Data Mining - Report

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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 Workflows in this document

All workflows described in the remainder of the document are available from the following public Dropbox folder in the `KNIME workflows/` subdirectory:

`https://www.dropbox.com/sh/h8mnk57f2invard/AADV6XmaKKJ_UzMIJ7IuC129a?dl=0`

Table 2 gives an overview of these workflows. They can be loaded into KNIME using the **File > Import KNIME Workflow** option, however note that in order to test them all *File Reader* nodes must be updated to refer to the unzipped data files in their correct location.

Table 2: Summary of KNIME workflows

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

Workflow	Purpose
`Data preprocessing and visualisation.knwf`	Includes nested workflows (wrapped metanodes) to clean, reduce and transform the data for use in data mining as well as simple visualisation. *Note* the nested workflows can be opened by double-clicking on the metanodes.

For convenience, the data files mentioned above are also included in the 'data/ subdirectory (as permitted under the Open Government Licence).

1.3 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.

1.4 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 *Additional 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".

1.5 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.

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.

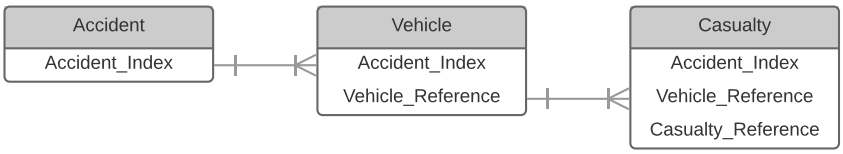

Figure 1: Simplified Entity Relationship diagram for data set

1.6 Applicability of data mining techniques

1.6.1 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 dimensions 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).

1.6.1.1 Transformation of nominal attributes

To allow clustering methods that assume numeric data (such as *k*-means) to be used on the dataset we can attempt to convert some of the nominal attributes into other forms. Such efforts fall into the category of what Witten et. al term 'data engineering' (2016, ch. 8).

For example, the various road classes used by the nominal `1st_Road_Class` and `2nd_Road_Class` attributes have a natural ordering of the level of development of the road, ranging from 'Unclassified' (the lowest level) to 'Motorway' (the highest level). In the KNIME workflow for Accidents these have been assigned to integers ranging from 0 to 5 to create a new `1st_Road_Level` attribute [figure?].

Note however that not all nominal attributes can be handled in this way - the `Police_Force` attribute does not have any 'natural' ordering (e.g. `Northumbria` is not less than `Durham`). Although numeric values could be assigned here, they would be arbitrary and so any clusters involving them would be coincidental. See the Critial Review section for further comments on this problem.

1.6.2 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.

Other researchers studying road traffic accident data over a six-year period in the United Arab Emirates (Taamneh, Taamneh and Alkheder, 2017) used agglomerative (bottom-up) hierarchical clustering to partition accidents into between one and six clusters, as a precursor to building an neural network classifier. WEKA was used to carry out the clustering and that complete linkage was used as the linkage criterion. However, no attempt was made to characterise the clusters that were found or evaluate cluster quality.

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.

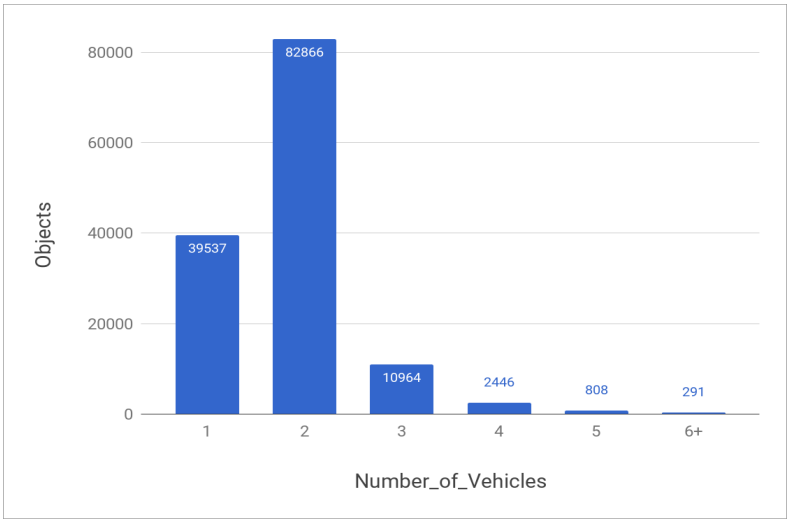

Figure 2: Histogram for `Number_of_Vehicles`

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.

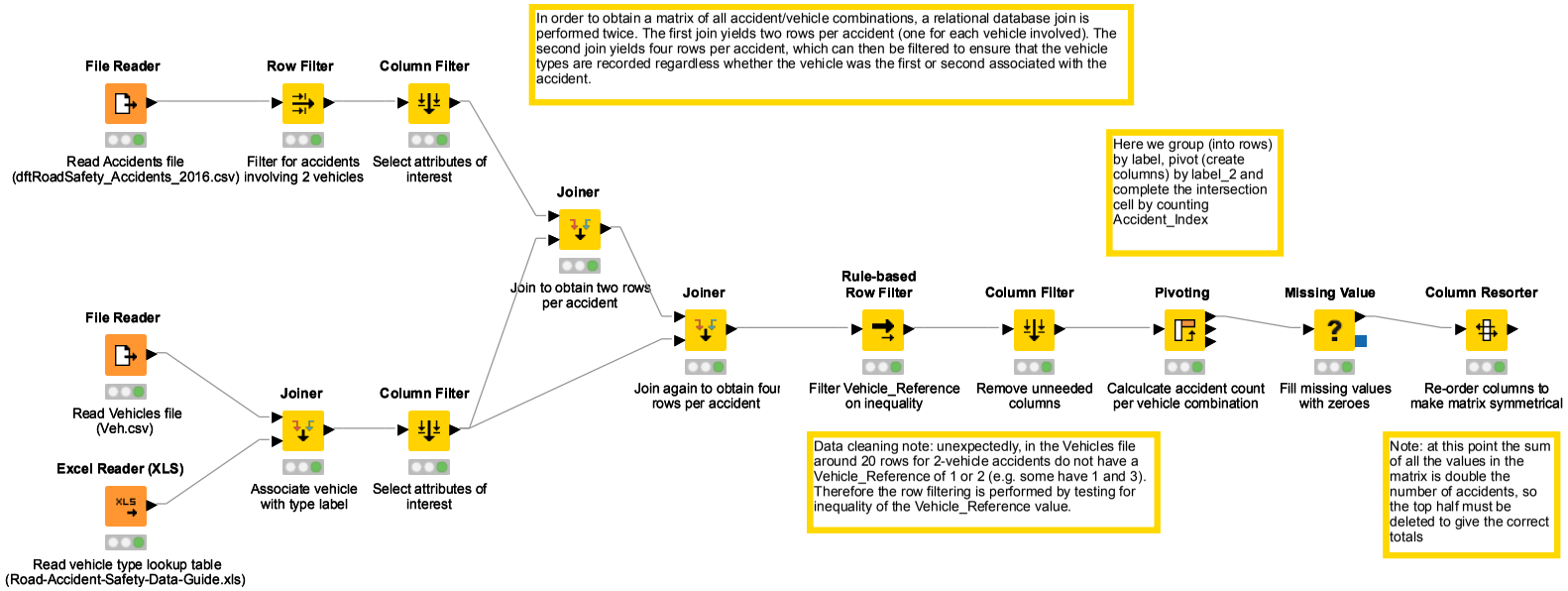

Figure 3: Workflow for vehicle type correlation matrix

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. The KNIME workflow given in Figure 5 was used to generate the box plot shown in Figure 6, which allows us 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.

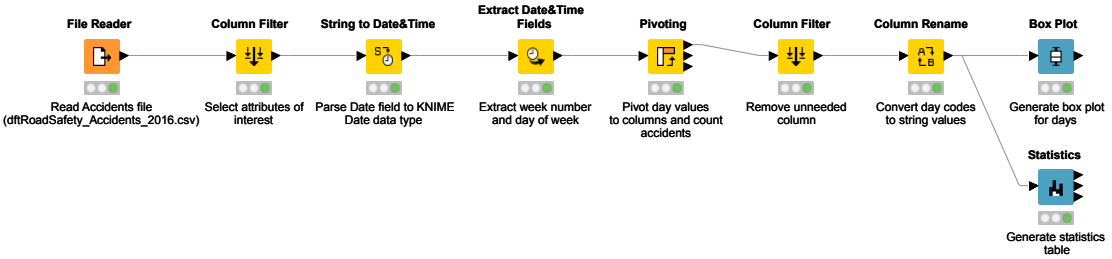

Figure 5: KNIME workflow for generating day of week box plot

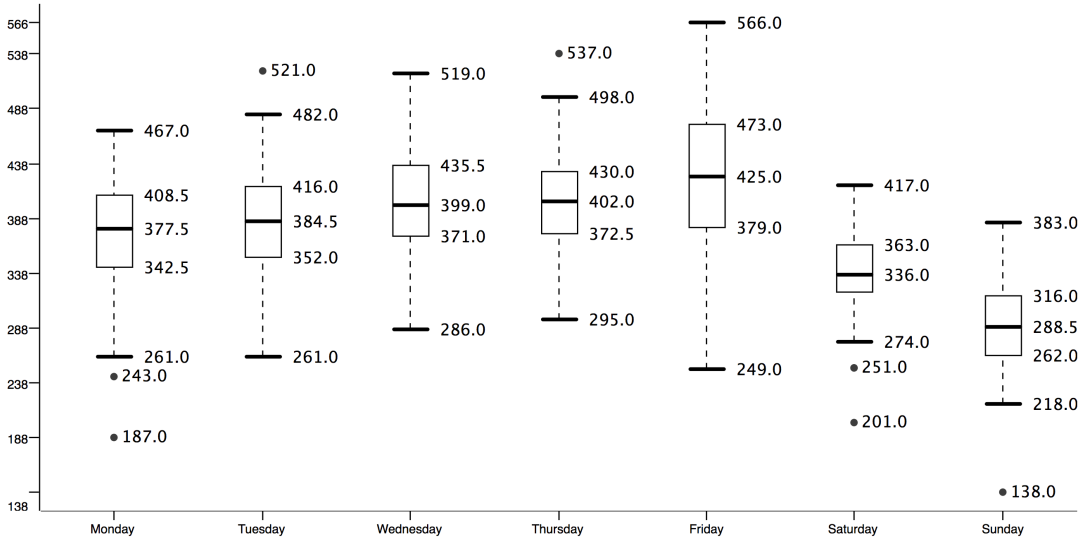

Figure 6: Box plot of accidents by day of week

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 3 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 3: 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 7 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 8 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).

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 9).

Since these attributes represent geographical coordinates, the shape of Great Britain is clearly visible on the plot. Moreover, the areas with the greatest concentration of accidents appears to correspond to more urban areas and those with greater population density (the South-East, Birmingham and Manchester/Liverpool areas) but this would require further investigation in order to prove.

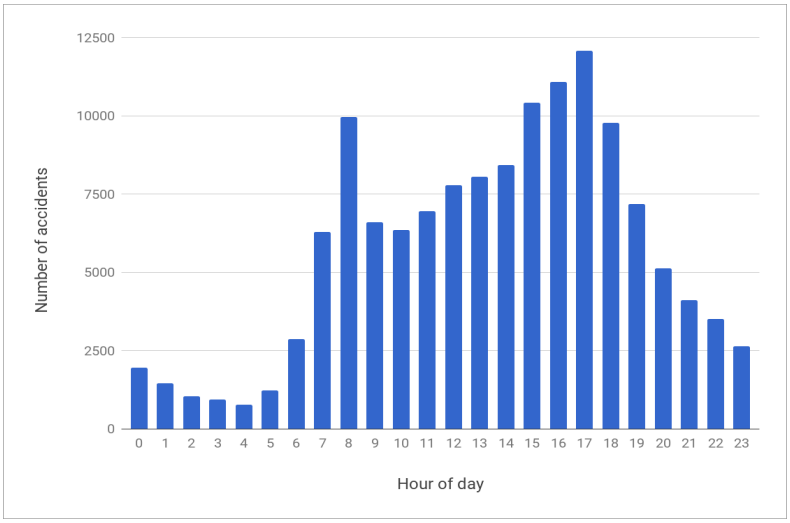

Figure 7: Histogram of number of accidents occuring during each hour of day

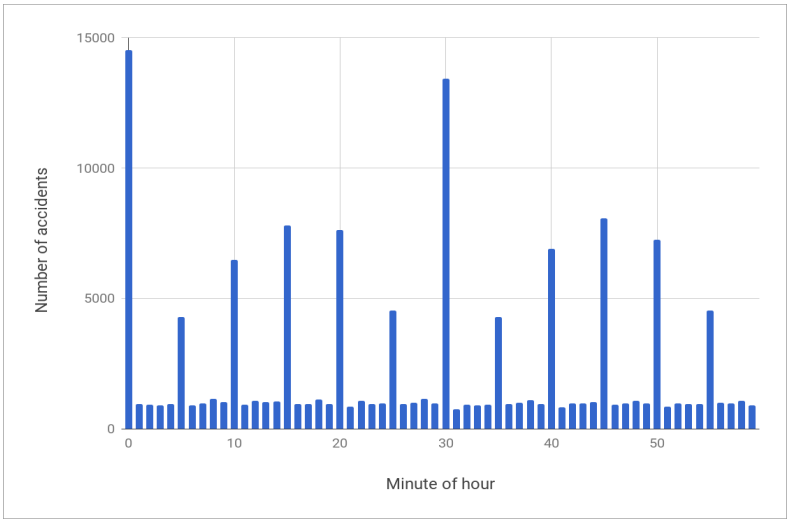

Figure 8: Histogram of number of accidents occuring during each minute of hour

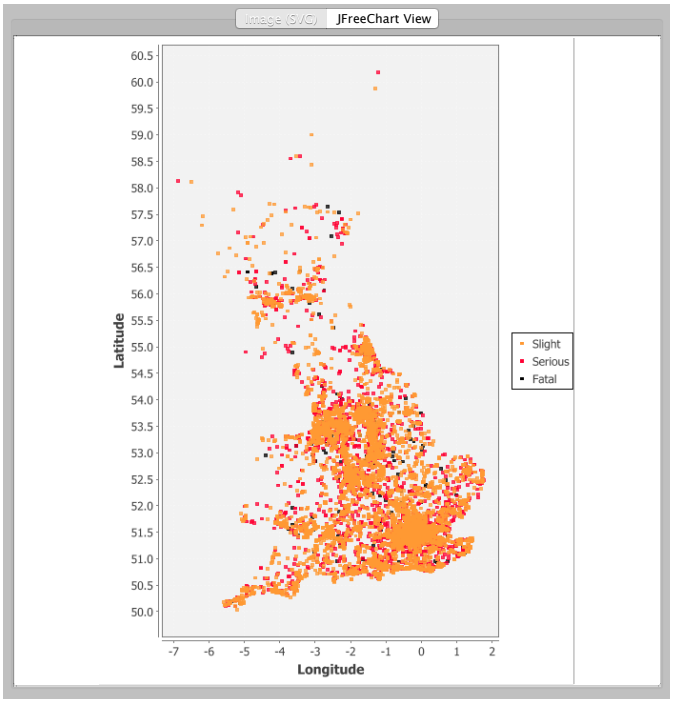

Figure 9: Scatter plot of motorcycle accident locations generated with KNIME

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)). 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.

WEKA 3.8.2 was installed and later downgraded to 3.8.0

The KValid package for silhouette analysis was installed from https://github.com/Theldus/KValid

2.10 Data preparation workflows

Figure 10 shows the top-level KNIME workflow used for the remainder of this report. Most of the tasks in this workflow are accomplished in the nested data pre-processing and transformation workflow shown in 11.

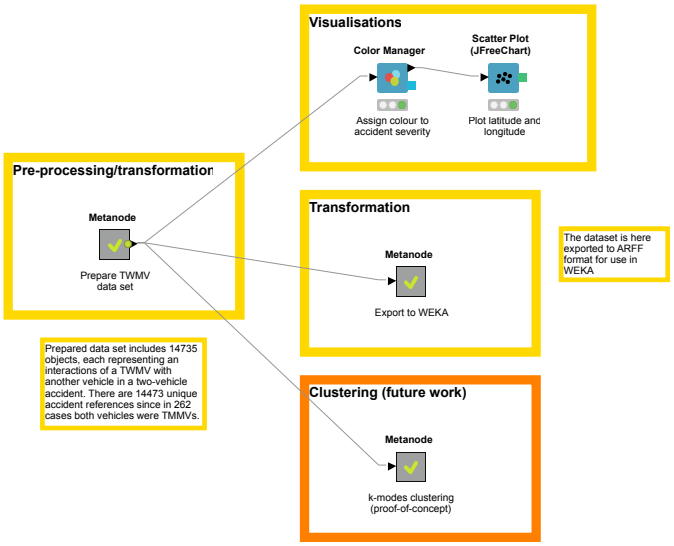

Figure 10: KNIME workflow for data processing and visualisation

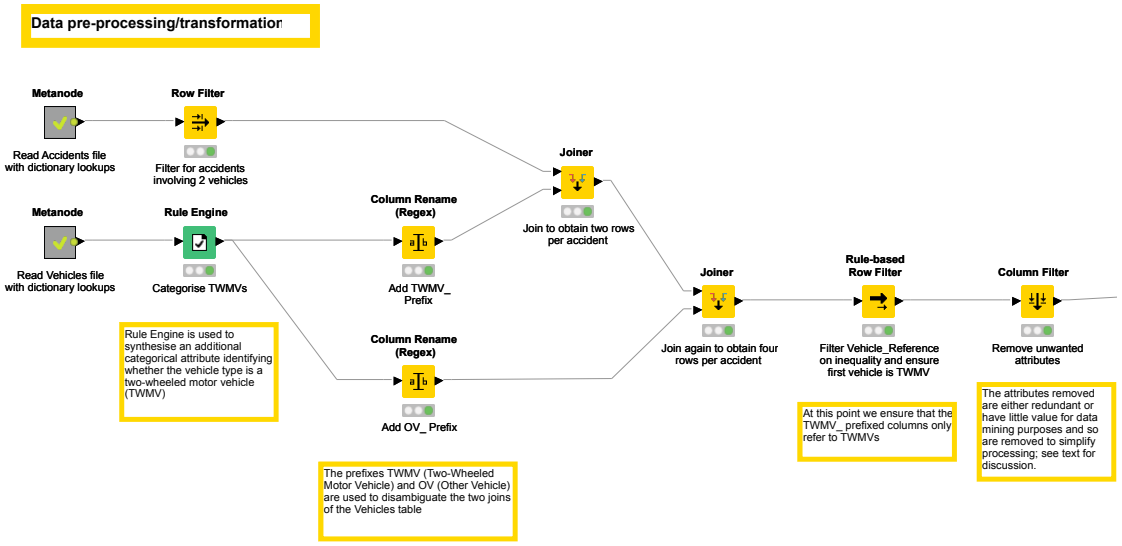

Figure 11: KNIME workflow for data preprocessing

Figures 12 and 13 show the workflows responsible for integrating the *Accidents* and *Vehicles* data files with their associated lookup tables as well as performing data reduction, out-of-range value handling and some feature engineering.

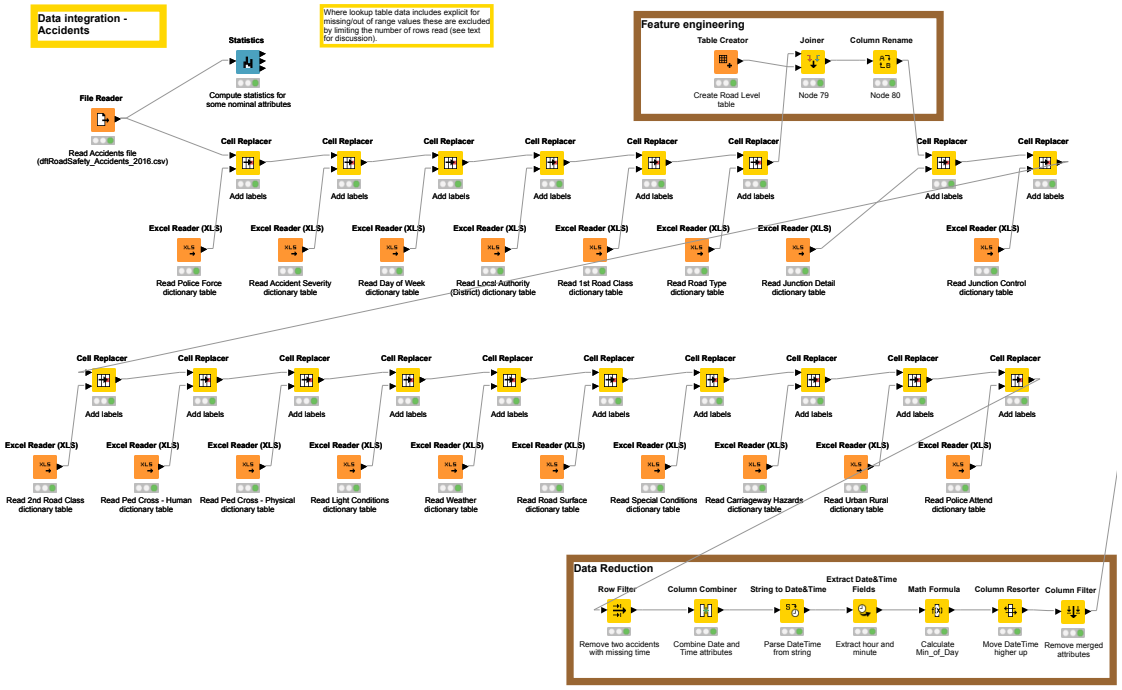

Figure 12: KNIME workflow for integration of accidents data file

The final stage in data preparation was the generation of a version of the data suitable for importing into WEKA; this is shown in Figure 14.

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

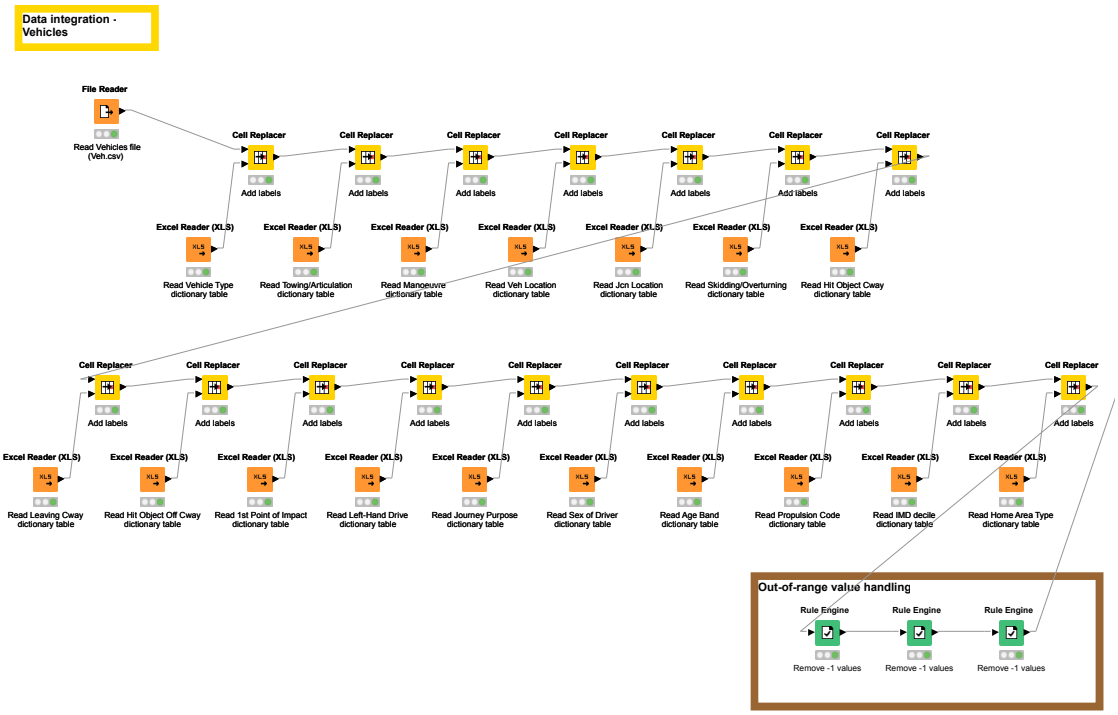

Figure 13: KNIME workflow for integration of vehicles data file

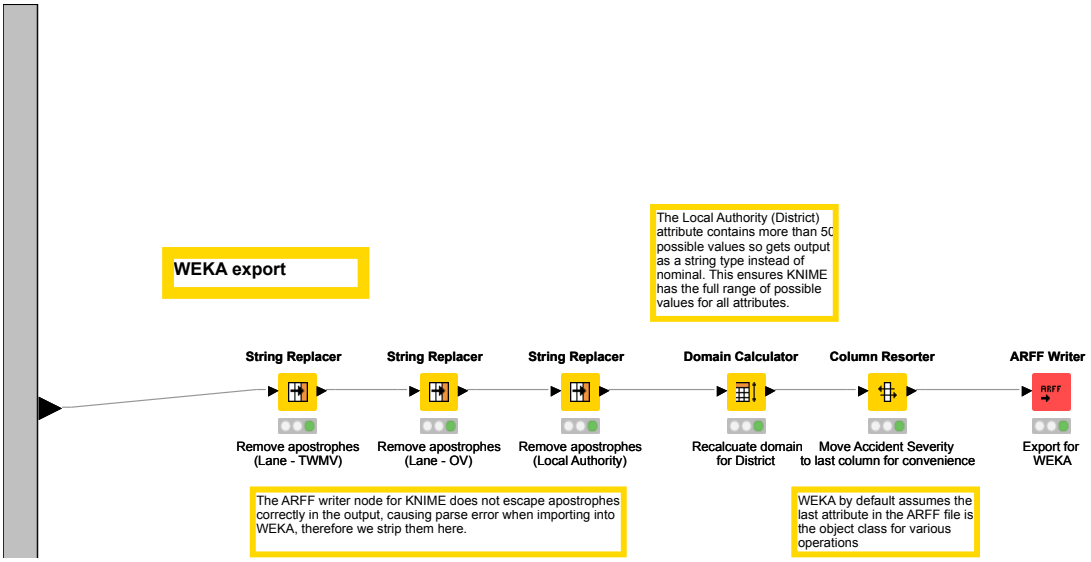

Figure 14: KNIME workflow for exporting to WEKA

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 15.

The NaiveBayes classifier is then run using the parameters shown in Table 4:

Table 4: 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

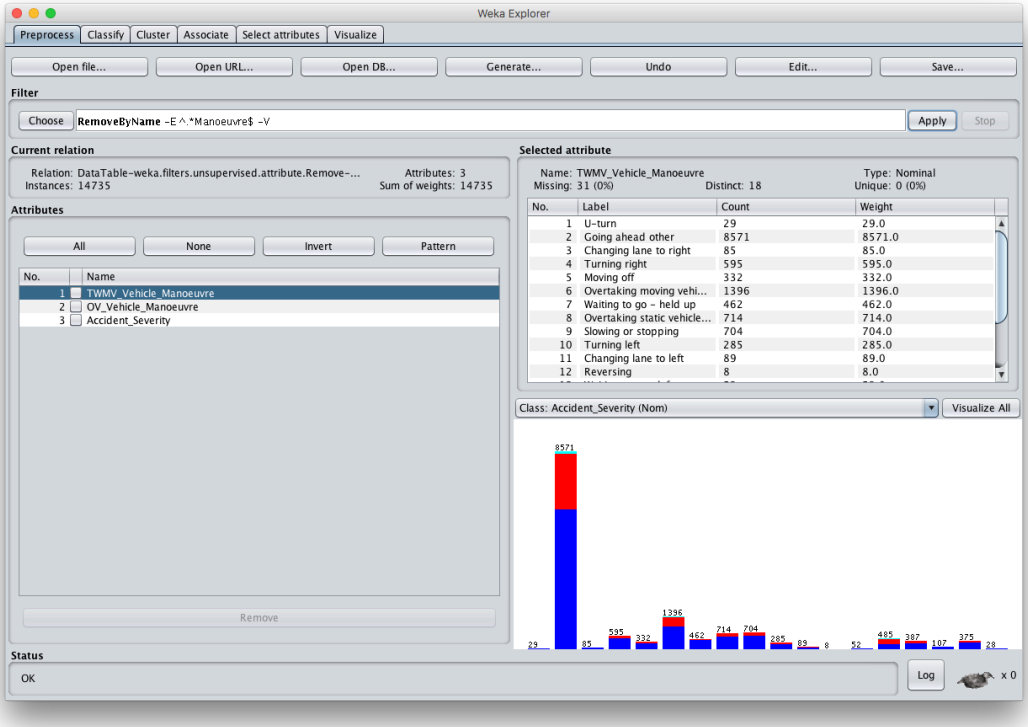

Figure 15: WEKA Explorer showing RemoveByName filter applied

`useSupervisedDiscretization` parameters are not relevant

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 5 shows counts for actual (rows) and predicted (columns) classes.

Table 5: 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, 2018a). 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 6.

Table 6: 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 5.

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 16 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'.

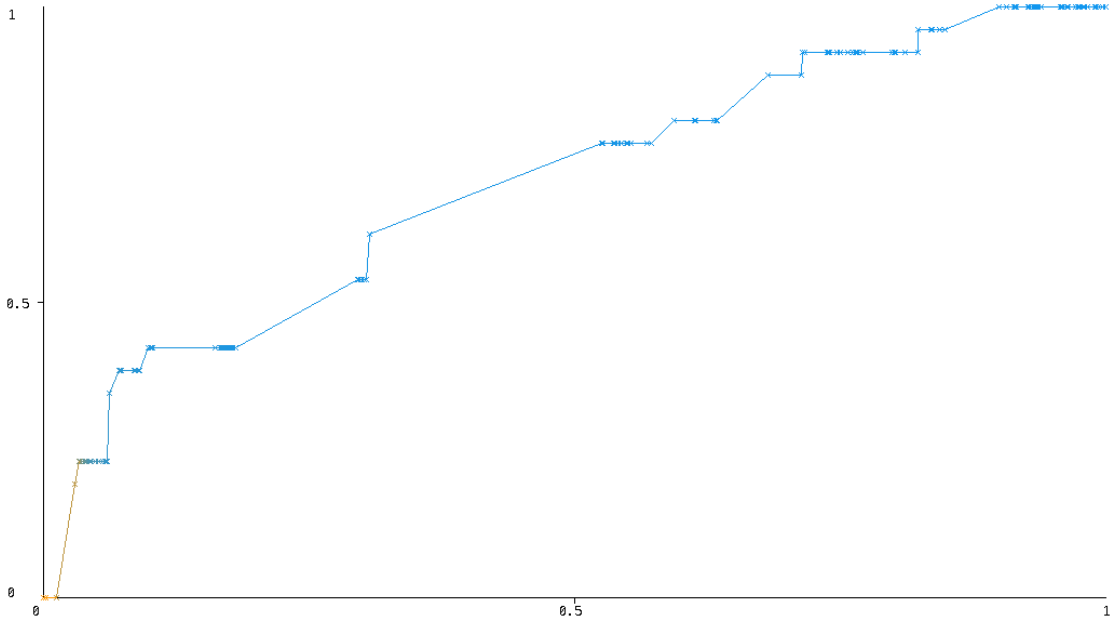

Figure 16: Initial ROC curve for fatal accidents (X axis = false positive rate, Y axis = true positive rate)

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

As Witten et. al (2016) point out, "optimizing classification rate without considering the cost of the errors often leads to strange results". The technique of cost-sensitive learning uses a cost matrix to assign different costs to the different types of classifier error. In this case because we are considering a three-class problem, we need to provide a 3x3 misclassification cost matrix.

The costs could be derived from the known costs of serious and fatal accidents in terms of emergency services, healthcare, etc. or based on a loose estimation of their relative impact. For the present study we use the second approach.

To perform cost-sensitive learning in WEKA the `CostSensitiveClassifier` was used. This classifier is described in the documentation as "a metaclassifier that makes its base classifier cost-sensitive." The same base classifier settings for NaiveBayes are used as previously described and the additional parameters shown in Table 7 are provided.

Table 7: Parameters for CostSensitiveClassifier in WEKA

Parameter	Value
batchSize	100
classifier	NaiveBayes
costMatrix	*see below*
costMatrixSource	Use explicit cost matrix
debug	False
minimizeExpectedCost	False
numDecimalPlaces	2
seed	1

A cost matrix was created through experimentation to assign a greater cost to cases where fatal accidents are not predicted correctly by the classifier. This is because the costs of false positives and false negatives are not equal for all cases. This matrix was then used for re-training. The matrix used is given in Table 8. Note that the cells where a 'fatal' accident is not categorised as fatal (false negatives for this class) show a greater cost.

Table 8: Misclassification cost matrix for retraining naïve Bayes classifer

Categorised as:	Slight	Serious	Fatal
Slight	0	1	1
Serious	1	0	1
Fatal	5	2	0

3.6 Final results

The confusion matrix in Table 9 show the results for the NaiveBayes classifier used in conjunction with CostSensitiveClassifier.

Table 9: Confusion matrix for cost-sensitive NaiveBayes classifier

	Slight	Serious	Fatal	Total	True positive rate (%)	False positive rate (%)
Slight	1050	6	24	1080	97.2	91.9
Serious	341	1	25	367	0.3	0.5
Fatal	20	0	6	26	23.1	3.4
Total	1411	7	55	1473		

In contrast with the original classifier test results in Table 5 the classifier performed worse overall with an accuracy of 71.8%. However, it correctly predicted the class of 6 (23.1%) of the fatal accidents in the test set. At the same time, it misclassified 3.4% of non-fatal accidents as fatal, and identified only 5.7% of serious accidents correctly. This suggests that it is possible to improve the accuracy of a classifier by making it cost-sensitive, but only at the expense of accuracy with respect to other classes.

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 clusterer and features

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 iterative *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 be used. We expect any clusters found to be disjoint (i.e. not overlapping). Other options considered but rejected were the agglomerative hierarchical clustering used by (Taamneh, Taamneh and Alkheder, 2017).

KNIME and WEKA do not have explicitly implementations of *k*-modes. However, on investigation it was found that WEKA's *SimpleKMeans* clusterer supports nominal attributes (this can be seen by viewing the 'Capabilities' window for the classifier, which includes 'Nominal attributes'). It can be determined from looking at the source of the `SimpleKMeans` and `NormalizableDistance` classes (University of Waikato, 2018b) that WEKA uses the mode instead of the mean when processing nominal attributes and calculates the distance between intances comprised of nominal attributes by counting the number of attributes that have different values. This suggests its implementation is similiar if not identical to *k*-modes and so is sufficient for our purposes.

In order to simplify processing and produce results that could be more easily interpreted, a small number of nominal attributes were selected for clustering, all related to vehicle manoeuvre and position in relation to junctions. This was in order to attempt to replicate some of Hill's (2005) findings. These attributes were as follows:

- `TWMV_Vehicle_Manoeuvre`
- `TWMV_Junction_Location`
- `OV_Vehicle_Manoeuvre`
- `OV_Junction_Location`
- `Accident_Severity`

The attributes used were selected from the input data set using the following WEKA filter:

```
weka.filters.unsupervised.attribute.Remove -V -R 27,29,46,48,65
```

4.2 Parameters

The *SimpleKMeans* clusterer was configured in WEKA with the parameters shown in Table 10.

Table 10: Initial parameters for SimpleKMeans clusterer in WEKA

Parameter	Value
canopyMaxNumCanopiesToHoldInMemory	100
canopyMinimumCanopyDensity	2.0
canopyPeriodicPruningRate	10000
canopyT1	-1.25
canopyT2	-1.0
debug	False
displayStdDevs	True
distanceFunction	EuclideanDistance -R first-last
doNotCheckCapabilities	False
dontReplaceMissingValues	False
fastDistanceCalc	False
initializationMethod	Random
maxIterations	500
numClusters	5
numExecutionSlots	1
perserveInstancesOrder	False
reduceNumberOfDistanceCalcsViaCanopies	False
seed	10

The justification for some of these parameters was:

- only one CPU was used and the seed was chosen arbitrarily; debug output is not required
- five clusters was selected through experimentation based on the relative sizes of clusters produced
- the default of maximum 500 iterations was suitable
- we wanted to see counts of nominal attributes (displayStdDevs provides this)
- we wanted missing values to be replaced with the mode
- random initialisation was used instead of canopy clustering
- the Euclidean distance function was used, which as described above uses the number of different attribute values for nominal attributes

4.3 Training and testing

The cluster mode selected in WEKA this time was 'use training set'. This is because we want the algorithm to use the entire dataset for training and it is not necessary to hold out part of the data for testing. We also do not need to use 'Classes to clusters evaluation' because we are interested in finding novel groupings in the data (unsupervised learning), not measuring the accuracy of the clustering algorithm in detecting already-labelled data (supervised learning).

4.4 Results

The clusters identified by *SimpleKMeans* with the parameters above are shown in Table 11 along with the cluster centroid given by the clusterer showing the mode for each nominal attribute.

It is notable that the manoeuvres/positions clusters identified make some intuitive sense. Clusters 1 and 3 resemble Hill's cluster 7 ("Accidents where a car ... turns right and a two wheeled motor vehicle is carrying out any manoeuvre"). The centroids for clusters 1 and 2 differ only in terms of severity, while cluster 4 might represent the situation where a car runs into a TWMV from behind at a junction ('rear-ender').

Table 11: Clusters identified by *SimpleKMeans* with clusters = 5

Cluster	Instances	Centroid
0	4801 (33%)	TWMV going ahead, approaching junction / OV turning right, approaching junction / Slight
1	3010 (20%)	Both vehicles going ahead, not near junction / Slight
2	1846 (13%)	Both vehicles going ahead, not near junction / Serious
3	4770 (32%)	TWMV going ahead, mid-junction / OV turning right, mid-junction / Slight
4	308 (2%)	TWMV going ahead, not near junction / OV slowing down or stopping, not near junction / Slight

However it would be useful to have a way of objectively measuring the quality of these clusters.

4.4.1 Silhouette index

One way of evaluating the quality of clusters is by using silhouette analysis (Rousseeuw, 1987). This can also be used to suggest the optimal value for *k*. An unofficial but open-source WEKA package **KValid** providing this functionality is available (Francis, 2017).

4.4.1.1 Installation

It appears that the **KValid** package is currently not compatible with changes to WEKA's classloading mechanism introduced in version 3.8.1. In order to test this package it was therefore necessary to download WEKA 3.8.0 instead. Once this is done, the KValid package can be installed locally using:

```
$ java weka.core.WekaPackageManager -install-package ~/path/to/KValid.zip
```

After this is done, **KValid** is listed as an option in the *Cluster* tab and can be used as a way of running *SimpleKMeans* with different values of *k* and plotting the silhouette index of each.

4.4.1.2 Parameters

The additional parameters used to run *KValid* are shown in Table 12. Note that not all parameters of *SimpleKMeans* are supported.

Table 12: Parameters for KValid in WEKA

Parameter	Value
cascade	True
minimumK	3
maximumK	10
showGraph	True
validationMethod	Silhouette index

These parameters cause KValid to try a range of values for *k* and plot the silhoutte index for each. The graph generated is shown in Figure 17. It shows a gradual upward trend with a local maxmimum at k = 6. This suggests that 6 may be a good balance between silhoutte index and simplicity/interpretability.

The WEKA Clusterer Visualize interface (opened by right-clicking on the results and selecting 'Visualize cluster assignments') for these options can be seen in Figure 18.

5 Critical review

5.1 Reflections on difficulties encountered

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.

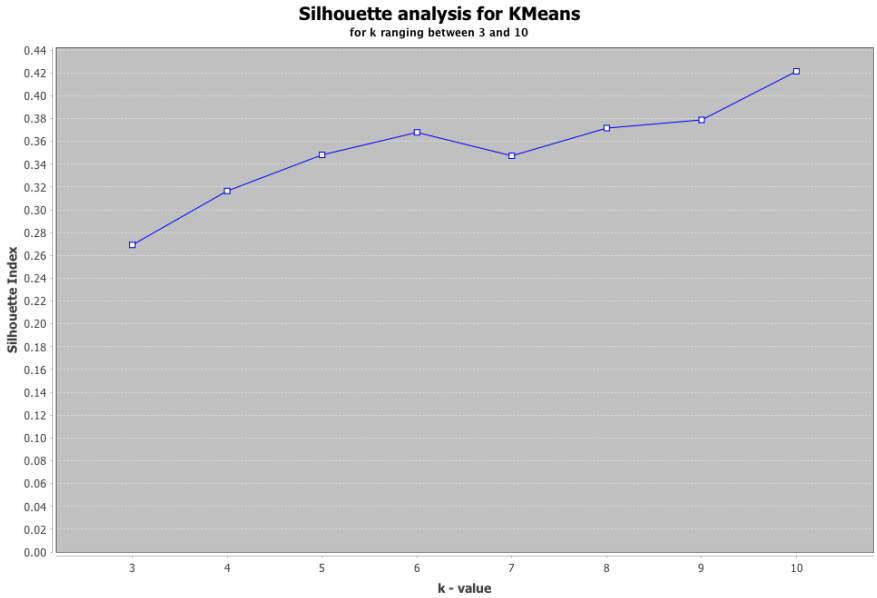

Figure 17: KValid silhouette graph for different *k* values

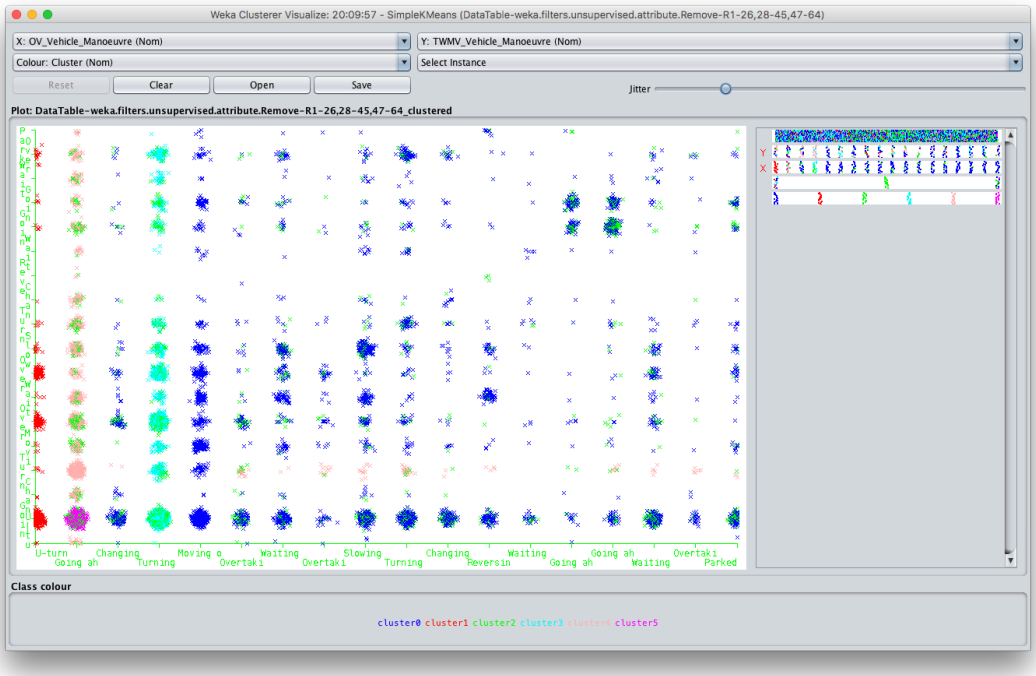

Figure 18: WEKA interface showing cluster assignments for SimpleKMeans

The initial accuracy of the naïve Bayes classifier was disappointing in that it failed to predict any fatal accidents, however this could perhaps have been anticipated through more detailed exploration of the data in the analysis phase. This might have revealed the 'class imbalance' problem and informed the choice of classification technique.

Although cost-sensitive learning improved the accuracy of the classifier, the selection of values for the cost matrix were highly arbitrary. In a real-world application they should have a clear basis in evidence. Moreover, other techniques for improving classifier accuracy, such as oversampling or undersampling data to produce a balanced class distribution, or using ensemble methods (Han, Kamber and Pei, 2012, p. 384) could have been attempted.

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. It would have been helpful during data analysis/preprocessing 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 have been beneficial here.

One difficulty of using *k*-means is that it is not guaranteed to find the overall best set of clusters but may terminate at a local optimum. As Bramer points out (2016, p. 319), results are dependent on the choice of initial cluster centroids, which when a random initialisation method is used (as with WEKA's *SimpleKMeans* here) means that altering the 'seed' parameter may produce different clusters. It would have been helpful to explore the effect of using different seeds and initialisation methods for this algorithm.

Of the published work on this dataset referenced, using *k*-means the study was able to support Hill's identification through cross-tabulation of accident clusters based on vehicle manoeuvre, particularly in the scenario of another vehicle turning right.

In terms of the tools used, KNIME is clearly a useful platform for data preprocessing and transformation. Once the concept of metanodes and nested workflows was understood, they provide a powerful way of organising and grouping areas of work (e.g. transformation, cleaning) and managing the mental overhead of complex workflows. However, WEKA appears to have built-in support for a wider set of data mining functionalities (indeed KNIME provides WEKA nodes to implement many of these).

5.2 Future work

Some suggestions for future work are given below.

5.2.1 Classification of 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 outlined below (after Han (2012)):

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.

5.2.2 Longitudinal study

Since data has been collected in the STATS19 format since 1979 (Administrative Data Liaison Service, 2018) there is considerable scope for looking at how patterns in the data have evolved over time. Castro and Kim (2015) compared datasets from both 2010 and 2012, while Ehsaei and Evdorides (2011) considered trends over the period 2001-2005. An area for further investigation could be to take the models trained here against the 2016 dataset and test them against releases from other years to evaluate any changes in accuracy.

5.2.3 Using *k*-modes in KNIME

Since KNIME does not have built-in support for *k*-modes, a *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 19 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)
```

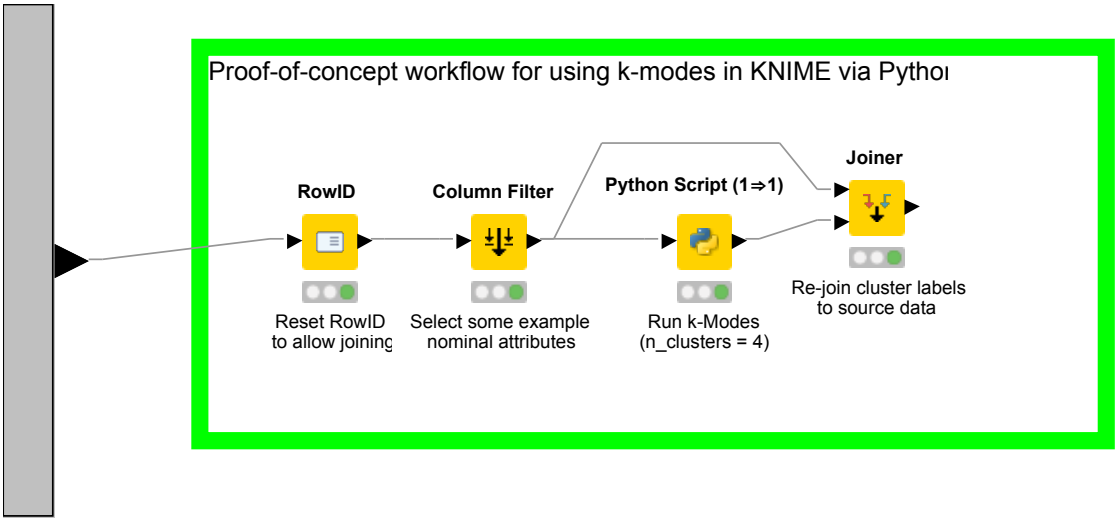

Figure 19: Proof-of-concept KNIME workflow for k-modes

The result of this workflow is an additional numeric attribute dataset that identifies the cluter with which each object has been associated. The results of this could be compared with the output of WEKA's `SimpleKMeans` clusterer described earlier.

5.2.4 Analysis of geographical locations

As shown earlier, plotting geographical coordinates (`Longitude` and `Latitude`) reveals a greater number of accidents in some areas of Great Britain. This intuitively seems to correspond to areas of greatest population density, however the relationship is unproven. It would be interesting to know which factors have the greatest correlation with the number of motorcycle accidents. One way of doing this would be to source population data for the UK and 'divide' the number of accidents plotted by it. Other datasets could be attempted for comparison, for example number of motorcycles registered to owners by postcode. The goal of such analysis would be to identify the most strongly correlated factors and perhaps reveal unexpected discrepancies where the number of accidents is higher than would be expected for an area.

5.2.5 Synthesising binary attributes

One weakness of transforming ordinal nominal attributes such as `1st_Road_Class` to integers described earlier is that it implies an equal distance between the possible values. This could be avoided by converting nominal attributes to synthetic binary attributes indicating the presence or absence of a value, which implies ordering without equal distance, following (Witten et al., 2016, ch. 8).

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