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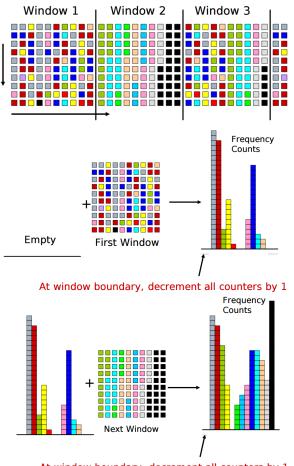
Knowledge Discovery in Databases II SS 2018

Exercise 6: Data Stream Clustering

Exercise 6-1 Lossy Counting

Before stream clustering, let's take a look at a more fundamental task in stream: count the occurrence of objects in a stream and output objects with a count larger or equal to some given threshold: $minSup \times L$, where L is the length of the stream up to now and minSup is the given threshold (minimum support).

Lossy Counting is one of the basic algorithms that solve this problem. Given the windows size as $w = \frac{1}{\epsilon}$, the lossy counting algorithm works as the follows: cut stream into windows, process one window a time and prune histogram entries with 0 counts at each window boundary. The illustration is given below:



At window boundary, decrement all counters by 1

Please prove that

(a) the maximum count error (the maximum difference between the real count and the estimated count) of the lossy counting algorithm is ϵL

Let W be the current windows id, then $\frac{1}{\epsilon}W = L \Rightarrow W = \epsilon L$. The count error of a given object is happened due to the reduction of count at each window boundary. Thus, including the current windows boundary, the maximum count error is $\Delta = W = \epsilon L$.

(b) the memory consumption, i.e., the number of entries stored in the histogram, is O(¹/_ϵ log(ϵL)). (Optional) Let W be the current window id. For each i ∈ [1, W], let d_i denote the number of entries in the histogram H which corresponds to window W − i + 1.

Thus, the item in the stream corresponding to such entry must occur at least *i* times in window B - i + 1 through W; otherwise, it would have been deleted. Since the size of each window is w, we have:

$$\sum_{i=1}^{j} id_i \le jw \quad for \ j = 1, 2, \dots, W \tag{1}$$

Now we want to prove:

$$\sum_{i=1}^{j} d_i \le \sum_{i=1}^{j} \frac{w}{i} \tag{2}$$

By induction:

- For j = 1, this is true.
- Assume it is true for j = 1, 2, ..., p 1, then for j = p, adding the inequality (1) for j = p to the aggregation of all p 1 instances of the inequality (2) gives us:

$$\sum_{i=1}^{p} id_i + \sum_{i=1}^{1} d_i + \sum_{i=1}^{2} d_i + \dots + \sum_{i=1}^{p-1} d_i \le pw + \sum_{i=1}^{1} \frac{w}{i} + \sum_{i=1}^{2} \frac{w}{i} + \dots + \sum_{i=1}^{p-1} \frac{w}{i}$$

The left hand side can be written as:

$$1 \cdot d_1 + 2 \cdot d_2 + \dots + p \cdot d_p + (d_1) + (d_1 + d_2) + \dots + (d_1 + d_2 + \dots + d_{p-1}) = p \cdot d_1 + p \cdot d_2 + \dots + p \cdot d_p = p \sum_{i=1}^p d_i$$

Similarly, the right hand side can be written as:

$$\frac{1 \cdot w}{1} + \frac{2 \cdot w}{2} + \dots + \frac{p \cdot w}{p} + (\frac{w}{1}) + (\frac{w}{1} + \frac{w}{2}) + \dots + (\frac{w}{1} + \frac{w}{2} + \dots + \frac{w}{p-1}) = \frac{pw}{1} + \frac{pw}{2} + \dots + \frac{pw}{p} = p\sum_{i=1}^{p} \frac{w}{i} + \frac{w}{i} + \frac{w}{2} + \dots + \frac{w}{p-1} = \frac{pw}{1} + \frac{w}{2} + \dots + \frac{w}{p-1} = \frac{pw}{1} + \frac{w}{2} + \dots + \frac{w}{p-1} = \frac{w}{1} + \frac{w}$$

Then we have:

$$p\sum_{i=1}^{p} d_i \le p\sum_{i=1}^{p} \frac{w}{i}$$
$$\Rightarrow \sum_{i=1}^{p} d_i \le \sum_{i=1}^{p} \frac{w}{i}$$

Thus the memory consumption at window W is $|H| = \sum_{i=1}^{W} d_i \le \sum_{i=1}^{W} \frac{w}{i} = \frac{1}{\epsilon} \log W = \frac{1}{\epsilon} \log \epsilon L$

(Here the inequality $\sum_{i=1}^{W} \frac{1}{i} \le \log W$ is used, as it is the harmonic series.)