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Analysis of hourly road accident counts using hierarchical clustering and cophenetic correlation coefficient (CPCC)

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Abstract

Road and traffic accidents are an important concern around the world. Road accidents not only affects the public health with different level of injury but also results in property damage. Data analysis has the capability to identify the different reasons behind road accidents i.e. traffic characteristics, weather characteristics, road characteristics and etc. A variety of research on road accident data analysis has already proves its importance. Some studies focused on identifying factors associated with accident severity while others focused on identifying the associated factors behind accident occurrence. These research analyses used traditional statistical methods as well as data mining methods. Data mining is frequently used method for analyzing road accident data in present research. Trend analysis is another important research area in road accident domain. Trend analysis can assist in identifying the increasing or decreasing accidents rate in different reasons. In this study, we have proposed a method to analyze hourly road accident data using Cophenetic correlation coefficient from Gujarat state in India. The motive of this study is to provide an efficient way to choose the best suitable distance metric to cluster the series of counts data that provide a better clustering result. The result shows that the proposed method is capable of efficiently group the different districts with similar road accident patterns into single cluster or group which can be further used for trend analysis or similar tasks.

Keywords: Accident analysis, Clustering, Cophenetic correlation coefficient, Data mining

Background

Road and traffic accidents are one of the major cause of fatality and disability across the world. Road accident can be considered as an event in which a vehicle collides with other vehicle, person or other objects. A road accident not only provides property damage but it may lead to partial or full disability and sometimes can be fatal for human being. Increasing number of road accidents is not a good sign for the transportation safety. The only solution requires the analysis of traffic accident data to identify different causes of road accidents and taking preventive measures.

A variety of research has been done on road accident data from different countries. Various research studies used different techniques to analyze road accident data using statistical techniques and provide fruitful outcomes [1–5]. Different other studies used data mining techniques to analyze road accident data and also claim that data mining techniques are more advanced and better than traditional statistical techniques [6–10, 21, 22]. Although, both the approaches provided good outcome that certainly useful for traffic accident prediction, [9, 11, 12] reveals that heterogeneity in road accident data exists and should be removed prior to the analysis of road accident data. They also suggested that use of suitable clustering techniques prior to the analysis of accident data reduces the heterogeneity from data and can help in revealing hidden information.

Besides all these studies that focused on analyzing road accident data and identifying factors that affects severity of road accident, trend analysis of road accident data can also be useful to understand the nature of road accidents in certain locations. Time series data consists of a set of data points or values which have been measured on a certain fixed interval of time [13]. Time series data is very important and useful to understand the nature of trend in different application such as detecting weather trend and forecasting stock market trend over a period of years. This is the motivating factor of this study. In this study, we have distributed 1 year road accident counts into 12 slots. Each slot is representing the total number of road accident that has occurred in 2 h of slots. More specifically, we have divided 24 h in 12 slots with 2 h in each slot and in time series data, slot1 is representing the total number of road accidents occurred in between 00:00 a.m. and 2:00 a.m. in 1 year period. So, we have a total of 60 counts for 5 year duration in our time series data. We have extracted this data for all 26 districts of Gujarat state. In order to analyze this data, we are using hierarchical clustering on all 26 time series data. The problem with hierarchical clustering of time series data is that it is quite difficult and unusual to manually decide the distance metric to be used with clustering algorithm. The wrong selection of distance metric certainly results in bad clusters. Our approach is fairly deal with this problem. Therefore, our method can be applied prior to clustering of data to find the best suitable distance metric for clustering. Hence, prior to clustering, we have used Cophenetic correlation coefficient (CPCC) [14] to compare various distance measures with all seven versions of agglomerative hierarchical clustering. CPCC can be defined as a measure of the correlation between the cophenetic distance of two time series data objects and the original distance matrix. The best distance measure that has the strong CPCC value is chosen for hierarchical clustering on time series data. Clustering on time series data and trend analysis of each cluster shows that all the time series objects in each cluster having similar patterns. Hence, in order to perform trend analysis of time series data from several locations or districts, our approach is suitable to apply prior to start trend analysis of road accidents. The results proves that our approach is capable to put all district that have similar accident patterns in one cluster, that will definitely ease the difficulty in handling road accident time series data of different locations together.

Methods

Time series normalization

Normalization of data is a data pre-processing step that refers to the process of assigning different data values into certain range e.g., 0 and 1. Normalization of time series data prior to analysis certainly assist in handling certain difficulties such as noise, amplitude scaling and offset translation [15]. Hence, it is good to perform normalization on time series data to generate better outcomes. We used z-score normalization method to normalize our time series data. Z-score normalization standardized the data points in a range of [0, 1]. Consider a time series T = {T_1, T_2,..., T_n}, z-score normalization standardize this time series into a normalize time series NT = {NT_1, NT_2,..., NT_n} such that

$$\mu(NT)\ \approx\ 0 \quad \text{and} \quad \sigma(NT) \approx 1$$

where μ(NT) and σ(NT) are the mean and standard deviation respectively of normalized time series NT. The z-score formula for normalizing time series is given by Eq. 1.

$$\mathrm{NT} = \sum_{i=1}^{n} \frac{t1 - \mu(\mathrm{T})}{\sigma(\mathrm{T})} \tag{1}$$

Distance measures

There are several distance measure exists [16] such as Euclidean distance, Pearson correlation coefficient, Spearman distance and etc. These distances play a very important role in clustering time series data. Some of the distance metric used in this study is briefly discussed as follows:

Euclidean distance

Euclidean distance is one of the popular and classic similarity measure used in various clustering algorithms such as K-means and hierarchical clustering. Euclidean distance can be defined as the distance between two points or vectors in Euclidean norm. Euclidean distance between two time series of equal length can be computed using Eq. 2 as follows:

$$\mathrm{D}_{\mathrm{Euclidean}}(\mathrm{T}_1, \mathrm{T}_2) = \sum_{j=1}^{n} \sqrt{\left(T_{1j} - T_{2j}\right)^2} \tag{2}$$

The above equation is used to calculate the distance between two time series of similar length of time sequence n.

City block distance

It is also known as Manhattan distance or absolute value distance. It represents distance between points in a city grid road. The city block distance between two time series objects can be calculated as

$$\mathrm{D}_{\mathrm{CityBlock}}(\mathrm{T}_1, \mathrm{T}_2) = \sum_{j=1}^{n} \sqrt{\left(T_{1j} - T_{2j}\right)} \tag{3}$$

Minkowski distance

The Minkowski distance can be defined as a metric in a normed vector space which can be considered as a generalization of both the Euclidean distance and the Manhattan distance. The Minkowski distance of order p between two points T1 and T2 where, T1 = ($T1_1$,$T1_2$,..., $T1_n$) and T2 = ($T2_1$, $T2_2$,..., $T2_n$) can be defined as

$$D_{Minkowski}(\mathrm{T}_1, \mathrm{T}_2) = \left(\sum_{i=1}^{n} |T_{1i} - T_{2i}|^p \right)^{\frac{1}{p}} \tag{4}$$

If p ≥ 1, the distance will be the result of Minkowski inequality. If p < 1, it violates the triangle inequality, hence, for p < 1, it cannot be considered as a metric.

Chebyshev distance

Chebyshev distance is a metric [17] that is defined on a vector space where the distance between two vectors is the greatest of their differences along any coordinate dimension [18]. The Chebyshev distance between two time series objects or points *p* and *q*, with standard coordinates $\mathrm{p_i}$ and $\mathrm{q_i}$ respectively, is

$$D_{Chebyshev} = \max(|p_i - q_i|) \tag{5}$$

This distance equals the limit of the $\mathrm{L_p}$ metrics

$$\lim_{k \to \infty} \left(\sum_{i=1}^{n} |p_i - q_i|^k \right)^{\frac{1}{k}}$$

Hence, it is also known as L_∞ metric.

Cosine distance

Cosine distance can be defined as a similarity measure between two time series objects that measures the cosine of angle between two time series objects. Cosine similarity is only a judgment of orientation but not magnitude. The cosine of two time series objects can be defined by the following equation:

$$a \cdot b = ||a|| \cdot \left||b|\right| \cdot \cos\theta$$

The cosine distance between two time series objects T1 and T2 can be calculated as

$$D_{Cosine} = 1 - \frac{T_1 \cdot T_2'}{\sqrt{\left(T_1 \cdot T_1'\right) \cdot (T_2 \cdot T_2)'}} \tag{6}$$

Correlation distance

Correlation distance [19] is a measure of statistical dependence between two time series objects. If the two objects are statistically independent, the correlation between them will be 0. The value for correlation distance ranges from.

[−1, +1] depending upon the negative correlation between two objects or positive correlation between two objects. The correlation distance between two time series objects T1 and T2 can be calculated as

$$D_{Correlation} = 1 - \frac{\left(T_1 - T_1'\right) \cdot \left(T_2 - T_2'\right)'}{\sqrt{\left(T_1 - T_1'\right)\left(T_1 - T_1'\right)'} \cdot \sqrt{\left(T_2 - T_2'\right) \cdot \left(T_2 - T_2'\right)'}} \tag{7}$$

Spearman distance

This distance based on the Spearman's correlation coefficient. It is a non-parametric measurement of the statistical dependence between two objects. It describes the strength of the relationship between two objects using a monotonic function. A value of -1 or $+1$ occurs when both the objects are good monotone function to each other. It can be calculated as

$$D_{Spearman} = 1 - \frac{\left(r_1 - r_1^{'}\right) \cdot \left(r_2 - r_2^{'}\right)^{'}}{\sqrt{\left(r_1 - r_1^{'}\right) \cdot \left(r_1 - r_1^{'}\right)^{'}} \sqrt{\left(r_2 - r_2^{'}\right) \cdot \left(r_2 - r_2^{'}\right)^{'}}} \tag{8}$$

where r_1 and r_2 are the coordinate-wise rank vectors of T_1 and T_2 such that $r_i = (T_{i1}, T_{i2}, \ldots, T_{in})$.

Cophenetic correlation coefficient (CPCC)

Hierarchical clustering linked together two data points or objects from the original data set at every level until no objects are there to link. The height of the link illustrates the distance between the two clusters which consists of those objects. This height is known as the Cophenetic distance between two objects. The CPCC values close to 1 are considered as good. CPCC can be used to compare the clustering result of same data set using different distance measures or clustering algorithms. In general, CPCC is a measure of how accurately a dendrogram preserves the pair-wise distances between the time series objects.

Suppose we have a time series data to be modeled using a clustering method to produce a dendrogram T_i i.e., a cluster model in which the close data points are clustered together in a hierarchical tree form.

Let d_{ij} is the Euclidean distance between the ith and jth time series objects and t_{ij} the dendrogrammatic distance between the two time series objects T_i and T_j. This distance is the height of the node at which these two points are first joined together.

Assuming $d_{ij}^{'}$ be the mean of the d_{ij} and $t_{ij}^{'}$ be the average of the t_{ij}, the cophenetic correlation coefficient can be denoted as

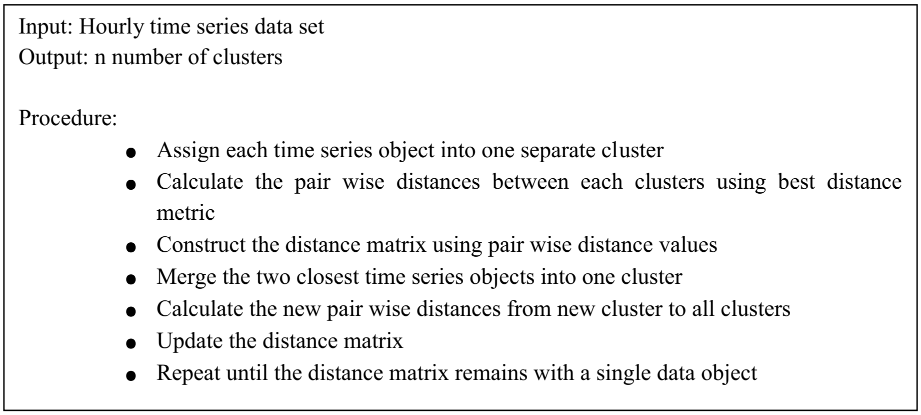
$$Coefficient_{CPCC} = \frac{\sum_{i<j} \left(d_{ij} - d_{ij}^{'}\right) \cdot \left(t_{ij} - t_{ij}^{'}\right)}{\sqrt{\left(\sum_{i<j} \left(d_{ij} - d_{ij}^{'}\right)^2\right) \cdot \left(\sum_{i<j} \left(t_{ij} - t_{ij}^{'}\right)^2\right)}} \tag{9}$$

We will use CPCC to calculate the performance of all distance metric discussed in "Distance measures" section to identify the best distance metric to be used for clustering of hourly road accident count data.

Hierarchical clustering

Hierarchical clustering [20] is a popular unsupervised learning technique that seeks to build a hierarchy of clusters. It is broadly categorized into two categories: agglomerative and divisive. Agglomerative clustering follows a bottom up approach, i.e. each data object starts in its own cluster, and further closed objects are merged together and forms new cluster. This process repeats till there are no objects remains to merge. Unlike agglomerative clustering, divisive clustering follows top down approach in which all data objects starts in one cluster and splitting among data objects continues till every data objects belongs to a single cluster. However, agglomerative clustering (running time complexity O(n^3)) is computationally efficient than divisive clustering algorithm (running time complexity O(2^n)). Therefore, in this paper, we have used agglomerative hierarchical clustering algorithm which is given as follows:

Algorithm1: Agglomerative Hierarchical clustering



Input: Hourly time series data set
Output: n number of clusters

Procedure:

- Assign each time series object into one separate cluster
- Calculate the pair wise distances between each clusters using best distance metric
- Construct the distance matrix using pair wise distance values
- Merge the two closest time series objects into one cluster
- Calculate the new pair wise distances from new cluster to all clusters
- Update the distance matrix
- Repeat until the distance matrix remains with a single data object

Data set description

The secondary data of hourly count of road accidents for the Gujrat state has been extracted from the data set provided by GVK_EMRI, Gujrat. The data set consists of road accidents count of 26 districts of Gujrat state from January 2010 to December 2014.

Results and discussion

Initially, all time series data of 26 districts are normalized using z-score normalization, i.e., all road accident counts for 26 districts are in such range that there mean is close to 0 and their standard deviation is close to 1.

Distance metric selection

After normalization of the time series data of 26 districts, the next task is to find out the best suitable distance metric to cluster the road accident time series data using hierarchical clustering. Hence, we have calculated the CPCC using all seven versions of agglomerative clustering algorithm with all discussed distance metrics on hourly time series counts of 26 districts of Gujarat. The result of this analysis is shown in Table 1.

Table 1 illustrates that agglomerative hierarchical clustering with average version achieves the highest CPCC value for all distance metric in comparison to other versions. Also, we can see that Euclidean and Minkowski distance metric has the highest and same CPCC value because, for $p = 2$, the Minkowski distance becomes Euclidean distance. Hence, we can choose any one of them to perform clustering on our hourly road accident time series data.

Table 1 CPCC analysis for 26 districts of Gujarat for different distance metric

Distance metric	Cophenetic correlation coefficient (CPCC)						
	Single	Complete	Average	Ward	Weighted	Median	Centroid
Euclidean	0.784227	0.791608	*0.826298*	0.63921	0.760709	0.739566	0.812102
Cityblock	0.795472	0.720603	0.822869	0.617237	0.814186	0.757599	0.800933
Minkowski	0.784227	0.791608	*0.826298*	0.63921	0.760709	0.739566	0.812102
Chebychev	0.747701	0.621421	0.78132	0.620067	0.756454	0.684826	0.730986
Cosine	0.73324	0.73852	0.779876	0.63823	0.692975	0.70216	0.760326
Correlation	0.733247	0.738506	0.779844	0.638203	0.692964	0.702147	0.760308
Spearman	0.750498	0.528649	0.773012	0.576422	0.725262	0.742434	0.757063

Italic symbol shows the highest CPCC values for average version for AGNES algorithm with Euclidean and Minkowski distance metric

Clustering result

CPCC provides us to perform with the agglomerative hierarchical clustering with average version using Euclidean distance as a distance metric. We then applied agglomerative hierarchical clustering algorithm on our hourly time series data of 26 districts of Gujarat. The dendrogram achieved as a result of clustering process is shown in Fig. 1. Figure 2

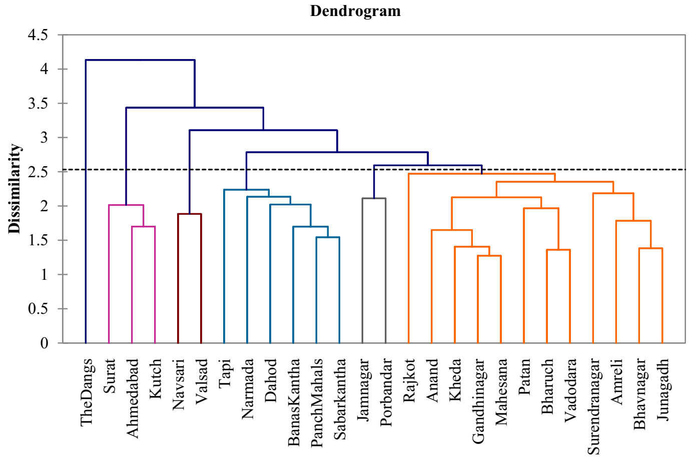


Fig. 1 Dendrogram achieved after applying hierarchical clustering

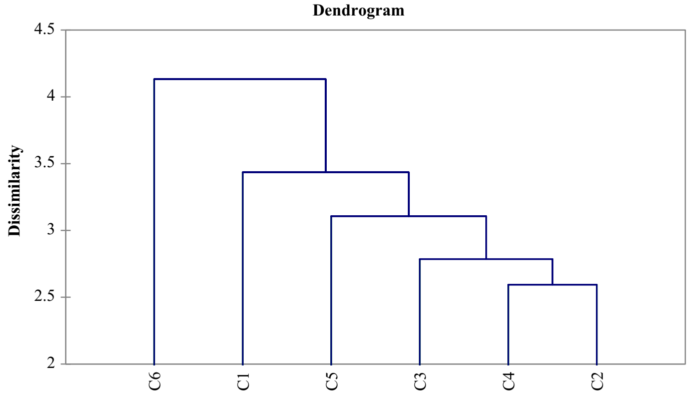


Fig. 2 Dendrogram showing number of clusters and their linkage

illustrates the number of clusters obtained and their linkage using agglomerative hierarchical clustering. The name of the districts and their cluster id is given in Table 2.

Discussion

The cluster 1 consists of 3 districts, cluster2 consists of 12 districts, cluster3 consists of 6 districts, cluster4 and cluster5 both consists of 2 districts and cluster6 consists of only 1 district of Gujarat state as shown in Table 2. The hourly distribution of the road accidents in this district is shown in Figs. 3 and 4. It can be seen from Figs. 3a–c and 4a–c that all districts in each clusters may have different number of accidents but they have similar hourly trend of road accidents. This trend is also following the similar pattern across the years. The more interesting pattern that is found in every cluster is that in every cluster and for every district the highest peak that represents the time slot of 8:00 p.m. to 10:00 p.m. and/or 10:00 p.m. to 12:00 p.m. In this duration the highest numbers of road accidents are reported and these accident counts are increasing every year which is a major concern. The last cluster6 that contains only one district has a slight variation in hourly road accident count for every year but it still preserves the peak at 8:00 p.m. to 10:00 p.m. for road accidents counts.

Hence, our technique of road accident hourly count analysis proves that using our approach we can obtain good quality cluster which consists of districts with similar pattern of road accidents in a group or cluster.

Conclusion and future work

This paper presents an approach that makes use of data mining clustering technique to cluster the hourly counts of road accidents of 26 districts of Gujrat for 5 years period that constitutes a time series data. Prior to analysis our approach uses CPCC to find the best distance metric that can be used to cluster our data using agglomerative hierarchical clustering. The Euclidean distance and Minkowski distance (for $p = 2$) found to be the best suitable distance metric for cluster analysis of 26 time series data. The clustering divides the 26 districts into 6 clusters. In each cluster, the districts with similar accident pattern of road accidents are grouped. The result illustrates that the most dangerous time for road accident is the 8:00 p.m. to 12:00 p.m. in almost all clusters except cluster6 that consists of only 1 district which has a slightly varied distribution of accidents across the years. The results simply show that proposed approach is capable to find good

Table 2 Number of clusters and associated districts

Cluster Id	Name of districts
1	Ahmedabad, Kutch, Surat
2	Amreli, Anand, Bharuch, Bhavnagar, Gandhinagar, Junagadh, Kheda, Mahesana, Patan, Rajkot, Surendranagar, Vadodara
3	BanasKantha, Dahod, Narmada, PanchMahals, Sabarkantha, Tapi
4	Jamnagar, Porbandar
5	Navsari, Valsad
6	The Dangs

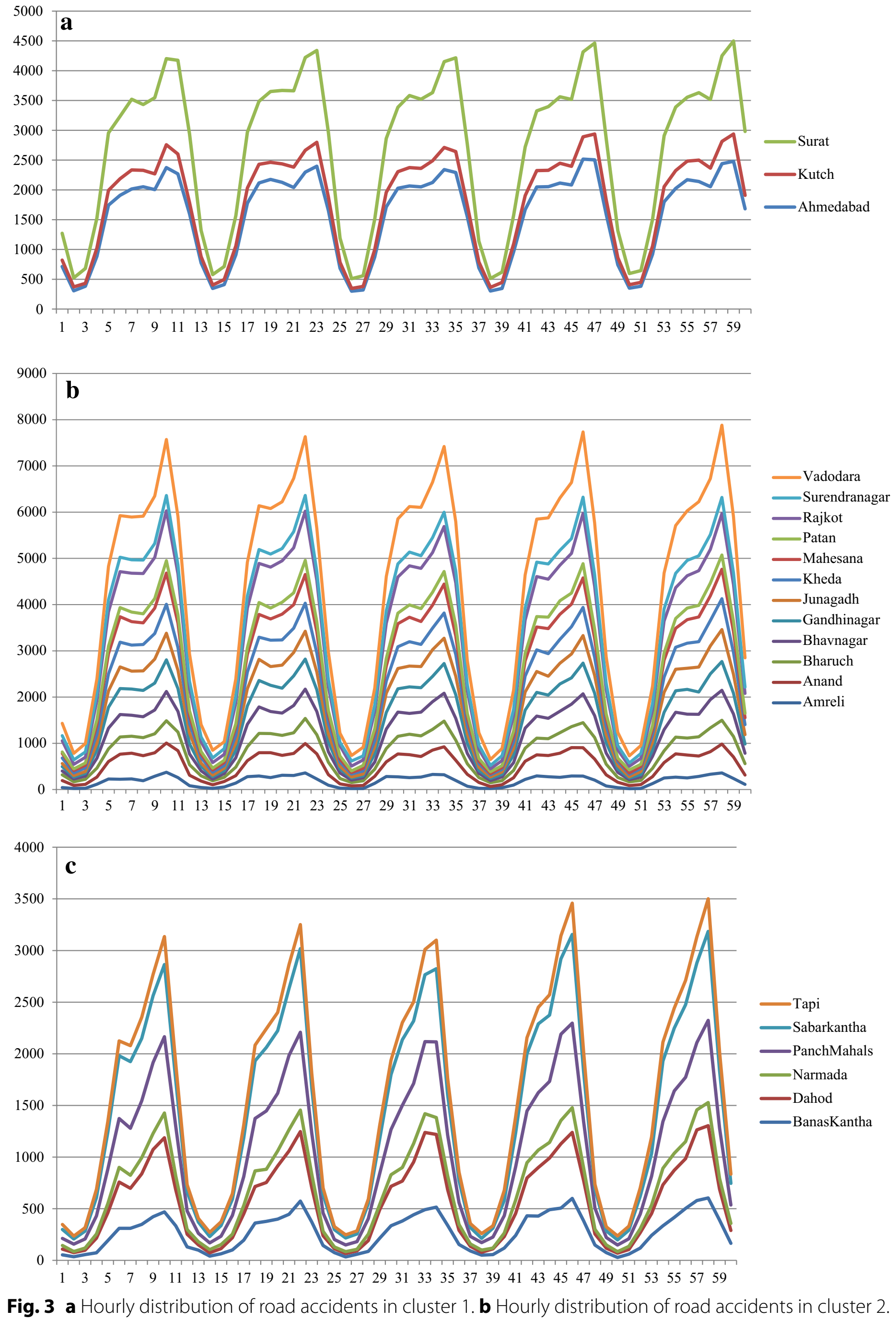


Fig. 3 **a** Hourly distribution of road accidents in cluster 1. **b** Hourly distribution of road accidents in cluster 2. **c** Hourly distribution of road accidents in cluster 3

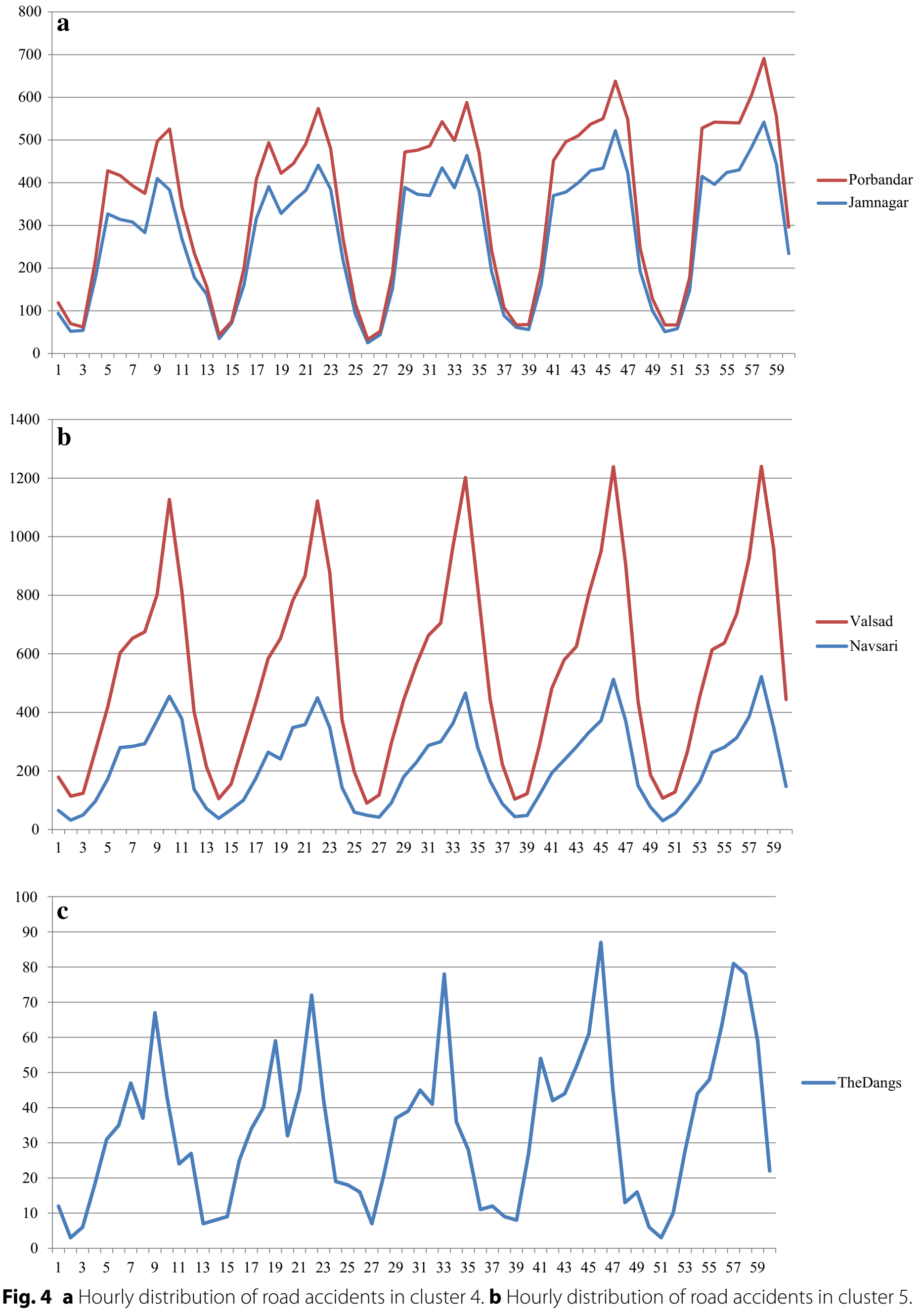


Fig. 4 **a** Hourly distribution of road accidents in cluster 4. **b** Hourly distribution of road accidents in cluster 5. **c** Hourly distribution of road accidents in cluster 6

clusters. The future work will consists of detailed analysis of these clusters with an objective to identify the various locations and factors behind road accidents that occurred during 8:00 p.m. to 10:00 p.m..

Authors' contributions

DT contributed for the underlying idea and helped drafting the manuscript. DT played a pivotal role guiding and supervising throughout, from initial conception to the final submission of this manuscript. SK developed and implemented the idea, designed the experiments, analyzed the results and wrote the manuscript. Both authors read and approved the final manuscript.

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Competing interests

The authors declare that they have no competing interests.

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