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Exploring the Data Stream Size using ICBMI and CBMI Algorithm

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Abstract: ICBMI and CBMIboth the algorithms react to changes in the data stream. By entering the second part of the Dataset, as the concept changes, the ICBMI gradually reduces the average of the data stream sizes while the CBMI abruptly reduces the data stream size to remove the obsolete transactions and their effects on the mining result. At this point, for the ICBMI, the average of data stream sizes now contains both these concepts. In fact the ICBMI, for some Missing Data, therefore the max frequency data streams reside in both new and old parts of the Dataset because it considers the complete history of the input stream and does not completely discard the previous concept.
Index Terms--stream Data, Multiple Imputation, Missing Data, ICBMI, and CBMI

I. INTRODUCTION

The first version of CBMI is computationally expensive, because it checks exhaustively all "large enough" sub data streams of the current data stream for possible cuts. Furthermore, the content of the data stream is kept explicitly, with the corresponding memory cost as the data stream grows. To reduce these costs a new version ICBMI is introduced. ICBMI uses ideas developed in data stream algorithms to find a good cut point quickly. This data structure is a variation of exponential histograms, a data structure that maintains an approximation of the number of 1's in a main stream Data Multiple Imputation of length W with logarithmic memory and update time. Also this structure adopted in a way that can provide this approximation simultaneously for about O(logW) sub data streams whose lengths follow a geometric law, with no memory overhead, with respect to keeping the count for a single data stream. That is, our data structure will be able to give the number of 1s among the most recently $t - 1$, $t - b_{cc}$, $t - b_{c2c}$,....,$t - b_{cic}$,… read bits, with the same amount of memory required to keep an approximation for the whole W. Keeping the exact counts for a fixed data stream size is probably impossible in sub linear memory. We go around this problem by shrinking or enlarging the data stream strategically, so what would otherwise be an approximate count happens to be exact.

II. PERFORMANCE OF CBMI AND ICBMI ALGORITHM

In this section we present our ICBMI algorithm. The ICBMI uses simplified Chernoff bound concepts to calculate the appropriate data stream size for mining Missing Data. It uses now the comparison of the two data stream sub-range observations and Data counts when a segment occurs within the data stream and then adjusts the data stream size appropriately. However, for an itemset, its max-frequency data stream moves forward if a data stream with higher frequency is found in the reminder of the input stream. The following table clearly represents the efficiency between ICBMI and the CBMI for different Datasets UNF-BARCLAY'S DATA SET, UNF-BOEING DATA SET, BARCLAY'S DATA SET, and BOEING DATA SET

```
Input: T = set of all observed transaction IDs
δ = required data streams
Output: t = set of all present Missing Data IDs
Initialise:  ∀i ∈ T, w_i ← 1
while( getNextTransaction) do
   for (i in T)
processData stream(W_i) →,p_i,t's, p_i^avg,|S_i|
          if ( itemExist(|S_i |)
                output i
          end if
w_i^* ← requiredData streamSize(p_i^avg ,δ)
if (itemexists ^ | S_2i | = 0)
w_i← max (min{ w_i /2, w_i^* } , 3)
          else if (detectTransaction(|S_i|,w_i, p_i^avg))
w_i← max{( w_i - 2),3}
          else if (w_i^* >w_i ^ |S_i| <w_i p_i^avg)
w_i← min{( w_i + 2), w_i^* }
          end if
 end for
end while
```

CBMI Algorithm

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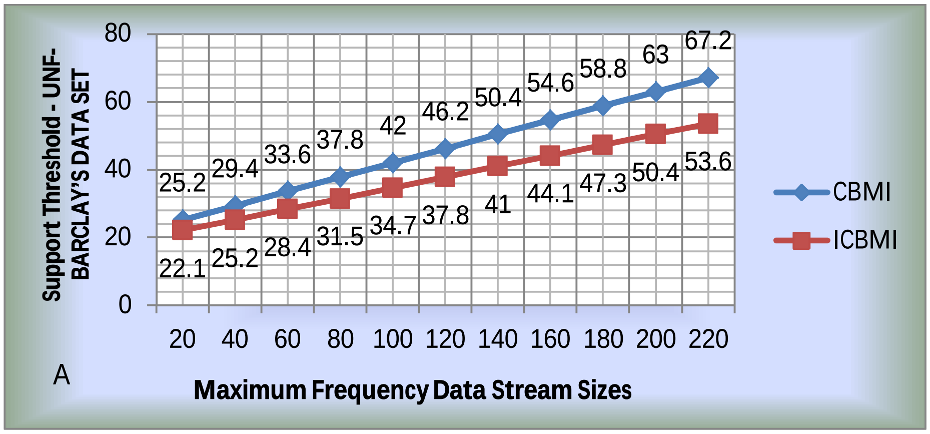
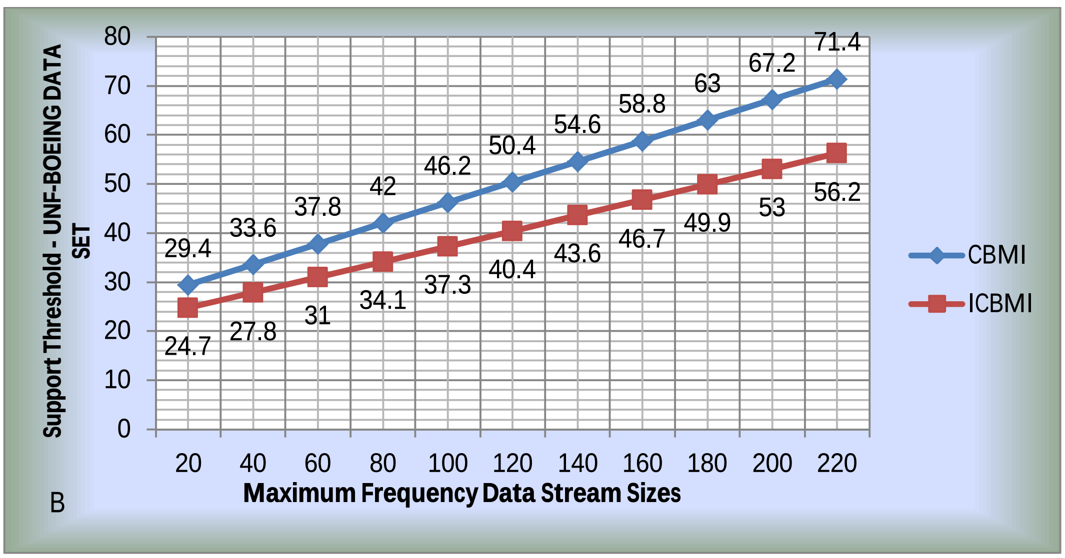
III.COMPARISON OF ICBMI AND CBMI

The Data and its max-frequency data stream information are now deleted, if its support falls below the Support Threshold. Through experiment, after each segment the, average of the Maximum Frequency Data Stream Sizes of the ICBMI was compared to the current data stream size of CBMI.



(a)



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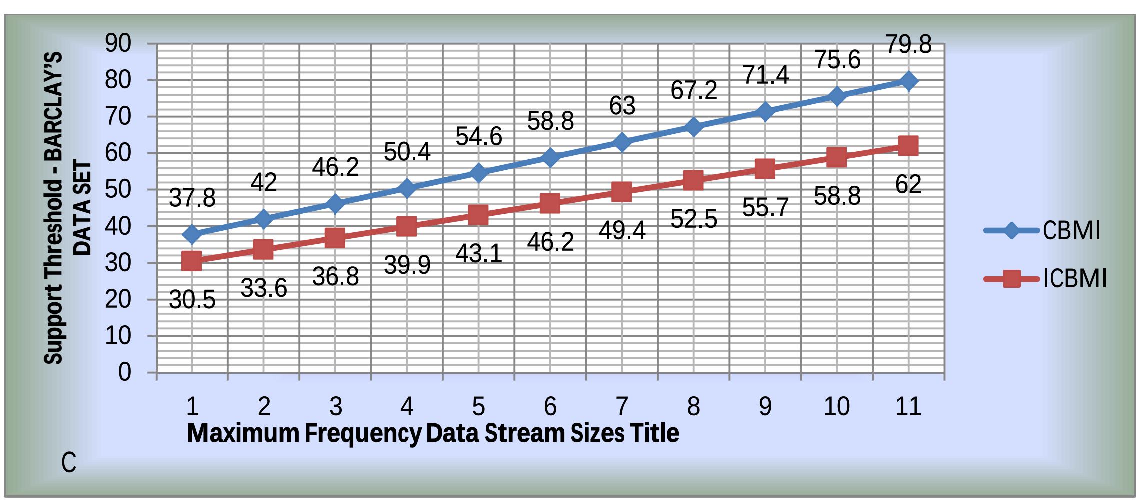
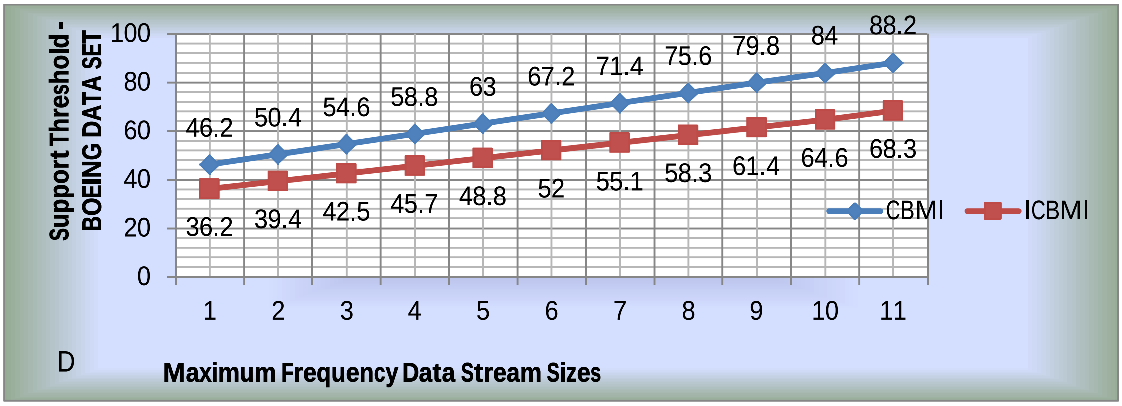


(c)



(d)

Fig. 2.Comparison of ICBMI and CBMI

The above figure shows how the data stream sizes of both the algorithms change as new segments are received. As shown in this figure1 (a), (b), (c) and (d) both the algorithms react to changes in the data stream. By entering the second part of the Dataset, as the concept changes, the ICBMI gradually reduces the average of the data stream sizes while the CBMI abruptly reduces the data stream size to remove the obsolete transactions and their effects on the mining result. At this point, for the ICBMI, the average of data stream sizes now contains both these concepts. In fact the ICBMI, for some Missing Data, therefore the max frequency data streams reside in both new and old parts of the Dataset because it considers the complete history of the input stream and does not completely discard the previous concept.

IV. CONCLUSION

Through experiment, after each segments the, average of the Maximum Frequency Data Stream Sizes of the ICBMI was compared to the current data stream size of CBMI. The ICBMI gradually reduces the average of the data stream sizes while the CBMI abruptly reduces the data stream size to remove the obsolete transactions and their effects on the mining result. At this point, for the ICBMI, the average of data stream sizes now contains both these concepts.In fact the ICBMI, for some Missing Data.

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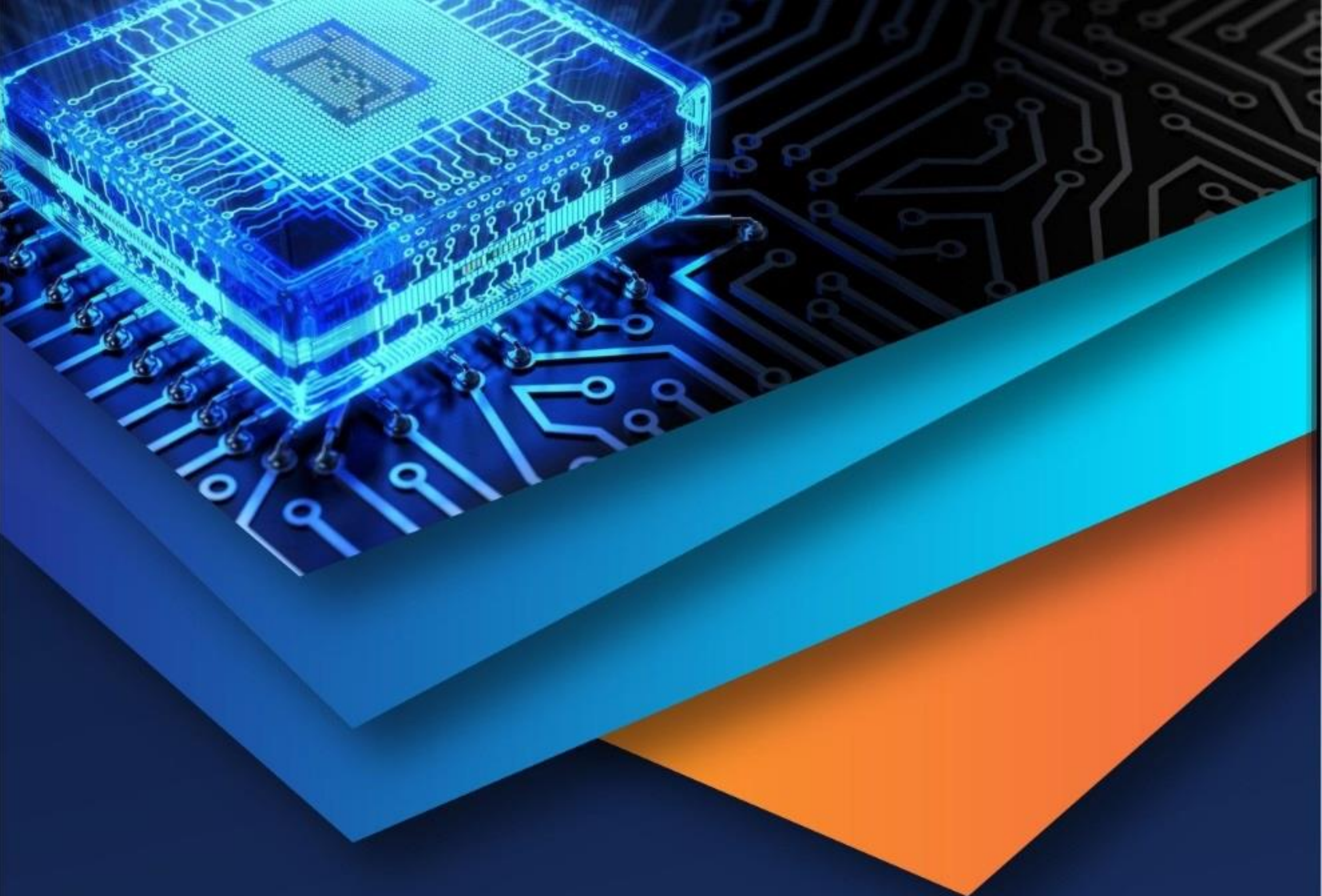

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