# Finding Banded Patterns in Big Data Using Sampling

***Abstract*—A mechanism for identifying bandings in large "zero-one" N-dimensional data sets, using a sampling technique, is presented. The challenge of identifying bandings in data is the large number of potential permutations that need to be considered. To circumvent this a banding score mechanism is proposed that avoids the need to consider large numbers of permutations. This has been incorporated into a proposed banded pattern mining algorithm, the Exact ND Banded Pattern Mining (END BPM) algorithm. Although this operates well on reasonably sized datasets, there is still a challenge with respect to large N-dimensional data sets that cannot be held in primary storage. To this end a sampling technique is also proposed. The approach is fully described and evaluated using the GB cattle movement database, a "real life" database the records all movements of cattle in GB.**

***Keywords—Banded Pattern in Big data, Banded Pattern Mining, Data Sampling***

## I. INTRODUCTION

A binary valued data set is said to feature banding if the dimension indexes can be ordered in such a way that the "ones" are arranged about the leading diagonal [1], [2]. Typically, given a reasonably complex data set, a perfect banding can not be achieved, but some "best" banding is always possible. The advantage offered by banding is firstly that it allows for more efficient (and effective) processing of large data sets than in the case where the data sets are not organised in this manner; this is particularly significant in the case of very large data sets. Secondly it is often noteworthy that a banding can be identified in a given data set, as this tells us something of significance about the data. Examples of 2D and 3D bandings are presented in Figures 1 and 2.

The challenge of banding has traditionally been the large number of permutations to be considered. Existing work on identifying bandings in data has thus been mostly directed at 2D data and is typically founded on a generate and test process of dimension permutations [1]–[5]. A 2-D binary data set can be viewed as a matrix holding 1s and 0s, if we ignores the 0s we are typically left with a sparse matrix (in this paper we consider the 1s in the matrix to be represented by "dots" and the 0s by "empty space"; thus we wish to arrange the dots to feature a banding). The problem of finding permutations of rows and columns in a given sparse matrix, such that the resulting matrix has a minimized bandwidth, is known to be NP-Complete [6]–[8]. To circumvent the need for this permutation generate and test process the central theme of this paper is the use of an ND banding score mechanism; a mechanism that includes the possibility of some cells in the matrix of interest holding more than one dot. The idea of using banding scores for Banded Pattern Mining (BPM) was first proposed in [9] where the authors proposed a 2D BPM mechanism such that the indexes in each dimension were allocated a banding score which could then be used to rearrange the indexes, thus avoiding the computationally expensive consideration of permutations. To the best knowledge of the authors very little work has been directed at ND data other than work on approximated bandings in 3D data described in [5]. However, it would be more desirable if an exact banding can be found. The first contribution of this paper is thus an Exact ND BPM (END BPM) algorithm that finds exact bandings in ND data which features the possibility that more than one dot may be located at individual locations in the data matrix. However, although this works well using reasonably sized ND data sets, large ND data sets that can not be held in primary storage still present a challenge; consequently the second contribution of this paper is a BPM sampling technique whereby large data sets can be banded.

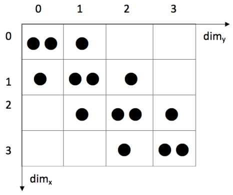

Fig. 1. $2D$ multiple dots configuration featuring a perfect banding

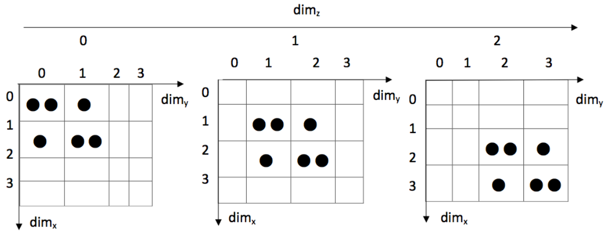

Fig. 2. $3D$ multiple dots configuration featuring a perfect banding

The concept of banded matrices, from the data analysis perspective, is significant with respect to many application domains; examples can be found in paleontology [10], network data analysis [11] and linguistics [4]. The evaluation of the proposed END BPM algorithm considered in this paper was conducted using the Great Britain (GB) cattle movement database, a government funded system managed by the Department of Environment, Food and Rural Affairs (DEFRA), introduced in 1998. The database records the movement of all cattle between locations in GB.

The contributions of this paper may thus be summarised as follows: (i) a mechanism for identifying exact banding in zero-one data sets, (ii) a mechanism for applying banding to very large data sets using a sampling technique and (iii) the application of the proposed mechanism to a real life data set. The rest of this paper is structured as follows. Section II presents a brief background review of some relevant work. Section III then presents the exact (multiple dots) banding score concept. Section IV presents the proposed END BPM algorithm that utilises the proposes exact banding score mechanism. This is followed in Section V by a worked example illustrating the operation of the END BPM algorithm in the context of a simple 2D data set that features multiple dots. Section VI then presents a description of the proposed END BPM sampling technique. The evaluation of the proposed approaches is presented in Section VII. Finally, some conclusions are given in Section VIII.

## II. Related Work

The idea of identifying banded patterns in data was first proposed in [1], [2]. Early work [1], [3] was entirely directed at finding patterns in 2D data, and focussed very much on using heuristics to identify permutations in the data. Two examples are: (i) the Minimum Banded Augmentation (MBA) algorithm [4] and (ii) the Barycentric (BC) algorithm [2].

The MBA algorithm focused on minimizing the distance of non-zero entries from the leading diagonal of a matrix by reordering the original matrix. Two variations of the MBA algorithm were proposed: "Fixed Permutation" (FP) and "Bidirectional Fixed Permutation" (BFP). The MBA-FP algorithm operated by "flipping" zero entries to one entries, while the MBA-BFP algorithm operated in a vice versa manner. Note also that MBA algorithms fixed the column permutations of the data matrix before executing the algorithms [3]. The basic idea was to solve optimally the consecutive one property on the permuted matrix $M$ and ensure that all row intervals would be pairwise overlapping, by going through all the extra rows and making them consecutive. As the fixed column permutation assumption was not a very realistic assumption with respect to many real world situations, heuristic methods were subsequently proposed in [3] to determine a suitable fixed column permutation.

The Barycentric (BC) algorithm [2] was originally proposed in the context of graph drawing, but has subsequently been used in the context of banded patterns. The BC approach produced good results, but proved difficult to scale up to encompass ND data because of the exponential increase in the number of permutations that need to be considered.

The idea proposed in this paper, as already noted, is to use a "banding score" mechanism to iteratively rearrange the elements in each dimension instead of considering large numbers of permutations. Relevant previous work with respect to the banding score idea [5], [9] has already been noted in Section I above.

## III. The Exact Banding Score Mechanism

The discovery of the presence of banding in zero-one ND data requires the rearrangement of the indexes in each dimensions, in a given data set so as to reveal a best banding (best here is defined in terms of the overall average distance of dots from the leading diagonal). The basic idea advocated in this paper is to iteratively reorder the indexes in each dimension according to an exact banding score until a "best" banding is arrived at. The exact banding score calculation mechanism, assuming the potential for more than one dot per location, is presented in this section.

Prior to considering the exact banding score mechanism a formal definition of the problem domain is required. The data space of interest is considered to comprise a set $\mathit{DIM}$ of $n$ dimensions, $\mathit{DIM} = \{dim_1, dim_2, \dots, dim_n\}$. Note that the dimensions are not necessarily of equal size. Each dimension $dim_i$ comprises a sequence of $k$ index values $\{e_{i1}, e_{i2}, \dots, e_{ik}\}$ where $i$ is the dimension identifier. The notation $e_{ij}$ thus indicates an item $e$ in dimension $dim_i$ with index $j$. Each location contains zero, one or more dots. The precise distribution of the dots depends on the nature of the application domain. Each dot (hypersphere in ND space) will be represented by a set of coordinates dimension (indexes) $\langle c_1, c_2, \dots, c_n\rangle$ (where $n$ is the number of dimensions) such that $c_1 \in dim_1$, $c_2 \in dim_2$ and so on. The challenge is then to rearrange the indexes in the dimensions so that the dots are arranged along the leading diagonal (or as close to it as possible).

The banding score $bs_{ij}$ for an index $e_{ij}$ in $DIM_i$ is calculated by first identifying the sets of locations $D_{ij}$ in the space where "dots" exist that feature index $j$ for dimension $dim_i$ ($D_{ij} = \{d_1, d_2, \dots\}$). Once the relevant set of dots has been identified the dots in $D_{ij}$ need to be weighted with respect to their proximity to the zero location in the data space (the location within the space where all indexes have the value 0) excluding the current dimension $i$. The weightings are equivalent to the distance of each dot from the origin. The set of weightings is given by $W_{ij} = \{w_1, w_2, \dots\}$ such that there is a one to one correspondence between the items in the set $W_{ij}$ and the set $D_{ij} = \{d_1, d_2, \dots\}$. The calculation of the weightings can be done using a number of mechanisms; the simplest and most natural, and that which was used with respect to this paper, is Euclidean distance. Thus the weighting $e_k$ for a dot at location $d_k$ will be given by:

$$w = \sqrt{\sum_{i=1}^{i=n, i!=j} (c_i)^2} \tag{1}$$

An alternative is to use Manhattan distance which, although not as precise, requires less computation.

To take into consideration the number of dots at each location we also contrive a set $Q_{ij} = \{q_1, q_2, \dots\}$ where $q_k$ holds a "number of dots" value. There is a one-to-one correspondence between $Q_{ij}$ and $D_{ij}$ (and consequently $W_{ij}$); thus $q_1$ corresponds to $d_1$, $q_2$ to $d_2$ ad so on.

The banding score $bs_{ij}$ for index $e_{ij}$ in $DIM_i$ is calculated by summing the distances, each multiplied by the appropriate $q_k$ value, and normalising this by dividing by the maximum possible value for the current configuration. More specifically:

$$bs_{ij} = \frac{\sum_{p=1}^{p=|W_{ij}|} w_p * Q_p}{\sum_{q=1}^{q=|M_{ij}|} m_q * Q'_q} \tag{2}$$

where: (i) $W_{ij}$ is the set of weightings calculated as described above; (ii) $Q$ is the corresponding set of location quantities (see above); (iii) $M_{ij}$ is the set of *maximum weightings* corresponding to the number of dots in $D_{ij}$, $M_{ij} = \{m_1, m_2, \dots\}$ ($|M_{ij}| = |D_{ij}|$), in descending order; and (iv) $Q'_q$ is the the set of location quantities $Q$ but in descending order. The calculation of the values for $M$ should be done using the same mechanism as used to calculate the values for $W$, thus Euclidean distance on the context of this paper. Note that the calculation of maximum weightings will need to be done repeatedly for each index $j$ in each dimension $dim_i$, thus it is expedient to do these calculations once and store them in a "maximum weighting table". Thus, given the above, if every location with index $j$ in a dimension $i$ is filled with a single dot the banding score $bs_{ij}$ will be 1.0 (the maximum banding score), if there is only a dot at the origin the banding score will be 0.0 (the minimum banding score).

Once we have the banding scores for for all indexes $j$ in a dimension $i$ we can rearrange the indexes in ascending order of banding score. We can then repeat this operation for the next dimension and so on. Once all the dimensions have been rearranged in this manner we can calculate a global banding score, $gbs$, for the resulting configuration by calculating the global banding score:

$$gbs = \frac{\sum_{i=1}^{i=|DIM|} \sum_{j=1}^{j=|dim_i|} bs_{ij}}{\sum_{k=1}^{k=|DIM|} |dim_k|} \tag{3}$$

Having rearranged all the indexes in all the dimensions once, does not necessarily mean that we have arrived at a best banding score. We can therefore repeat the entire operation and continue to do so until the $gbs$ value has been maximised (or some maximum number of iterations has been reached).

## IV. The Exact BD Banded Pattern Mining (END BPM) Algorithm

The END BPM algorithm is presented in Algorithm 1. Note that the algorithm includes an input value $max$, this is used to set a limit on the number of iterations. After each iteration of the entire data space the current global banding score, $gbs'$, is calculated (line 18), and compared with the global banding score attained so far (line 19). If $gbs'$ is greater than $gbs$ we exit with the configuration from the previous iteration (line 20). Otherwise we set $gbs$ to $gbs'$ (line 22), and $DIM$ to $DIM'$ (line 23), and repeat. We continue in this manner until a best $gbs$ value is arrived at or the pre-specified maximum number of iterations is reached. The result is the data space $D$ reconfigured according to the redefined set $DIM$.

## V. Worked Example

The operation of the proposed END BPM algorithm is illustrated in the section using a worked example. Given the 2 dimensional 4 × 4 configuration given in Figure 3; the configuration features $Dim = \{x, y\}$, $dim_x = \{0, 1, 2, 3\}$ and $dim_y = \{0, 1, 2, 3\}$ with multiple dots in some cells. The input $D$ to the END BPM algorithm is thus:

$$D = \{\langle 0,0\rangle, \langle 0,1\rangle, \langle 0,1\rangle, \langle 0,1\rangle, \langle 0,1\rangle, \langle 0,2\rangle, \langle 0,3\rangle, \langle 1,1\rangle, \\ \langle 1,2\rangle, \langle 1,2\rangle, \langle 1,2\rangle, \langle 1,3\rangle, \langle 2,0\rangle, \langle 2,3\rangle, \langle 2,3\rangle, \langle 3,0\rangle\}.$$

**Algorithm 1** The END BPM Algorithm

```
 1: Input
 2: $D$ = Binary valued input data set
 3: $DIM$ = The set of indexes, one set per dimension
 4: $max$ = The maximum number of iterations
 5: Output
 6: $D'$ = The original data set $D$ rearranged so as to display
          as near a banding as possible

 7: $gbs = 1$ (The global banding score so far)
 8: $counter = 0$
 9: while $counter < max$ do
10:   for all $dim_i \in DIM$ do
11:     for $j = 1$ to $j = |dim_i|$ do
12:       $bs_{ij}$ = Banding score for element $j$ in $|dim_i|$
              calculated using Equation 2
13:     end for
14:     $dim'_i$ = The set $dim_i$ rearranged according to the
              calculated $bs$ (in ascending order)
15:   end for
16:   $DIM' = \{dim'_1, dim'_2, \dots, dim'_n\}$
17:   $D'$ = Data set $D$ rearranged according to $DIM'$
18:   $gbs'$ = gbs for $DIM'$ calculated using Equation 3
19:   if $gbs' > gbs$ then
20:     break
21:   else
22:     $gbs = gbs'$
23:     $DIM = DIM'$
24:     $D = D'$
25:   end if
26:   $counter = counter + 1$
27: end while
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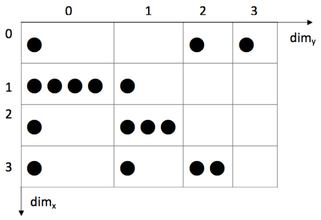


Fig. 3. Input "Dot matrix" for worked example

Considering dimension $x$ first, we calculate the banding scores (taking into account the number of dots per location) using Equation 2. This produces the banding scores 0.60, 0.83, 0.75 and 0.00, calculated as shown in Table I. We thus rearrange the elements in $dim_x$ in ascending order of their banding scores to produce the result shown in Figure 4.

$$D = \{\langle 0,0\rangle, \langle 1,0\rangle, \langle 1,1\rangle, \langle 1,1\rangle, \langle 1,1\rangle, \langle 1,1\rangle, \langle 1,2\rangle, \langle 1,3\rangle, \\ \langle 2,0\rangle, \langle 2,3\rangle, \langle 2,3\rangle, \langle 3,1\rangle, \langle 3,2\rangle, \langle 3,2\rangle, \langle 3,2\rangle, \langle 3,3\rangle\}.$$

Considering dimension $y$ next, we calculate the banding scores as shown in Table II. This produces the banding scores 0.50, 0.50, 0.91 and 0.89. The elements in $y$ are more or less already in ascending order of $bs$; we only need to swap the last two elements (the effect is that the index with the greater number of dots is moved to be nearer the centre of the data space). The result is as shown in Figure 5. We now have:

| # Element | Dist from origin | Max. dist. from origin | $bs$ |
|---|---|---|---|
| 0 | $(0*1)+(1*4)$<br>$+(2*1)+(3*1)$<br>$=9.0$ | $(0*1)+(1*1)$<br>$+(2*1)+(3*4)$<br>$=15.0$ | 0.60 |
| 1 | $(1*1)+(2*3)$<br>$+(3*1)=10.0$ | $(1*1)+(2*1)$<br>$+(3*3)=12.0$ | 0.83 |
| 2 | $(0*1)+(3*2)$<br>$=6.0$ | $(2*1)+(3*2)$<br>$=8.0$ | 0.75 |
| 3 | $(0*1)=0.0$ | $((3*1)=3.0$ | 0.00 |
|  |  | Total | 2.18 |

TABLE I. CALCULATION OF BANDING SCORES FOR DIMENSION $x$ (ITERATION 1)

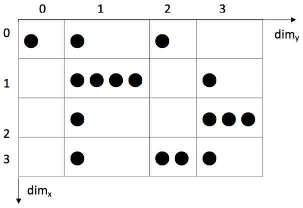


Fig. 4. Dot matrix after rearrangement of $dim_x$ (iteration 1)

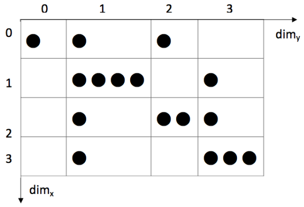


Fig. 5. Dot matrix after rearrangement of $dim_y$ (iteration 1)

$$D' = \{\langle 0,0\rangle, \langle 1,0\rangle, \langle 1,1\rangle, \langle 1,1\rangle, \langle 1,1\rangle, \langle 1,1\rangle, \langle 1,2\rangle, \langle 1,3\rangle, \langle 2,0\rangle, \langle 2,2\rangle, \langle 2,2\rangle, \langle 3,1\rangle, \langle 3,2\rangle, \langle 3,3\rangle, \langle 3,3\rangle, \langle 3,3\rangle\}.$$

The $gbs$ for this configuration is then calculated using Equation 3 (the sum of the individual banding scores divided by the total number of indexes in the configuration):

$$gbs' = \frac{0.0}{3.0} + \frac{9.0}{15.0} + \frac{6.0}{8.0} + \frac{10.0}{12.0} +$$

$$\frac{3.0}{6.0} + \frac{7.0}{14.0} + \frac{8.0}{9.0} + \frac{10.0}{11.0} = 0.6122$$

$gbs' \leq gbs$ ($gbs$ was set to 1 on start up) thus $gbs = gbs'$ and $D = D'$.

The process is then repeated because we have reduced the $gbs$ value and because the maximum number of iterations has not yet been reached. Thus the new banding scores $0.00$, $0.60$, $0.50$ and $1.00$ are produced for dimension $x$ calculated as shown in Table III, and we rearrange the elements in $x$ accordingly; the result is as shown in Figure 6. Similarly, the new banding scores $0.50$, $0.79$, $0.78$ and $1.00$ are produced for dimension $y$ calculated as shown in Table IV, as a result the elements in $y$ rearranged accordingly. The result is as shown in Figure 7 (we only needed to swap the second and third indexes). We now have:

$$D' = \{\langle 0,0\rangle, \langle 1,0\rangle, \langle 1,2\rangle, \langle 1,2\rangle, \langle 2,0\rangle, \langle 2,1\rangle, \langle 2,1\rangle, \langle 2,1\rangle, \langle 2,1\rangle, \langle 2,2\rangle, \langle 2,3\rangle, \langle 3,1\rangle, \langle 3,2\rangle, \langle 3,3\rangle, \langle 3,3\rangle, \langle 3,3\rangle\}.$$

| # Element | Dist from origin | Max. dist. from origin | $bs$ |
|---|---|---|---|
| 0 | $(0*1)+(1*1)$<br>$+(2*1)=3.0$ | $(1*1)+(2*1)$<br>$+(3*1)=6.0$ | 0.50 |
| 1 | $(1*4)+(3*1)$<br>$=7.0$ | $(2*1)+(3*4)$<br>$=14.0$ | 0.50 |
| 2<br>2 | $(1*1)+(3*3)$<br>$=10.0$ | $(2*1)+(3*3)$<br>$=11.0$ | 0.91 |
| 3 | $(1*1)+(2*2)$<br>$+(3*1)=8.0$ | $(1*1)+(2*1)$<br>$+(3*2)=9.0$ | 0.89 |
|  |  | Total | 2.80 |

TABLE II. CALCULATION OF BANDING SCORES FOR DIMENSION $y$ (ITERATION 1)

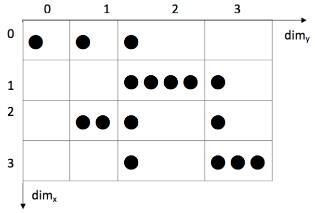


Fig. 6. Dot matrix after rearrangement of $dim_x$ (iteration 2)

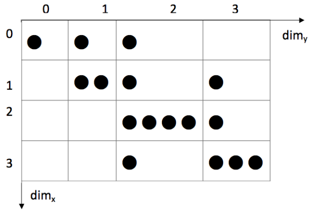


Fig. 7. Dot matrix after rearrangement of $dim_y$ (iteration 2)

The new $gbs'$ value is calculated as follows:

$$gbs = \frac{0.0}{3.0} + \frac{4.0}{8.0} + \frac{9.0}{15.0} + \frac{12.0}{12.0} +$$

$$\frac{3.0}{6.0} + \frac{7.0}{9.0} + \frac{11.0}{14.0} + \frac{11.0}{11.0} = 0.6392$$

The $gbs' = 0.6392$ is greater (worse) than the previously calculated value of $gbs = 0.6122$, so the algorithm exits with $D$ from the previous iteration.

$$D = \{\langle 0,0\rangle, \langle 1,0\rangle, \langle 1,1\rangle, \langle 1,1\rangle, \langle 1,1\rangle, \langle 1,1\rangle, \langle 1,2\rangle, \langle 1,3\rangle, \langle 2,0\rangle, \langle 2,2\rangle, \langle 2,2\rangle, \langle 3,1\rangle, \langle 3,2\rangle, \langle 3,3\rangle, \langle 3,3\rangle, \langle 3,3\rangle\}.$$

## VI. END BPM WITH SAMPLING

The END BPM algorithm works well and, as will be demonstrated in the evaluation section presented later in this paper, produces a better banding than the MBA-FP and MBA-BFP [4] and BC [2] algorithms. However, processing large data sets (data sets that will not fit into primary storage) remains a challenge, especially when the data sets under consideration comprised four or more dimensions. The proposed solution is to adopt a sampling technique where we identify a best banding using a subset $S$ of the dot records in $D$ as shown in algorithm 2. The challenge when using sampling is to select an appropriately representative subset of the original dataset. From the literature we can identify a number of different sampling techniques; however, with respect to the evaluation

| # Element | Dist from origin | Max. dist. from origin | $bs$ |
|---|---|---|---|
| 0 | $(0*1) = 0.0$ | $(3*1) = 3.0$ | 0.00 |
| 1 | $(0*1) + (1*4)$<br>$+(2*1) + (3*1)$<br>$= 9.0$ | $(0*1) + (1*1)$<br>$+(2*1) + (3*4)$<br>$= 15.0$ | 0.60 |
| 2 | $(0*1) + (2*2)$<br>$= 4.0$ | $(1*2) + (3*2)$<br>$= 8.0$ | 0.50 |
| 3 | $(1*1) + (2*1)$<br>$(3*3) = 12.0$ | $(1*1) + (2*1)$<br>$(3*3) = 12.0$ | 1.00 |
|  |  | Total | 2.10 |

TABLE III. CALCULATION OF BANDING SCORES FOR DIMENSION $x$ (ITERATION 2)

| # Element | Dist from origin | Max. dist. from origin | $bs$ |
|---|---|---|---|
| 0 | $(0*1) + (1*1)$<br>$+(2*1) = 3.0$ | $(1*1) + (2*1)$<br>$+(3*1) = 6.0$ | 0.50 |
| 1 | $(2*4) + (3*1)$<br>$= 11.0$ | $(2*1) + (3*4)$<br>$= 14.0$ | 0.79 |
| 2 | $(1*2) + (2*1)$<br>$+(3*1) = 7.0$ | $(1*1) + (2*1)$<br>$+(3*2) = 9.0$ | 0.78 |
| 3 | $(2*1) + (3*3)$<br>$= 11.0$ | $(2*1) + (3*3)$<br>$= 11.0$ | 1.00 |
|  |  | Total | 3.07 |

TABLE IV. CALCULATION OF BANDING SCORES FOR DIMENSION $y$ (ITERATION 2)

presented later in this work we have adopted a stratified sampling technique [12], [13] where we divide up the data sets into subgroups and select records from each subgroup.

**Algorithm 2** END BPM with Samplimg Algorithm

```
Input
$D =$ Binary valued input data set
$DIM =$ the set of indexes per dimension
$max =$ The maximum number of iterations
Output
$D' =$ The original data set $D$ rearranged so as to display
        as near a banding as possible and $gbs'$

$S =$ A subset of records from $D$
$S' = end\_bpmAlgorith(S, DIM, max)$ (Algorithm 1)
$D' =$ Data set $D$ rearranged according to $S'$
$gbs' =$ Final global banding score calculated using
        Equation 3
```

## VII. EVALUATION

This section presents an evaluation and discussion of the proposed END BPM algorithm with and without sampling. All the reported experiments were conducted using data extracted from the Great Britain (GB) Cattle Tracking System (CTS). This system is therefore described in Sub-section VII-A. All experiments were run using an iMac running OSX with 16 GB Memory and a 2.7 GHz Intel Core i5 Processor. The algorithms were implemented in JAVA. The first set of reported experiments, presented in Sub-section VII-B, compared the operation of the END BPM algorithm with the AND BPM [5], MBA-FP and MBA-BFP [4] and the BC [2] algorithms from the literature (see Section II). Because MBA-FP, MBA-BFP and BC were designed with respect to 2D data, the comparison was conducted in the 2D context. The second set of reported experiments, presented in Sub-section VII-C compared the operation of the END BPM algorithm with the AND BPM in the context of large ND data. The third set of reported experiments considered the application of the END BPM sampling algorithm in the context of large ND data. The results obtained from these experiments are presented in Sub-section VII-D. To determine the quality of a banding an independent measure was used, as opposed to $gbs$ or the measures used by the MBA-FP, MBA-BFP and BC algorithms, namely the average distance of dots from the leading diagonal; we refer to this as the AD measure.

### A. The GB Cattle Tracking System

The GB CTS was setup in 1998 in response to a cattle disease outbreak. The system is maintained by the British Cattle Movement Service (BCMS), a branch of the UK Department of Environment, Food and Rural Affairs (DEFRA). Central to the system is the cattle movement database which records all movement of cattle in GB. The database can be conveniently divided into blocks of one month, each comprising some 100MB of data. The database features details concerning the "sender" location, "receiver" location and the animal moved. The data can thus be divided according to the geogrphic location of the sender or receiver; for the evaluation presented here we used the counties in which individual senders were located. The database describes individual cattle movements, but cattle are typically moved in batches. Therefore we collapsed records describing cattle movements that occurred on the same day, and with respect to the same sender and receiver locations and the same breed of cattle. To do this we added an extra attribute "number of animal moved". For the evaluation presented here datasets for the years 2003 to 2006 were used.

For the 2D evaluation, presented in Sub-section VII-B below, we only used the CTS data for the year 2003. The two dimensions were *attributes* and *records*. In total 16 data sets were generated by considering only four counties (Aberdeenshire, Cornwall, Lancashire and Norfolk) and dividing the year into four quarters. The datasets each comprised six attributes: (i) animal gender, (ii) animal age, (iii) cattle type (dairy or beef), (iv) the "type" of the sender location, (v) the "type" of the receiver location and (vi) the number of cattle moved. These were either nominal or continuously valued attributes and thus had to be translated into a zero-one format. This was done using the LUCS-KDD ARM DN discretisation-normalisation software[1]. Some statistics concerning this data set are presented in Table V.

For the large scale study presented in Sub-section VII-D, we constructed 3D, 4D and 5D data sets from the CTS database, featuring the four counties considered in the previous experiments. In the case of the 3D data set the three dimensions were: (i) records and (ii) attributes (as for the 2D data sets) and (iii) time in months. For the 4D data sets the four dimensions were: (i) records, (ii) attributes (as for the 2D data sets), (iii) eastings and (iv) northings. For the 5D data set the dimensions were: (i) records, (ii) attributes, (iii) eastings, (iv) northings and (v) time in months. The eastings and northings were discretised into 10 ranges. Some statistics concerning this data set are presented in Tables VI , VII and VIII. To construct the sample set $S$ we considered the individual months across the four identified counties. This gave us $12 \times 4 \times 4 = 192$ data subsets from which we randomly selected 2000 records per subset to give our 3D, 4D and 5D sample sets comprising 24000 records each ($192 \times 24000 = 4,608,000$). Some statistics concerning

[1] http://www.csc.liv.ac.uk/~/KDD/Software/LUCS_KDD_DN_ARM.

this sample data sets are presented in Tables IX, X and XI respectively.

It should perhaps also be noted here that there have been a number of previous studies directed at the CTS database. Green and Kao [14] conducted an analysis of the CTS database confirming that as the distance between holding area locations increases the number of movement records decreases. Also Puteri et al [15] confirmed that by applying trend mining techniques to the CTS data, when envisioned in terms of a social network, trends describing cattle movement across time and geographcal space could be identified. Robinson and Christley [16] also identify a number of trends in the CTS database, demonstrating that the UK cattle population are in constant flux.

TABLE V. NUMBER RECORDS PER CTS DATA SET USED FOR THE 2D EVALUATION PRESENTED IN SUB-SECTION VII-B

| Counties | Q1 | Q2 | Q3 | Q4 |
|---|---|---|---|---|
| Abd | 42962 | 46187 | 41181 | 47842 |
| Corn | 40501 | 39626 | 40226 | 49890 |
| Lanc | 34325 | 40926 | 45276 | 47392 |
| Norf | 11526 | 14311 | 9460 | 11680 |

TABLE VI. NUMBER OF ITEMS (INDEXES) PER DIMENSION FOR THE 16 3D CTS DATA SETS

| Counties | Years | # Recs. | # Atts. | # Time |
|---|---|---|---|---|
| Aberdeenshire | 2003 | 178172 | 95 | 12 |
| | 2004 | 173612 | 95 | 12 |
| | 2005 | 157033 | 95 | 12 |
| | 2006 | 236206 | 95 | 12 |
| Cornwall | 2003 | 170243 | 98 | 12 |
| | 2004 | 169053 | 98 | 12 |
| | 2005 | 154569 | 98 | 12 |
| | 2006 | 167281 | 98 | 12 |
| Lancashire | 2003 | 167919 | 94 | 12 |
| | 2004 | 217566 | 94 | 12 |
| | 2005 | 157142 | 94 | 12 |
| | 2006 | 196292 | 94 | 12 |
| Norfolk | 2003 | 46977 | 95 | 12 |
| | 2004 | 46246 | 95 | 12 |
| | 2005 | 35914 | 95 | 12 |
| | 2006 | 45150 | 95 | 12 |

TABLE VII. NUMBER OF ITEMS PER DIMENSION FOR THE 16 4D CTS DATA SETS

| Counties | Years | # Recs. | # Atts. | # Eings. | # Nings. |
|---|---|---|---|---|---|
| Aberdeenshire | 2003 | 178172 | 95 | 10 | 10 |
| | 2004 | 173612 | 95 | 10 | 10 |
| | 2005 | 157033 | 95 | 10 | 10 |
| | 2006 | 236206 | 95 | 10 | 10 |
| Cornwall | 2003 | 170243 | 98 | 10 | 10 |
| | 2004 | 169053 | 98 | 10 | 10 |
| | 2005 | 154569 | 98 | 10 | 10 |
| | 2006 | 167281 | 98 | 10 | 10 |
| Lancashire | 2003 | 167919 | 94 | 10 | 10 |
| | 2004 | 217566 | 94 | 10 | 10 |
| | 2005 | 157142 | 94 | 10 | 10 |
| | 2006 | 196292 | 94 | 10 | 10 |
| Norfolk | 2003 | 46977 | 95 | 10 | 10 |
| | 2004 | 46246 | 95 | 10 | 10 |
| | 2005 | 35914 | 95 | 10 | 10 |
| | 2006 | 45150 | 95 | 10 | 10 |

### B. 2D Study and Comparison

For the 2D experiments we recorded the AD measure and the runtime. In each case we set the $max$ value to 10. The results are presented in Tables XII and XIII. In Table XII both the AD independent metric and the $gbs$ metric are reported. Inspection of Table XII indicates that the END BPM and AND BPM algorithm produces better $gbs$ values (note that the best $gbs$ value is 1.0) and AD results than the other banding algorithms considered. In Table XIII the run time (in seconds) is presented. From this table it can clearly be see that the MBA-BFP, MBA-FP and BC algorithms require considerably more processing time than the proposed END BPM algorithm and the existing approximate AND BPM algorithm. The AND

TABLE VIII. NUMBER OF ITEMS PER DIMENSION FOR THE 16 5D CTS DATA SETS

| Counties | Years | # Recs. | # Atts. | # Eings. | # Nings. | # Time |
|---|---|---|---|---|---|---|
| Aberdeenshire | 2003 | 178172 | 95 | 10 | 10 | 12 |
| | 2004 | 173612 | 95 | 10 | 10 | 12 |
| | 2005 | 157033 | 95 | 10 | 10 | 12 |
| | 2006 | 236206 | 95 | 10 | 10 | 12 |
| Cornwall | 2003 | 170243 | 98 | 10 | 10 | 12 |
| | 2004 | 169053 | 98 | 10 | 10 | 12 |
| | 2005 | 154569 | 98 | 10 | 10 | 12 |
| | 2006 | 167281 | 98 | 10 | 10 | 12 |
| Lancashire | 2003 | 167919 | 94 | 10 | 10 | 12 |
| | 2004 | 217566 | 94 | 10 | 10 | 12 |
| | 2005 | 157142 | 94 | 10 | 10 | 12 |
| | 2006 | 196292 | 94 | 10 | 10 | 12 |
| Norfolk | 2003 | 46977 | 95 | 10 | 10 | 12 |
| | 2004 | 46246 | 95 | 10 | 10 | 12 |
| | 2005 | 35914 | 95 | 10 | 10 | 12 |
| | 2006 | 45150 | 95 | 10 | 10 | 12 |

TABLE IX. NUMBER OF SAMPLED DATA ITEMS PER DIMENSION FOR THE 16 3D CTS DATA SETS

| Counties | Years | # Recs. | # Atts. | # Time |
|---|---|---|---|---|
| Aberdeenshire | 2003 | 24000 | 95 | 12 |
| | 2004 | 24000 | 95 | 12 |
| | 2005 | 24000 | 95 | 12 |
| | 2006 | 24000 | 95 | 12 |
| Cornwall | 2003 | 24000 | 98 | 12 |
| | 2004 | 24000 | 98 | 12 |
| | 2005 | 24000 | 98 | 12 |
| | 2006 | 24000 | 98 | 12 |
| Lancashire | 2003 | 24000 | 94 | 12 |
| | 2004 | 24000 | 94 | 12 |
| | 2005 | 24000 | 94 | 12 |
| | 2006 | 24000 | 94 | 12 |
| Norfolk | 2003 | 24000 | 95 | 12 |
| | 2004 | 24000 | 95 | 12 |
| | 2005 | 24000 | 95 | 12 |
| | 2006 | 24000 | 95 | 12 |

TABLE X. NUMBER OF SAMPLED DATA ITEMS PER DIMENSION FOR THE 16 4D CTS DATA SETS

| Counties | Years | # Recs. | # Atts. | # Eings. | # Nings. |
|---|---|---|---|---|---|
| Aberdeenshire | 2003 | 24000 | 95 | 10 | 10 |
| | 2004 | 24000 | 95 | 10 | 10 |
| | 2005 | 24000 | 95 | 10 | 10 |
| | 2006 | 24000 | 95 | 10 | 10 |
| Cornwall | 2003 | 24000 | 98 | 10 | 10 |
| | 2004 | 24000 | 98 | 10 | 10 |
| | 2005 | 24000 | 98 | 10 | 10 |
| | 2006 | 24000 | 98 | 10 | 10 |
| Lancashire | 2003 | 24000 | 94 | 10 | 10 |
| | 2004 | 24000 | 94 | 10 | 10 |
| | 2005 | 24000 | 94 | 10 | 10 |
| | 2006 | 24000 | 94 | 10 | 10 |
| Norfolk | 2003 | 24000 | 95 | 10 | 10 |
| | 2004 | 24000 | 95 | 10 | 10 |
| | 2005 | 24000 | 95 | 10 | 10 |
| | 2006 | 24000 | 95 | 10 | 10 |

TABLE XI. NUMBER OF SAMPLED DATA ITEMS PER DIMENSION FOR THE 16 5D CTS DATA SETS

| Counties | Years | # Recs. | # Atts. | # Eings. | # Nings. | # Time |
|---|---|---|---|---|---|---|
| Aberdeenshire | 2003 | 24000 | 95 | 10 | 10 | 12 |
| | 2004 | 24000 | 95 | 10 | 10 | 12 |
| | 2005 | 24000 | 95 | 10 | 10 | 12 |
| | 2006 | 24000 | 95 | 10 | 10 | 12 |
| Cornwall | 2003 | 24000 | 98 | 10 | 10 | 12 |
| | 2004 | 24000 | 98 | 10 | 10 | 12 |
| | 2005 | 24000 | 98 | 10 | 10 | 12 |
| | 2006 | 24000 | 98 | 10 | 10 | 12 |
| Lancashire | 2003 | 24000 | 94 | 10 | 10 | 12 |
| | 2004 | 24000 | 94 | 10 | 10 | 12 |
| | 2005 | 24000 | 94 | 10 | 10 | 12 |
| | 2006 | 24000 | 94 | 10 | 10 | 12 |
| Norfolk | 2003 | 24000 | 95 | 10 | 10 | 12 |
| | 2004 | 24000 | 95 | 10 | 10 | 12 |
| | 2005 | 24000 | 95 | 10 | 10 | 12 |
| | 2006 | 24000 | 95 | 10 | 10 | 12 |

BPM algorithm is faster because, as the name suggests, it makes approximations in the banding calculation that do not manifest themselves unless considering 3D data and above. The main point to note here is that the proposed END BPM and AND BPM algorithm produces better bandings than the MBA-BFP, MBA-FP and BC algorithms.

TABLE XIII. RUNTIME (IN SECONDS) FOR THE FIVE BANDING MECHANISMS CONSIDERED (BEST TIMES IN BOLD FONT)

| Data Set | END BPM | AND BPM | MBA-FP | MBA-BFP | BC |
|---|---|---|---|---|---|
| 42962 | **30.40** | **28.74** | 64.59 | 60.62 | 51.36 |
| 46187 | **52.32** | **51.17** | 76.77 | 65.40 | 54.60 |
| 41181 | **26.48** | **25.89** | 62.42 | 59.41 | 43.74 |
| 47842 | **35.03** | **34.98** | 79.31 | 75.46 | 61.94 |
| 40501 | **24.95** | **23.00** | 56.69 | 60.31 | 41.36 |
| 39626 | **13.27** | **12.55** | 64.01 | 56.88 | 39.80 |
| 40226 | **28.61** | **26.82** | 62.42 | 60.84 | 40.10 |
| 49890 | **47.50** | **47.03** | 89.17 | 82.54 | 61.15 |
| 34325 | **19.61** | **18.62** | 49.31 | 50.34 | 21.76 |
| 40926 | **27.99** | **26.17** | 58.08 | 60.08 | 34.61 |
| 45276 | **41.39** | **40.53** | 75.61 | 69.78 | 46.57 |
| 47392 | **43.83** | **42.86** | 77.91 | 78.97 | 50.69 |
| 11526 | **02.77** | **02.54** | 09.92 | 10.47 | 03.85 |
| 14311 | **03.26** | **02.27** | 13.84 | 12.68 | 05.34 |
| 9460 | **02.03** | **01.98** | 07.89 | 07.85 | 02.86 |
| 11680 | **02.66** | **02.60** | 10.42 | 10.44 | 03.53 |

### *C. Comparison Between END BPM and AND BPM Algorithms*

This subsection presents evaluation of the proposed END BPM in comparison with the AND BPM algorithms, in terms of *gbs* values and run-times, using 16 datasets from the GB cattle movement in context of 3D dataset banded in terms of 2D, 4D dataset banded in terms of 3D and 5D dataset banded in terms of 4D. Table XIV and Table XV reports the *gbs* values (here the best *gbs* value is 0.0) and the run time (in seconds). From Table XIV, the result confirms that the END BPM algorithm is more accurate than the AND BPM algorithm. Although in terms of run-time presented in Table XV, the result shows that the END BPM algorithm is slower than the AND BPM algorithm. Note that as stated in Subsection VII-B, the AND BPM algorithm makes approximation banding calculation that manifest only when considering 3D datasets and above. Table XIV, confirms that the *gbs* values for the 3D dataset banded in terms of 2D are the same for END BPM and the AND BPM algorithms. However in the case of the 4D and 5D datasets, the result shows that the AND BPM algorithm produce the worst gbs values.

TABLE XIV. ND BANDING RESULTS, IN TERMS OF *gbs*, FOR THE END BPM AND AND BPM ALGORITHMS CONSIDERED

| Counties / | END BPM | | | AND BPM | | |
|---|---|---|---|---|---|---|
| Year id | $3D$ | $4D$ | $5D$ | 3D | 4D | 5D |
| **Aberdeenshire** | gbs | gbs | gbs | gbs | gbs | gbs |
| 2003 | **0.3770** | **0.2929** | **0.2352** | 0.3770 | 0.4006 | 0.4226 |
| 2004 | **0.3686** | **0.2420** | **0.2027** | 0.3686 | 0.3526 | 0.3814 |
| 2005 | **0.3869** | **0.3113** | **0.2496** | 0.3869 | 0.4155 | 0.4470 |
| 2006 | **0.3670** | **0.2397** | **0.2002** | 0.3670 | 0.3449 | 0.3780 |
| **Cornwall** | | | | | | |
| 2003 | **0.4039** | **0.2911** | **0.2401** | 0.4039 | 0.4180 | 0.4426 |
| 2004 | **0.3944** | **0.3181** | **0.2178** | 0.3944 | 0.3743 | 0.4050 |
| 2005 | **0.3696** | **0.2730** | **0.2271** | 0.3696 | 0.3943 | 0.4175 |
| 2006 | **0.3886** | **0.3081** | **0.2520** | 0.3886 | 0.4336 | 0.4554 |
| **Lancashire** | | | | | | |
| 2003 | **0.4105** | **0.2947** | **0.2434** | 0.4105 | 0.4199 | 0.4429 |
| 2004 | **0.3593** | **0.2817** | **0.2384** | 0.3593 | 0.3959 | 0.4179 |
| 2005 | **0.3974** | **0.2940** | **0.2456** | 0.3974 | 0.4142 | 0.4437 |
| 2006 | **0.3970** | **0.2847** | **0.2382** | 0.3970 | 0.4071 | 0.4369 |
| **Norfolk** | | | | | | |
| 2003 | **0.4265** | **0.3095** | **0.2716** | 0.4265 | 0.4575 | 0.4696 |
| 2004 | **0.3607** | **0.2820** | 0.2350 | 0.3607 | 0.4005 | 0.4266 |
| 2005 | **0.4058** | **0.3215** | **0.2572** | 0.4058 | 0.4422 | 0.4540 |
| 2006 | **0.3802** | **0.2566** | **0.2134** | 0.3802 | 0.3634 | 0.3948 |

TABLE XV. RUNTIME (IN SECONDS) FOR THE END BPM AND AND BPM ALGORITHMS CONSIDERED

| Counties / | END BPM | | | AND BPM | | |
|---|---|---|---|---|---|---|
| Year id | $3D$ | $4D$ | $5D$ | 3D | 4D | 5D |
| **Aberdeenshire** | RT | RT | RT | RT | RT | RT |
| 2003 | 01.58 | 02.68 | 24.69 | **01.05** | **01.47** | **09.97** |
| 2004 | 01.92 | 01.92 | 26.93 | **01.35** | **01.39** | **12.41** |
| 2005 | 01.85 | 02.95 | 15.66 | **01.57** | **01.61** | **09.19** |
| 2006 | 01.48 | 01.79 | 18.41 | **01.30** | **01.42** | **07.41** |
| **Cornwall** | | | | | | |
| 2003 | 01.51 | 01.71 | 24.09 | **01.02** | **01.38** | **09.61** |
| 2004 | 02.55 | 03.41 | 35.62 | **01.92** | **01.74** | **19.61** |
| 2005 | 01.53 | 02.90 | 27.43 | **01.34** | **02.19** | **11.92** |
| 2006 | 02.27 | 06.01 | 41.89 | **01.06** | **02.40** | **25.41** |
| **Lancashire** | | | | | | |
| 2003 | 01.59 | 02.97 | 55.19 | **01.26** | **02.07** | **30.02** |
| 2004 | 01.48 | 02.91 | 39.29 | **01.06** | **02.15** | **19.09** |
| 2005 | 01.57 | 02.62 | 29.11 | **01.30** | **01.87** | **17.84** |
| 2006 | 01.62 | 02.43 | 28.31 | **01.20** | **02.37** | **17.49** |
| **Norfolk** | | | | | | |
| 2003 | 01.17 | 05.09 | 20.84 | **01.01** | **02.24** | **10.72** |
| 2004 | 02.99 | 05.94 | 80.20 | **01.00** | **03.41** | **27.99** |
| 2005 | 01.15 | 02.16 | 16.41 | **00.95** | **01.74** | **11.66** |
| 2006 | 01.52 | 01.83 | 17.92 | **01.00** | **01.29** | **10.99** |

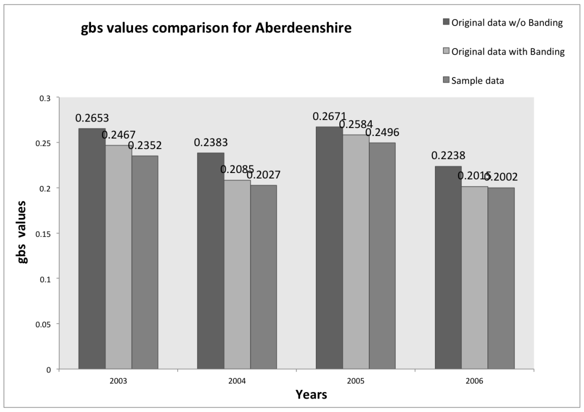
### *D. ND Study and Comparison*

This subsection presents an evaluation of the END BPM algorithm in terms of ND data, and in terms of sampling. With respect to the ND experiments using sampling it should be noted that it does not make sense to reorder the records dimension as we are segmenting the data according to this dimension. Thus banding was applied to remaining dimensions in the sample, hence the 3D data set was banded in terms of 2D, the 4D data set in terms of 3D, and so on. Consequently, it is entirely possible to have more than one dot per location hence the multiple dot banding score mechanism presented in Section III (note that the banding mechanism will work equally well where we have data sets with a maximum of one dot per location).

The results obtained from the ND experiments are presented in Tables XVI and XVII. In Table XVI, the *gbs* metric is reported and in Table XVII, the run time (in seconds) is presented. In this case, to determine the effectiveness of END

TABLE XII. 2D BANDING EVALUATION RESULTS IN TERMS OF AD AND $gbs$, FOR THE FIVE BANDING MECHANISMS CONSIDERED (BEST RESULTS IN BOLD FONT)

| Data | END BPM | | AND BPM | | MBA-FP | | MBA-BFP | | BC | |
|---|---|---|---|---|---|---|---|---|---|---|
| Set | AD | gbs | AD | gbs | AD | gbs | AD | gbs | AD | gbs |
| 42962 | **0.9995** | **0.7762** | **0.9995** | **0.7717** | 0.9996 | 0.7076 | 1.0000 | 0.7266 | 0.9998 | 0.6756 |
| 46187 | **0.9996** | **0.7463** | **0.9996** | **0.7267** | 0.9999 | 0.7085 | 1.0000 | 0.7068 | 0.9998 | 0.6575 |
| 41181 | **0.9995** | **0.7675** | **0.9995** | **0.7447** | 0.9996 | 0.6867 | 1.0000 | 0.7267 | 0.9997 | 0.6508 |
| 47842 | **0.9995** | **0.7696** | **0.9995** | 0.7395 | 0.9999 | 0.7285 | 1.0000 | 0.6307 | 0.9997 | 0.6652 |
| 40501 | **0.9994** | **0.7711** | **0.9994** | **0.7666** | 0.9995 | 0.6781 | 0.9998 | 0.7438 | 0.9996 | 0.6972 |
| 39626 | **0.9993** | **0.7595** | **0.9993** | **0.7317** | 0.9993 | 0.7048 | 0.9999 | 0.7307 | 0.9996 | 0.7107 |
| 40226 | **0.9994** | **0.7713** | **0.9994** | **0.7470** | 0.9995 | 0.7065 | 0.9999 | 0.7355 | 0.9997 | 0.7045 |
| 49890 | **0.9995** | **0.7484** | **0.9995** | **0.7397** | 0.9996 | 0.6940 | 0.9999 | 0.6993 | 0.9997 | 0.6857 |
| 34325 | **0.9993** | **0.7684** | **0.9993** | 0.7376 | 0.9997 | 0.7630 | 0.9999 | 0.7556 | 0.9995 | 0.7059 |
| 40926 | **0.9994** | **0.7730** | **0.9994** | **0.7595** | 0.9995 | 0.7575 | 0.9999 | 0.7350 | 0.9997 | 0.7167 |
| 45276 | **0.9995** | **0.7823** | **0.9995** | 0.7114 | 0.9996 | 0.7536 | 0.9999 | 0.6993 | 0.9996 | 0.6857 |
| 47392 | **0.9995** | **0.7725** | **0.9995** | 0.7635 | 0.9997 | 0.7696 | 1.0000 | 0.7661 | 0.9999 | 0.7101 |
| 11526 | **0.9984** | **0.7504** | **0.9984** | **0.7370** | 0.9999 | 0.6974 | 0.9999 | 0.7072 | 0.9989 | 0.6996 |
| 14311 | **0.9985** | **0.7807** | **0.9985** | **0.7449** | 0.9986 | 0.7035 | 0.9995 | 0.7338 | 0.9987 | 0.6942 |
| 9460 | **0.9976** | **0.7784** | **0.9976** | **0.7325** | 0.9977 | 0.7188 | 0.9986 | 0.7314 | 0.9983 | 0.7165 |
| 11680 | **0.9982** | **0.7379** | **0.9982** | **0.7395** | 0.9999 | 0.7351 | 0.9999 | 0.7091 | 0.9985 | 0.6921 |



(a)

BPM, we use the $gbs$ value produced. The table presents gbs values with repect to: (i) the sample data, (ii) the original data set with banding from the sample and (iii) the original data set in its raw form without banding. Table XVI shows the gbs values obtained (note that the best $gbs$ value is 0.0). The column presents the four counties (Aberdeenshire, Cornwall, Lancashire and Norfolk) in GB, the years and the datasets considered. From Table XVI, it can thus be seen that by imposing the banding identified in the sample on the entire data set the gbs for the entire data set can be improved. In most cases the sample bandings is better than the eventual global banding (this is to be expected), however in one case Aberdeenshire 2006, we got it exactly right.

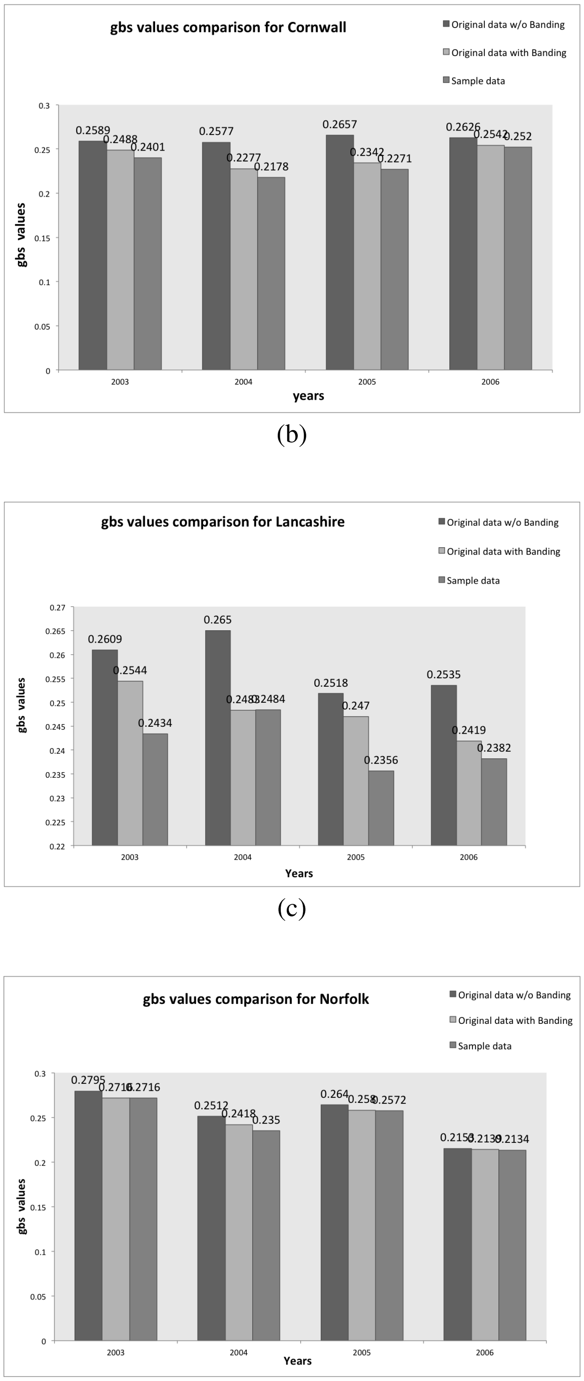
To enhance appreciation of the results obtained, the results from Table XVI is presented in bar graph form in Figure 8. From the graph, it can again be seen that there is an improvement in banding on the original data after applying the banding from the sample data to the original data. Figures 9 and 10 presents the results from Tables XVII and XV in bar graph form.

## VIII. CONCLUSIONS

This paper has described a banding mechanism for large scale zero-one data analysis. The aim is to identify bandings in large data sets using an exact banded pattern mining algorithm

TABLE XVI. EFFECTIVENESS RESULTS, IN TERMS OF $gbs$, FOR THE END BPM ALGORITHM CONSIDERED

| Counties | Year | Dataset | END BPM | | |
|---|---|---|---|---|---|
| | id | Num. Recs. | $3D$ | $4D$ | $5D$ |
| **Aberdeenshire** | | | gbs | gbs | gbs |
| Sample data | 2003 | 24000 | **0.3770** | **0.2929** | **0.2352** |
| Original data with Banding | | 178173 | 0.3811 | 0.3061 | 0.2467 |
| Original data w/o Banding | | 178173 | 0.3937 | 0.3261 | 0.2653 |
| Sample data | 2004 | 24000 | **0.3686** | **0.2420** | **0.2027** |
| Original data with Banding | | 173612 | 0.3710 | 0.2497 | 0.2085 |
| Original data w/o Banding | | 173612 | 0.3947 | 0.2956 | 0.2383 |
| Sample data | 2005 | 24000 | **0.3869** | **0.3113** | **0.2496** |
| Original data with Banding | | 157033 | 0.3977 | 0.3206 | 0.2584 |
| Original data w/o Banding | | 157033 | 0.3987 | 0.3290 | 0.2671 |
| Sample data | 2006 | 24000 | **0.3670** | **0.2397** | **0.2002** |
| Original data with Banding | | 236206 | 0.3709 | **0.2397** | 0.2015 |
| Original data w/o Banding | | 236206 | 0.3733 | 0.2743 | 0.2238 |
| **Cornwall** | | | | | |
| Sample data | 2003 | 24000 | **0.4039** | **0.2911** | **0.2401** |
| Original data with Banding | | 170243 | 0.4048 | 0.2996 | 0.2488 |
| Original data w/o Banding | | 170243 | 0.4370 | 0.3139 | 0.2589 |
| Sample data | 2004 | 24000 | **0.3944** | **0.3181** | **0.2178** |
| Original data with Banding | | 169053 | 0.4023 | 0.3243 | 0.2277 |
| Original data w/o Banding | | 169053 | 0.4043 | 0.3281 | 0.2577 |
| Sample data | 2005 | 24000 | **0.3696** | **0.2730** | **0.2271** |
| Original data with Banding | | 154569 | 0.3786 | 0.2822 | 0.2342 |
| Original data w/o Banding | | 154569 | 0.4142 | 0.3245 | 0.2657 |
| Sample data | 2006 | 24000 | **0.3886** | **0.3081** | **0.2520** |
| Original data with Banding | | 167281 | 0.3901 | 0.3092 | 0.2542 |
| Original data w/o Banding | | 167281 | 0.4060 | 0.3220 | 0.2626 |
| **Lancashire** | | | | | |
| Sample data | 2003 | 24000 | **0.4105** | **0.2947** | **0.2434** |
| Original data with Banding | | 167919 | 0.4136 | 0.3076 | 0.2544 |
| Original data w/o Banding | | 167919 | 0.4206 | 0.3139 | 0.2609 |
| Sample data | 2004 | 24000 | **0.3593** | **0.2817** | **0.2384** |
| Original data with Banding | | 217566 | 0.3769 | 0.2943 | 0.2483 |
| Original data w/o Banding | | 217566 | 0.3908 | 0.3237 | 0.2650 |
| Sample data | 2005 | 24000 | **0.3974** | **0.2940** | **0.2456** |
| Original data with Banding | | 157142 | 0.4007 | 0.2948 | 0.2470 |
| Original data w/o Banding | | 157142 | 0.4059 | 0.3061 | 0.2518 |
| Sample data | 2006 | 24000 | **0.3970** | **0.2847** | **0.2382** |
| Original data with Banding | | 196292 | 0.3999 | 0.2856 | 0.2419 |
| Original data w/o Banding | | 196292 | 0.4011 | 0.3085 | 0.2535 |
| **Norfolk** | | | | | |
| Sample data | 2003 | 24000 | **0.4265** | **0.3095** | **0.2716** |
| Original data with Banding | | 46977 | 0.4270 | 0.3103 | **0.2716** |
| Original data w/o Banding | | 46977 | 0.4370 | 0.3319 | 0.2795 |
| Sample data | 2004 | 24000 | **0.3607** | **0.2820** | **0.2350** |
| Original data with Banding | | 46246 | 0.3653 | 0.2925 | 0.2418 |
| Original data w/o Banding | | 46246 | 0.3698 | 0.3076 | 0.2512 |
| Sample data | 2005 | 24000 | **0.4058** | **0.3215** | **0.2572** |
| Original data with Banding | | 35914 | 0.4075 | 0.3222 | 0.2580 |
| Original data w/o Banding | | 35914 | 0.4148 | 0.3291 | 0.2640 |
| Sample data | 2006 | 24000 | **0.3802** | **0.2566** | **0.2134** |
| Original data with Banding | | 45150 | 0.3817 | 0.2568 | 0.2139 |
| Original data w/o Banding | | 45150 | 0.3986 | 0.2600 | 0.2153 |



(b)

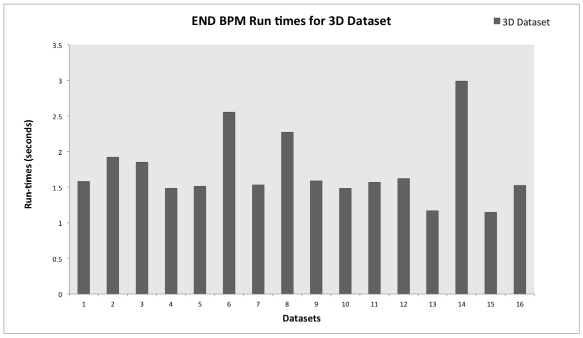
(c)

(d)

Fig. 8. GBS values comparison using the Great Britain (GB) cattle movement data for four counties: (a) Aberdeensire, (b) Cornwall, (c) Lancashire and (d) Norfolk.

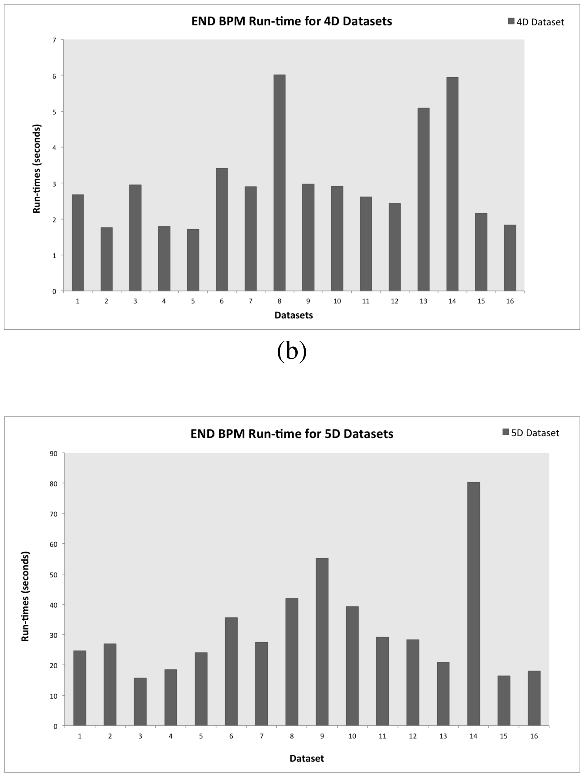
TABLE XVII. EFFECIENCY RESULTS, IN TERMS OF RUNTIME (SECOND)S, USING END BPM ALGORITHM CONSIDERED (BEST RESULTS IN BOLD FONT)

| Counties | Year | Datasets | END BPM run-time (seconds) | | |
|---|---|---|---|---|---|
| | id | Num. Recs. | $3D$ | $4D$ | $5D$ |
| **Aberdeenshire** | | | RT | RT | RT |
| Sample data | 2003 | 24000 | **01.58** | **02.68** | **24.69** |
| Original data with Banding | | 178173 | 14.18 | 16.08 | 47.85 |
| Original data w/o Banding | | 178173 | 14.02 | 19.36 | 45.63 |
| Sample data | 2004 | 24000 | **01.92** | **01.76** | **26.93** |
| Original data with Banding | | 173612 | 13.13 | 15.84 | 45.80 |
| Original data w/o Banding | | 173612 | 13.16 | 16.20 | 48.54 |
| Sample data | 2005 | 24000 | **01.85** | **02.95** | **15.66** |
| Original data with Banding | | 157033 | 12.98 | 14.24 | 47.88 |
| Original data w/o Banding | | 157033 | 13.61 | 15.97 | 44.28 |
| Sample data | 2006 | 24000 | **01.48** | **01.79** | **18.41** |
| Original data with Banding | | 236206 | 14.47 | 15.87 | 56.01 |
| Original data w/o Banding | | 236206 | 17.22 | 21.01 | 47.55 |
| **Cornwall** | | | | | |
| Sample data | 2003 | 24000 | **01.51** | **01.71** | **24.09** |
| Original data with Banding | | 170243 | 14.86 | 50.87 | 51.92 |
| Original data w/o Banding | | 170243 | 17.73 | 16.94 | 46.87 |
| Sample data | 2004 | 24000 | **02.55** | **03.41** | **35.62** |
| Original data with Banding | | 169053 | 18.28 | 22.44 | 77.18 |
| Original data w/o Banding | | 169053 | 15.40 | 28.43 | 75.38 |
| Sample data | 2005 | 24000 | **01.53** | **02.90** | **27.43** |
| Original data with Banding | | 154569 | 14.32 | 14.61 | 43.53 |
| Original data w/o Banding | | 154569 | 14.82 | 21.13 | 42.04 |
| Sample data | 2006 | 24000 | **02.27** | **06.01** | **41.89** |
| Original data with Banding | | 167281 | 14.50 | 17.6 | 94.80 |
| Original data w/o Banding | | 167281 | 17.63 | 19.43 | 92.51 |
| **Lancanshire** | | | | | |
| Sample data | 2003 | 24000 | **01.59** | **02.97** | **55.19** |
| Original data with Banding | | 167919 | 13.94 | 16.59 | 104.30 |
| Original data w/o Banding | | 167919 | 17.74 | 18.02 | 91.92 |
| Sample data | 2004 | 24000 | **01.48** | **02.91** | **39.29** |
| Original data with Banding | | 217566 | 15.25 | 19.99 | 85.90 |
| Original data w/o Banding | | 217566 | 17.97 | 23.65 | 82.91 |
| Sample data | 2005 | 24000 | **01.57** | **02.62** | **29.11** |
| Original data with Banding | | 157142 | 16.08 | 16.65 | 69.82 |
| Original data w/o Banding | | 157142 | 15.75 | 26.76 | 70.47 |
| Sample data | 2006 | 24000 | **01.62** | **02.43** | **28.31** |
| Original data with Banding | | 196292 | 14.72 | 18.83 | 82.79 |
| Original data w/o Banding | | 196292 | 25.57 | 22.43 | 78.59 |
| **Norfolk** | | | | | |
| Sample data | 2003 | 24000 | **01.17** | **05.09** | **20.84** |
| Original data with Banding | | 469773 | 11.73 | 12.09 | 20.90 |
| Original data w/o Banding | | 46977 | 14.42 | 14.07 | 22.64 |
| Sample data | 2004 | 24000 | **02.99** | **05.94** | **80.20** |
| Original data with Banding | | 46246 | 16.42 | 27.05 | 85.48 |
| Original data w/o Banding | | 46246 | 15.71 | 16.27 | 83.48 |
| Sample data | 2005 | 24000 | **01.15** | **02.16** | **16.41** |
| Original data with Banding | | 35914 | 10.85 | 11.23 | 18.69 |
| Original data w/o Banding | | 35914 | 16.96 | 14.55 | 17.41 |
| Sample data | 2006 | 24000 | **01.52** | **01.83** | **17.92** |
| Original data with Banding | | 45150 | 11.10 | 12.30 | 21.77 |
| Original data w/o Banding | | 45150 | 15.09 | 15.61 | 19.98 |



(a)

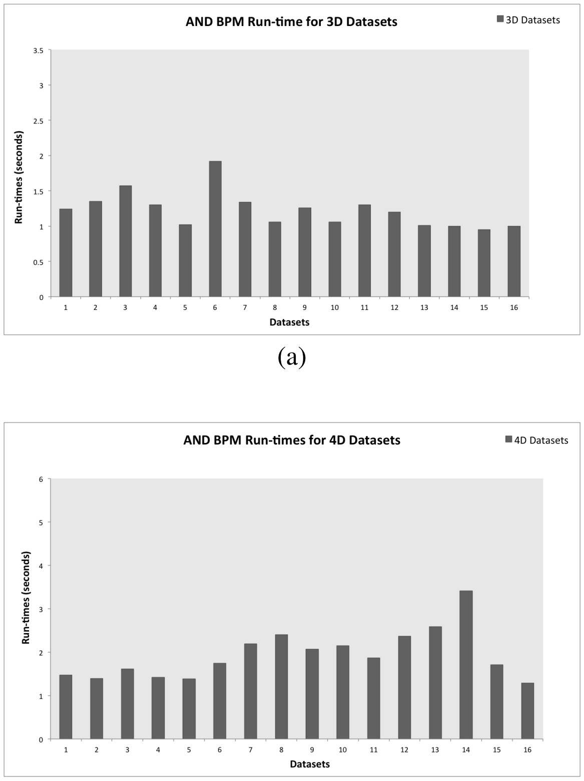
The proposed mechanism has been evaluated using a benchmark and sample data sets derived from the Great Britain (GB) cattle movement database. We have shown that the proposed END BPM mechanism is able to identify accurate bandings in large data sets within reasonable computational time. The results presented confirms that the END BPM algorithms works well in ND (in terms of effectiveness). For future work the authors intend to extend their research to address situations where we seek to sequentially establish bandings in large datasets using sequence of data segments. Whatever the case, the authors have been greatly encouraged by the results



(b)

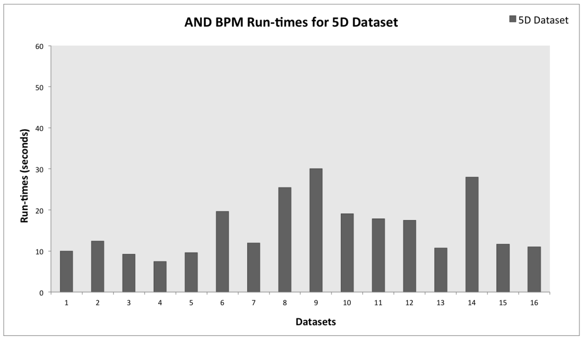
(c)

Fig. 9. END BPM Runtime (in seconds) using the Great Britain (GB) cattle movement sampling dataset in the context of: (a) 3D, (b) 4D and (c) 5D.



(a)

(b)



(c)

Fig. 10. AND BPM Runtime (in seconds) using the Great Britain (GB) cattle movement dataset in the context of: (a) 3D, (b) 4D and (c) 5D.

produced so far, as presented in this paper.

## REFERENCES

[1] H. Mannila and E. Terzi, "Nested and segmented nested." in *Proceedings of the 13h ACM SIGKDD international conference on knowledge discovery and data mining, New York, NY, USA, 2007*, 2007, pp. 480–489.

[2] E. Makinen and H. Siirtola, "The barycenter heuristic and the reorderable matrix." *Informatica*, vol. 29, pp. 357–363, 2005.

[3] G. C. Gemma, E. Junttila, and H. Mannila., "Banded structures in binary matrices," *Knowledge Discovery and Information System*, vol. 28, pp. 197–226, 2011.

[4] E. Junttila, "Pattern in permuted binary matrices," Ph.D. dissertation, 2011.

[5] "Withheld for anonymous refereeing purpose," 2014.

[6] K. Y. Cheng, "Minimising the bandwidth of sparse symmetric matrices," in *Computing*, vol. 11, pp. 103–110.

[7] A. E. Cuthill and J. McKee, "Reducing the bandwidth of sparse symmetric matrices." in *Proceedings of the 24th National Conference of ACM*, 1969, pp. 157–172.

[8] C. H. Papadimitrious, "The np-completeness of the bandwidth minimisation problem," in *Computing*, vol. 16, 1976, pp. 263–270.

[9] ., "Withheld for anonymous refereeing purpose," 2014.

[10] J. Atkins, E. Boman, and B. Hendrickson., "Spectral algorithm for seriation and the consecutive ones problem," *SIAM J. Comput.*, vol. 28, pp. 297–310, 1999.

[11] A. Banerjee, C. Krumpelman, J. Ghosh, S. Basu, and R. Mooney, "Model-based overlapping clustering." in *Proceedings of Knowledge Discovery and DataMining*, 2005, pp. 532–537.

[12] P. S. Levy and S. Lemeshow, "Sampling of populations: Methods and applications," *New York: Wiley and Sons*, 2008.

[13] M. A. Burnam and P. Koegel, "Methodology for obtaining a representative sample of homeless persons: The los angeles skid row study." *Evaluation Review*, vol. 12, p. 117152, 1988.

[14] D. Green and R. Kao, "Data quality of the cattle tracing system in great britain." *Veterinary Record*, vol. 161, pp. 439–443, 2007.

[15] N. N. Puteri, R. Christley, . ", and C. Setzkorn, "Trend mining in social networks: A study using a large cattle movement database," *Advances in Data mining, Applications and Theoretical Aspects LNCS*, vol. 6171, pp. 464–475, 2010.

[16] S. Robinson and R. Christley, "Identifying temporal variation in reported birth, death and movements of cattle in britain." in *BMC Veterinary Research*, 2006, pp. 2–11.