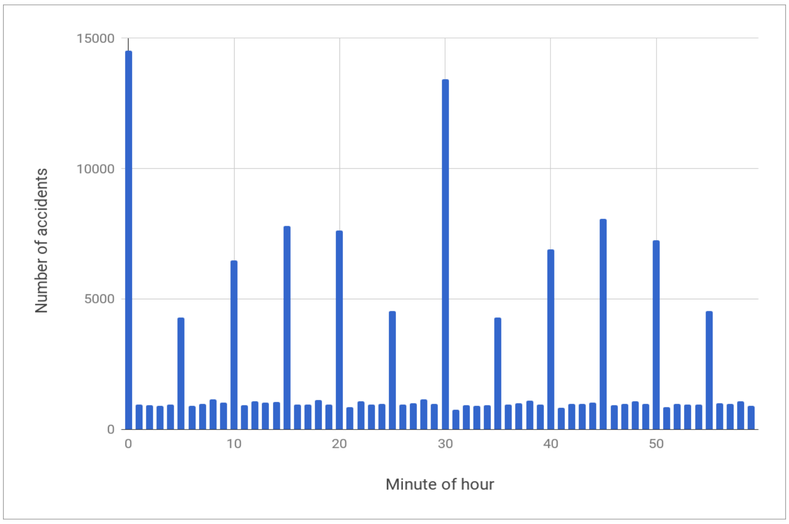


Figure 7: Histogram of number of accidents occuring during each minute of hour

2.4.1 `Longitude` and `Latitude`

By using the *Scatter Plot* and *Color Manager* nodes in KNIME we can see the distribution of values for the `Longitude` and `Latitude` attributes (for two-vehicle accidents involving TWMVs), with colours used to indicate accident severity (Figure 8).

Since these attributes represent geographical coordinates, the shape of Great Britain is clearly visible in the map. Moreover, the areas with the greatest concentration of accidents appears to correspond to more urban areas and possibly those with greater population density (the South-East, Birmingham and Manchester/Liverpool areas).

2.5 Data Preprocessing

We can use the knowledge that the majority (around 60%) of accidents involve two vehicles to focus this study and eliminate some of the complexity that arises from one-to-many data relationships. By considering only accidents involving two vehicles, we can 'denormalise' the *Accident* and *Vehicle* files to allow for further processing.

2.6 Reducing dimensions

As the dataset contains a very large number of dimensions, the amount of storage space and processing time required to cross-tabulate every possible combination of attributes and then examine could be prohibitive (an example of the so-called 'curse of dimensionality' (Han, Kamber and Pei, 2012, p. 158)).

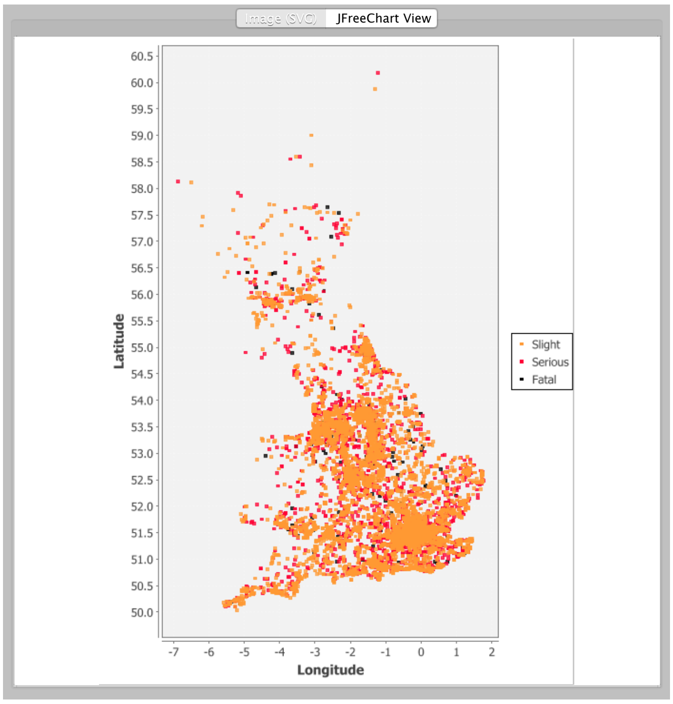


Figure 8: Scatter plot of motorcycle accident locations generated with KNIME

In order to simplify exploration of the data in WEKA the following attributes were removed from the data before exporting to ARFF format:

- `1st_Road_Number` and `2nd_Road_Number`
- `TWMV_Was_Vehicle_Left_Hand_Drive?` (the value of this is always `No` since it does not make sense for TWMVs)
- `Vehicle_IMD_Decile` (this attribute is not described in the lookup tables, and inspecting it in KNIME shows that its values are always identical to `Driver_IMD_Decile`)

2.7 Importing into WEKA

In order to import the dataset into WEKA for exploration it must to be converted to WEKA's ARFF format (Paynter, 2002) which includes type information. The *ARFF Writer* node in KNIME supports creating files in this format, however it does not seem to support WEKA's `DATE` type but outputs these attributes as STRING instead. In order to work around this the file must be post-processed after generation, such as by using `sed(1)`:

```
sed -ipe "s/^@ATTRIBUTE DateTime.*/@ATTRIBUTE DateTime DATE yyyy-MM-dd'T'HH:mm/" \
    Accidents-2Veh-TWMV.arff
```

2.8 Missing values

There are two different types of missing values in the datset. For example, the *Accidents* file contains 7 objects with missing longitude/latitude and 37 with a missing speed limit, represented as empty strings and the literal `NULL` in the input CSV, respectively (this can be determined through the *Statistics* node in KNIME). However, the lookup tables show that many of the nominal attributes (e.g. `Road_Type`) support an explicit code for missing or unknown values, usually `-1` defined as *Data missing or out of range*. Some attributes also specify an additional code defined as 'Unknown' or 'Not known'.

For consistency and to enable WEKA to identify and handle missing values, all such nominal value codes were folded to 'true' missing values during pre-processing in KNIME by limiting the number of rows read by the *Excel Reader* node prior to being looked up by *Cell Replacer*. Note that this process did not include values such as `Unclassified` for `Road_Type`, since despite the name this is a valid type of road rather than missing data.

NB two accidents have a missing value for `Time`.

2.9 Choice of tools

KNIME 3.5.1 was chosen … (talk about metanodes, documentation etc.)

Python 2.7.13 with the `pandas`, `protobuf` and `jedi` extensions (installed as per the KNIME documentation and the `kmodes` extension (installed following the steps on the the k-modes GitHub repo)

Other extensions used: - matplotlib - scikit-learn

In addition, the histogram and heat map figures in the report were prepared using Google Sheets for improved visual clarity.

3 Classification

Classification is a data mining functionality that divides up objects (instances) into a number of categories or classes. These classes are typically mutually exclusive and exhaustive (Bramer, 2016, p. 21).

In order to perform classification on the dataset it is necessary to select a suitable attribute to represent the 'class' of each accident. The `Accident_Severity` attribute was selected as it represents a significant feature of the accident that we would like to be able to predict based on other features. In real world terms, this means that an accurate classifier model could predict which types of accidents are likely to be the most serious based on their other characteristics.

3.1 Choice of classifier and features

Hill used cross-tabulation to identify clusters of vehicle maneouvres that are heavily represented in the accident data, including a group where another vehicle turns right while the TWMV performs any manoeuvre (2005, p. p10). It is of interest to know which combination(s) of maneouvres are likely to result in a severe or fatal accident. Put another way, we would like to be able to predict the probability of an accident belonging to a given severity class, based on the maneouvres involved. We will assume that the type of each manoeuvre is independent of the other.

The naïve Bayes algorithm uses probability theory to find the most likely classification (Bramer, 2016, p. 22). It is called naïve because the algorithm operates on the assumption that the effect of each attribute value on the classification is equally important and independent of the other attributes, but is known to often give surprisingly good results in practice (Bramer, 2016, p. 26). By exploring this relatively straightforward probablistic model, we follow Witten et al.'s advice to try the simplest things first (2016, ch. 4).

Another reason for choosing this algorithm is that the dataset contains a large number of missing values, and naïve Bayes naturally handles missing values by not including such attributes in its calculations (Witten et al., 2016, ch. 4). By contrast, algorithms such as decision trees require special handling for missing values (such as treating them as values in their own right, or splitting instances - (Witten et al., 2016, ch. 3)).

3.2 Parameters

The naïve Bayes approach assumes that all attributes are nominal (Bramer, 2016, p. 29) therefore other attribute types must be converted to that type, or discarded.

For a first attempt we take the approach of discarding all attributes except for the ones relating to vehicle maneouvres and the accident severity, i.e. `TWMV_Vehicle_Manoeuvre`, `OV_Vehicle_Maneouvre` and `Accident_Severity`. The `RemoveByName` WEKA filter can be used to remove all other attributes as follows:

```
weka.filters.unsupervised.attribute.RemoveByName -E ^.*Manoeuvre$ -V
```

The WEKA Explorer interface with this filter applied is shown in Figure 9.

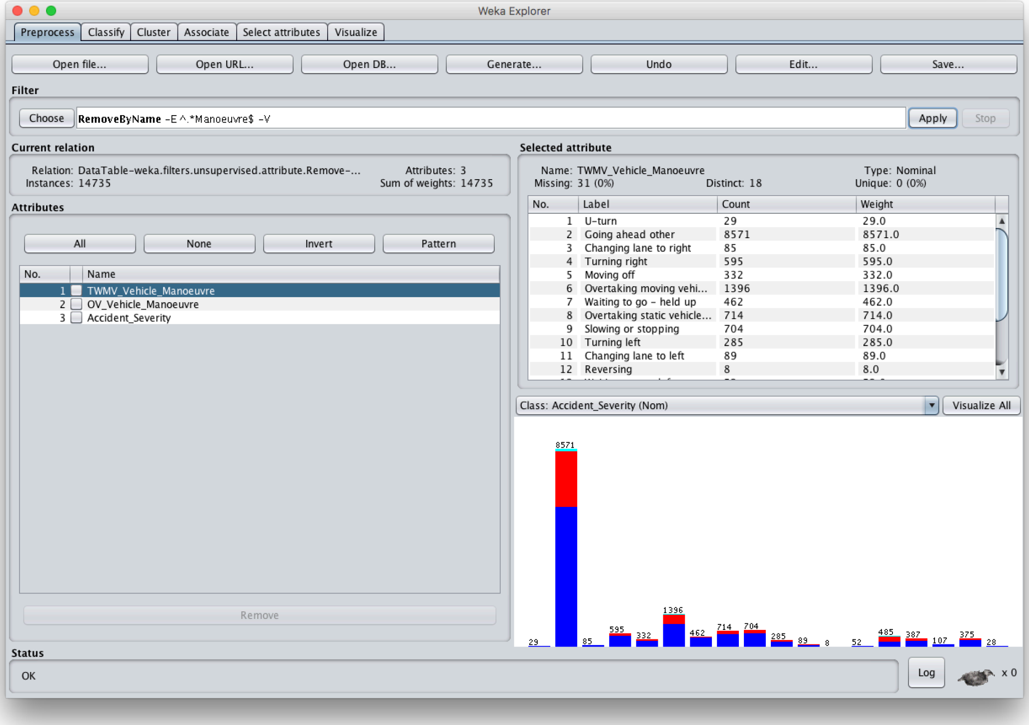
The NaiveBayes classifier is then run using the parameters shown in Table 3:

Table 3: Initial parameters for NaiveBayes classifier in WEKA

Parameter	Value
batchSize	100
debug	False
displayModelInOldFormat	False
doNotCheckCapabilities	False
numDecimalPlaces	2
useKernelEstimator	False
useSupervisedDiscretization	False

The motivation for these parameters are as follows:

- The default value for batch size is acceptable, and debug output is not required
- Precision of greater than two decimal places when outputting the model is not needed
- Numeric attributes have already been removed used so the `useKernelEstimator` and `useSupervisedDiscretization` parameters are not relevant



Filter

RemoveByName -E ^.*Manoeuvre$ -V

Current relation

Relation: DataTable-weka.filters.unsupervised.attribute.Remove-...
Instances: 14735
Attributes: 3
Sum of weights: 14735

Attributes

No.		Name
1	□	TWMV_Vehicle_Manoeuvre
2	□	OV_Vehicle_Manoeuvre
3	□	Accident_Severity

Selected attribute

Name: TWMV_Vehicle_Manoeuvre
Missing: 31 (0%)
Distinct: 18
Type: Nominal
Unique: 0 (0%)

No.	Label	Count	Weight
1	U-turn	29	29.0
2	Going ahead other	8571	8571.0
3	Changing lane to right	85	85.0
4	Turning right	595	595.0
5	Moving off	332	332.0
6	Overtaking moving vehi...	1396	1396.0
7	Waiting to go - held up	462	462.0
8	Overtaking static vehicle...	714	714.0
9	Slowing or stopping	704	704.0
10	Turning left	285	285.0
11	Changing lane to left	89	89.0
12	Reversing	8	8.0

Class: Accident_Severity (Nom)

Status

OK

Figure 9: WEKA Explorer showing RemoveByName filter applied

3.3 Training and testing

The data were partitioned into a training and test set using the holdout method with a 90%/10% split via the 'Percentage split' option in WEKA, which divides up the data after shuffling it randomly. This means the model is trained with the training set and tested with the remainder to estimate its accuracy. It is important that the model is not also tested using the data that were used to construct it in order to avoid obtaining an over-optimistic estimate of its accuracy (Witten et al., 2016, ch. 5). As the dataset is very large, cross-validation was considered but deemed unnecessary.

3.4 Results

The overall recognition rate of the Bayesian classifier on the test data after training was 73.7%, meaning it predicted that proportion of classes in the test data correctly; this is also known as its accuracy (Han, Kamber and Pei, 2012, p. 366). The confusion matrix in Table 4 shows counts for actual (rows) and predicted (columns) classes.

Table 4: Confusion matrix for NaiveBayes classifier

	Slight	Serious	Fatal	Total	True positive rate (%)	False positive rate (%)
Slight	1065	15	0	1080	98.6	93.4
Serious	346	21	0	367	5.7	1.8
Fatal	21	5	0	26	0.0	0.0
Total	1432	41	0	1473		

It is interesting to note that few serious accidents were correctly identified, no fatal accidents were correctly identified. All figures are given to one decimal place.

3.4.1 Accuracy baseline

In order to have a baseline accuracy against which to compare the model, we can use a method such as ZeroR (University of Waikato, 2018). This allows us to demonstrate whether the classifier is a significant improvement on simply guessing the class based on the most prevalent one (i.e. the mode).

When ZeroR was used as a classifier in WEKA, with the entire dataset used for testing (since holding out some of the data is unnecessary), the overall accuracy was also 72.4%. Detailed results are shown in the confusion matrix in Table 5.

Table 5: Confusion matrix for ZeroR classifier

	Slight	Serious	Fatal	Total	True positive rate (%)	False positive rate (%)
Slight	10673	0	0	10673	100.0	100.0
Serious	3862	0	0	3862	0.0	0.0
Fatal	200	0	0	200	0.0	0.0
Total	14735	0	0	14735		

Since 'Slight' is the most common class, 100% of these instances are correctly classified by ZeroR, however no 'Serious' or 'Fatal' accidents are correctly classified.

3.4.2 Class imbalance

The 'class imbalance problem' describes a situation where the class (or classes) of interest are rare (Han, Kamber and Pei, 2012, p. 367). This applies to the current dataset, since we are interested to know which circumstances produce the worst accidents, and fatal accidents represent just over 1% of the dataset. Moreover, the cost of more severe accidents (both financial and social) is likely to be greater than for slight accidents.

To assess this it is helpful to consider the true positive rate (sensitivity) and false positive rate for each class as well as the model's overall accuracy. The true positive (TP) rate is the proportion of instances of each class where the class label was predicted correctly, while the FP rate is the proportion of instances that were mislabelled with the class. These figures are both included in Tables **??** and 4.

3.4.3 Receiver operating characteristic curves

Receiver operating characteristic (ROC) curves can be used to visualise the trade-off between the true positive rate and false positive rates for a given class (Han, Kamber and Pei, 2012, p. 374). Since naïve Bayesian classifiers return a class probability for each prediction they can be used to plot ROC curves as an aid to tuning the learning approach. Figure 10 shows such a curve for the model produced above with respect to the 'fatal' accident severity. This is produced in WEKA by right-clicking on the result and selecting 'Visualize threshold curve > Fatal'.

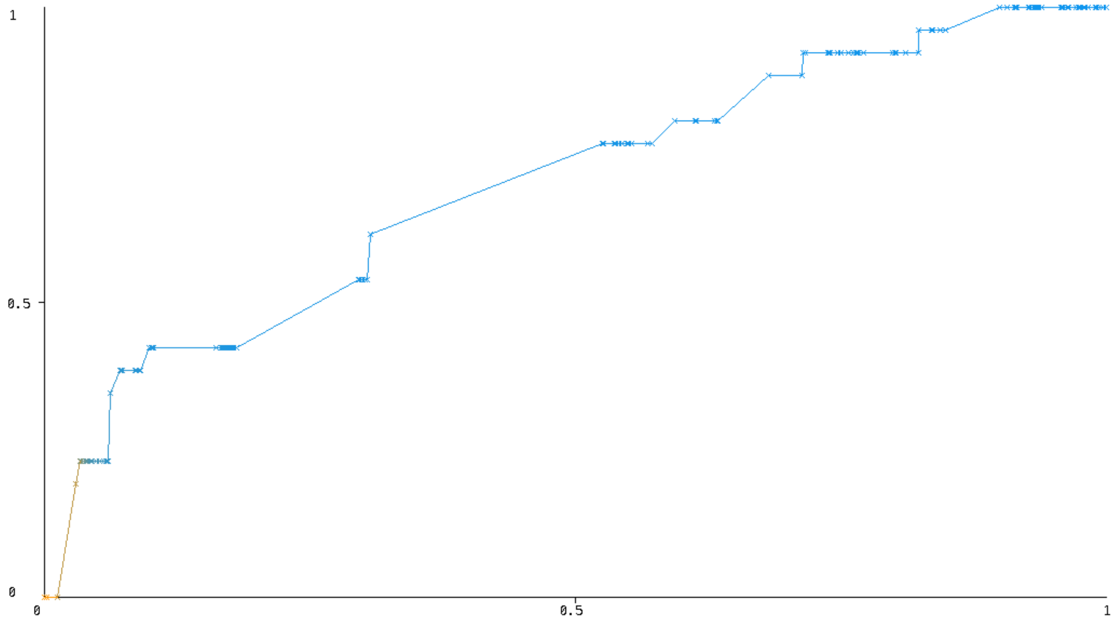


Figure 10: Initial ROC curve for fatal accidents (X axis = false positive rate, Y axis = true positive rate)

The closer to the diagonal the curve is, the less accurate the model is with respect to predicting the class. We can also use the area under the curve as a measure of its accuracy, which here is 0.70.

3.5 Tuning strategy

As mentioned above, severe and fatal accidents are likely to have a greater social and economic impact and be in greater need of further investigation. They also represent a relatively small proportion of the dataset. We would like to be able to improve the accuracy of the naïve Bayes classifier with respect to correctly identifying these classes of accident.

3.5.1 Cost-sensitive learning

This technique uses a cost matrix to assign different costs to the different types of classifier error

3.6 Final results

4 Clustering

As mentioned previously, clustering is a form of unsupervised data mining in which objects that are similar are grouped together (Bramer, 2016, p. 312).

4.1 Choice of algorithm

5 Critical review

5.1 Difficulties and mistakes

5.1.1 Choice of dataset

The selection of the dataset used in the study clearly created a number of additional challenges. Some of these related to the extensive amount of pre-processing required on the data, for example to denormalise the *Accidents* and *Vehicles* tables. Furthermore, the class distribution is heavily skewed towards 'slight' accidents, which required further effort in the classification task to ensure that more serious accidents could be predicted.

5.2 Future work

5.2.1 Missing values

Missing values could occur because of a number of reasons, such as error on behalf of the police officer or during data entry. However, as Witten et. al (2016) point out, some missing values can be due to a conscious decision rather than error. One area for further investigation could be to identify those missing values which may mean 'not applicable'. For example, 28% of instances have a missing value for 2nd_Road_Class - this could be because there was no second road. Reviewing official guidance on completing the form (Department for Transport, 2004) might inform further data preprocessing to handle these values correctly.

5.2.2 Using Bayes' Theorem to classify fatal maneouvres

Following the work done in the Classification task, a new Bayesian classifier could be built that can predict the severity of an accident based on the maneouvres involved, with a variable threshold. This was not attempted in this study, but some of the calculations required are described below:

Let A be an accident involving two manoeuvres (the 'evidence', in Bayesian terms). H is the hypothesis that A is fatal, that is it belongs to the 'fatal' class. We want to determine $P(H|A)$, the probability of this hypothesis conditioned on the observed maneouvres (the posterior probability).

$P(H)$ is the prior probability of H, here meaning the probability that any accident will be fatal regardless of maneouvres. This can be estimated by counting the number of fatal accidents in the dataset and dividing it by the total number of accidents: 200/14735 = 0.014.

$P(A|H)$ is the posterior probability of A conditioned on H, i.e. the probability that an accident involves two specific maneouvres, given we know the accident is fatal. By assuming there is no dependency between the maneouvres m_1 and m_2, we can calculate this as $P(m_1|H) \times P(m_2|H)$ by counting the number instances in the training set where each maneouvre occurs for a fatal accident. For example, there are 27 accidents where the TWMV was overtaking a moving vehicle out of 200 fatal accidents, so $P(m_1|H)$ here is 27/200 = 0.135.

$P(A)$ is the prior probability of A, meaning the probability that any accident in the dataset involves the two given maneouvres, i.e. $P(m_1) \times P(m_2)$.

We could then use Bayes' theorem to estimate the probability that any new accident with those manoeuvres is fatal:

$$P(H \mid A) = \frac{P(A \mid H)\, P(H)}{P(A)}$$

The final step would be to determine a probability threshold for identifying an accident as fatal. For example, we could say that if the probability is > 0.75 then the accident is fatal, and test by holding out some of the data. The results from this investigation could be used to validate Hill's findings described earlier.

5.2.3 Longitudinal study

Since the same STATS19 format has been used since [TBC] there is considerable scope for looking at how patterns in the data have evolved over time. (Castro and Kim, 2015) looked at datasets from both 2010 and 2012, while (Ehsaei and Evdorides, 2011) considered trends over the period [TBC]. An area for further investigation could be to take the models trained here against the 2016 dataset and test them against releases from previous years to evaluate any changes in accuracy.

5.2.3.1 Clustering nominal data

Partioning methods of cluster analysis find mutually exclusive clusters that are spherical in shape, using a distance function to measure the similarity of objects within a cluster and therefore minimise the amount of within-cluster variation (Han, Kamber and Pei, 2012, p. 489). Of these methods, the popular *k*-means algorithm uses the arithmetic mean to find the centroid of each cluster and therefore needs numerical attributes. The *k*-modes method put forward by Huang (1998) is an extension to *k*-means which supports nominal (categorical) attributes, utilising the mode instead of the mean. Because of the large amount of nominal attributes in the dataset, *k*-modes could be used as a more effective clustering approach.

Since KNIME and Weka do not have built-in support for *k*-modes, a KNIME *Python Script* node could be used to provide the algorithm using an external Python interpreter, using a popular open-source implementation (de Vos, 2018). The workflow shown in Figure 11 and basic Python code is given below:

```
import numpy as np
import pandas as pd
from kmodes.kmodes import KModes

kmodes_huang = KModes(n_clusters=4, init='Huang', verbose=1)
clusters = kmodes_huang.fit_predict(input_table)

output_table = pd.DataFrame(data=clusters, dtype=np.int64)
```

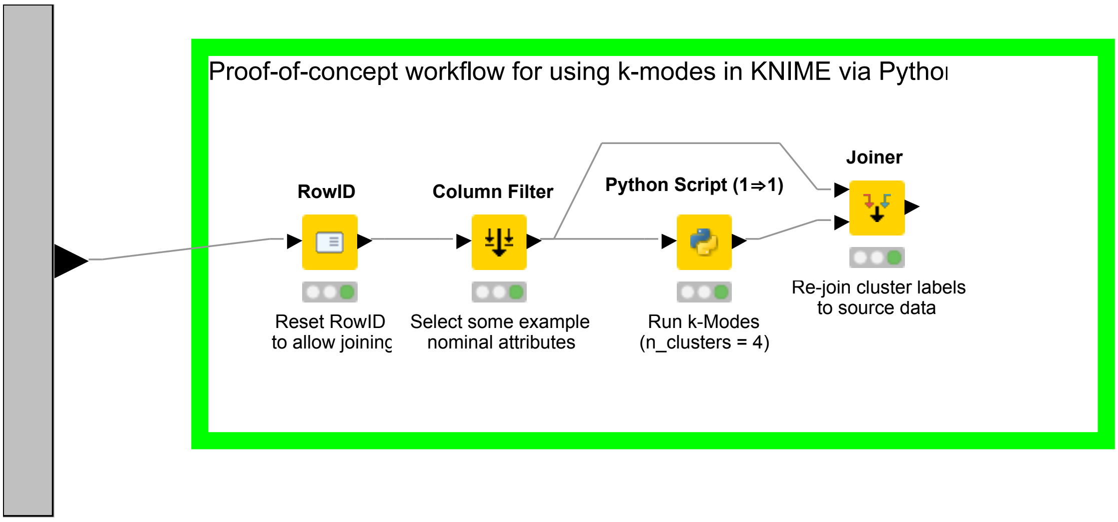

Proof-of-concept workflow for using k-modes in KNIME via Pythoı
RowID
Column Filter
Python Script (1⇒1)
Joiner
Reset RowID to allow joininc
Select some example nominal attributes
Run k-Modes (n_clusters = 4)
Re-join cluster labels to source data

Figure 11: Proof-of-concept KNIME workflow for k-modes

The result of this workflow is an additional numeric attribute dataset that identifies the cluter with which each object has been associated. Further areas of study could involve how to visualise and characterise such clusters, for example using silhouettes (Rousseeuw, 1987) to evaluate cluster quality and suggest the optimal number of clusters .

5.3 Clustering geographical data

6 Appendix: Summary of KNIME workflows

Table 6 summarises the KNIME workflows included with this report.

Table 6: Summary of KNIME workflows

Workflow	Purpose
Accident date distribution	Creates a box plot for accidents by day of the week and statistics table
Vehicle Type correlation matrix (Figure 3)	Generates a correlation matrix of vehicle types in two-accident collisions suitable for rendering as a heat map
Accident date distribution	Generates a box plot showing distribution of accident dates and statistical summary

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