



A Survey Of Synopsis Construction In Data Streams

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1.Introduction

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Computational & Storage costs & The large volume

Desiderata:

Broad Applicability
 One Pass Constraint
 Time and Space Efficiency
 Robustness

➢Evolution Sensitive

Methods:

- ≻Sampling methods
- ≻Histograms
- ➤Wavelets
- ➢Sketches
- Micro-cluster based summarization

2. RoadMap:



2. Sampling Methods:

2.1 Random Sampling with a Reservoir2.2 Concise Sampling

2. Sampling Methods

Advantages:

- ≻Easy and Efficient
- ➢Any data mining application or database operation & Provable error guarantees
- ≻Multi-dimensional



2. Sampling Methods

Some properties:

- ► Markov inequality: $P(X > a) \le E[X]/a = \mu/a$
- ► Chebychev inequality(the random variable $(X-\mu)^2/\sigma^2$) $P(|X-u| > a) \le \sigma^2/a^2$
 - X independent & identical Bernoulli random variables

$$P(X < (1 - \delta)\mu) \le e^{-\mu\sigma^2/2}$$
$$P(X > (1 + \delta)\mu) \le \max\{2^{-\delta\mu}, e^{-\mu\delta^2/4}\}$$

► Hoeffding inequality: a set of k independent random variables the range [a, b] $P(|X - \mu| > \delta) \le 2e^{-2k \cdot \delta^2 / (b-a)^2}$



2.1 Random Sampling with a

Reservoir

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One-pass & N are not known & Dynamically

Algorithm:

- A reservoir of size k.
- Initialization :Chosen 1~k points in the data stream.
 The first k points in the data streams are added to the reservoir .
- > Subsequent : Form (k+1)th to N
 - a) Each point has a k/i probability of being selected.
 (i is the order of points)
 - a) Current points in the reservoir are sampled with equal probability (1/k) and subsequently removed.

2.1 Random Sampling with a

Reservoir

eg: If *k* = 1000, form 1001 to *N*;



The probability of the 1001*th* point being included in the reservoir is 1000/1001.

Assumption:

- a) The (i + 1)th point is added to the reservoir with probability k/(i + 1).
- b) First *i* points have equal probability of being included in the reservoir and have probability equal to k/(i+1).

This sampling approach feasible.

2. Rese Prod

- 1. If i = k+1, the probability of the (k+1)th point being included in the reservoir is k/k+1. And first k points are included in the reservoir and have probability equal to k/(k+1).
- 2. If j=i,the hypothesis is right, the probability of the *i* th point being included in the reservoir is k / i. And first *i*-1 points are included in the reservoir and have probability equal to k / i.
- 3. If j=i+1? we need to proof :The (i + 1)th point is added to the reservoir with probability k/(i + 1). First *i* points have equal probability of being included in the reservoir and have probability equal to k/(i+1).

2.1 Random Sampling with a

Reservoir Proof (Induction):



The probability of first *i* points being included in the reservoir have two components.

- 1) Appearing in the reservoir before the (i+1)th selection.
- $\widehat{2}$ To ensure the first i choice is not replaced.
- Known from the 2. Before the (i+1)th selection, first i points are included in the reservoir and have probability equal to k / i.
- > The probability of replacing:

the (i+1)th point is selected and the probability is k/i+1, the point in the reservior is choosed as the probability 1/k, so the probability of the first i points being replaced is k/(i+1) *1/k=1/i+1the point in the reservoir in not replaced: 1 - 1/(i+1)=i/i+1so the first i points included in the reservoir is k/i *i/(i+1) = k/i+1

2.2 Concise Sampling

- > Increasing the sample size
- > The available main memory restrictions
- The fact: the number of distinct values of an attribute is often significantly smaller than the size of the data stream.

Definition 1:

A concise sample is a uniform random sample of the data set such that values appearing more than once in the sample are represented as a value and a count.

Most applicable while performing univariate sampling along a single dimension.

2.2 Concise Sampling



Maintained as a set S of *<value, count>* pairs.

- \succ count = 1.(do not maintain the count explicitly)
- \succ the value as a singleton.

Definition 2:

Let $S = \{ \langle v_1, c_1 \rangle, \dots, \langle v_j, c_j \rangle, v_{j+1}, \dots, v_l \}$ be a concise sample. Then sample-size(S) = $e - j + \sum_{i=1}^{j} c_i$, and footprint(S) = e + j.

Some conclusions:

- > The footprint size \leq the true sample size.
- If the count of any distinct element is larger than 2, then the footprint size is strictly smaller than the sample size.

The algorithm :



For extracting a concise sample of footprint m.

- First, repeat m times: select a random tuple from the relation and extract its value.
- Next, replace every value occurring multiple times with a <value, count> pair.
- Then, continue to sample until either adding the sample point would increase the concise sample footprint to m + 1 or n samples have been taken.



- if the corresponding value count-pair is already included in the set S, then only increment the count by 1. the footprint size does not increase.
- if the value of the current point is distinct from all the values encountered so far, or it exists as a singleton then the foot print increases by 1. Either a singleton needs to be added, or a singleton gets converted to a value-count pair with a count of 2.

2.2 Incremental of Concise Sampling

The increase in footprint size may potentially require the removal of an element from sample S in order to make room for the new insertion.

- > Setting up an entry threshold τ (initially 1) for new tuples to be selected for the sample with the probability $1/\tau$
- > Picking a new (higher) value of the threshold τ'
- Reducing the count of a value with probability τ/τ' , until at least one value-count pair reverts to a singleton or a singleton is removed.

Subsequent points from the stream are sampled with probability $1/\tau'$

Thanks !

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