GlobalDataLoader in Multi DeepLearning Task

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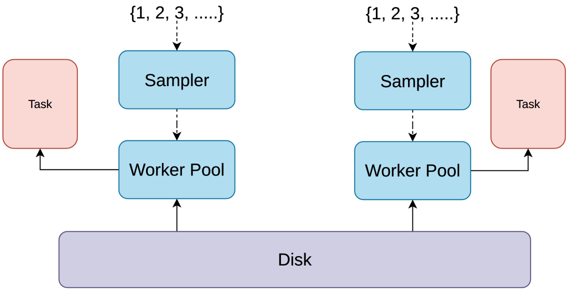
Introduction

Data loading

- Sampler sample some index randomly
- Worker read the data from disk and decode them
- Task fecth data and start training



Problem

Problem

The data will be repeatedly read and processed by different tasks.

Configuration

Multiple tasks with worker = 4, batch size = 32
GPU: Tesla T4 with 16G memory, CPU: 48 Intel(R) Xeon(R) Gold 5118

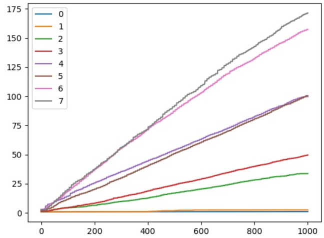


Figure: data loading time

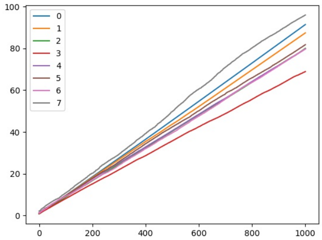
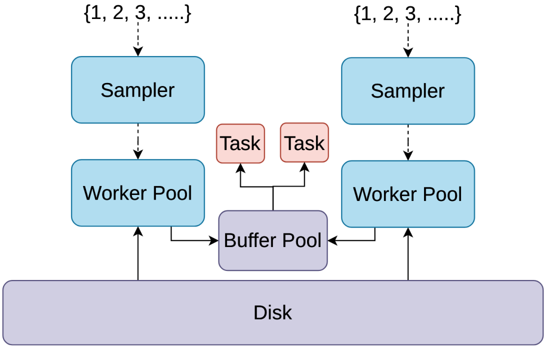


Figure: data training time

Optimization

Global Buffer Pool

- If data in buffer pool, there is no need to read data from disk



Problem

- Random replacement algorithm

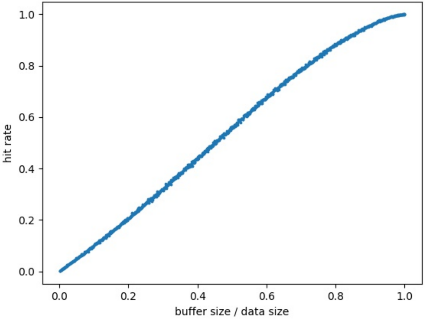
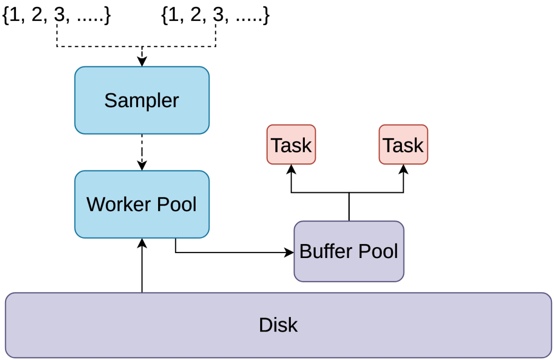


Figure: hit rate with buffer size

Optimization

Global Sampler

- Make the sampled elements have a greater probability of being equal



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Sampling: problem description

Defination

Assume there are two sets $\{S_1, S_2\}$, we should randomly select 2 elements $\{e_1, e_2\}$ from them. The algorithm should to make sure to:

$$\begin{aligned} p(e_1) &= \frac{1}{|S_1|} \\ p(e_2) &= \frac{1}{|S_2|} \\ &Maximize(p(e_1 = e_2)) \end{aligned} \tag{1}$$

Independently Sampling Algorithm

Assumption

There are two sets: S_1, S_2, and their length is n_1, n_2
The intersection set of them is S_i, whose length is n_i
We divide the set S_1 into S_i and $S_{d1} = S_1 - S_i$
We divide the set S_2 into S_i and $S_{d2} = S_2 - S_i$
Sample(S): randomly select an element in S

Example

$S_1 = \{1, 2, 3, 4, 5\} = \{1, 2, 3\} \cup \{4, 5\}$
$S_2 = \{1, 2, 3, 6, 7\} = \{1, 2, 3\} \cup \{6, 7\}$

Independently Sampling Algorithm

S1

- $step_{11}$:randomly select a set from S_i and S_{d1}
- $step_{21}$:if S_{d1}, e_1=Sample(S_{d1})
- $step_{31}$:if S_i, e_1=Sample(S_i)

S2

- $step_{12}$:randomly select a set from S_i and S_{d2}
- $step_{22}$:if S_{d2}, e_2=Sample(S_{d2})
- $step_{32}$:if S_i, e_2=Sample(S_i)

Probability

$$p(e_1 = e_2) = \frac{n_i}{n_1 * n_2} \tag{2}$$

Dependently Sampling Algorithm I

Insight

The $step_{31}$ is same as $step_{32}$ (randomly select an element e from S_i).

Example

$S_1 = \{1, 2, 3\} \cup \{4, 5\}$; $S_2 = \{1, 2, 3\} \cup \{6, 7\}$

- Firstly, randomly sampling element e_i in $\{1, 2, 3\}$
- As for S_1, if select set $\{1, 2, 3\}$ with probability $p_1(S_i) = 0.6$, then we can let $e_1 = e_i$
- As for S_2, select set $\{1, 2, 3\}$ with probability $p_2(S_i) = 0.6$, then we can let $e_2 = e_i$
- $p(e_1 = e_2) = p_1(S_i) * p_2(S_i) = 0.36$

Dependently Sampling Algorithm I

Algorithm

- $step_0$: $e_i = \text{Sample}(S_i)$

S1

- $step_{11}$:randomly select a set from S_i and S_{d1}
- $step_{21}$:if S_{d1},$e_1 = \text{Sample}(S_{d1})$
- $step_{31}$:if S_i, $e_1 = e_i$

S2

- $step_{12}$:randomly select a set from S_i and S_{d2}
- $step_{22}$:if S_{d2}, $e_2 = \text{Sample}(S_{d2})$
- $step_{32}$:if S_i, $e_2 = e_i$

Probability

$$p(e_1 = e_2) = \frac{n_i}{n_1} * \frac{n_i}{n_2} = \frac{n_i^2}{n_1 * n_2} \quad (3)$$

Dependently Sampling Algorithm I

Insight

The $step_{11}$ and $step_{12}$ are similar. We can merge them.

Example

$S_1 = \{1, 2, 3\} \cup \{4, 5\}$; $S_2 = \{1, 2, 3\} \cup \{6, 7\}$

- Firstly, we randomly select a set from $\{1, 2, 3\}$ and $\{4, 5\}$
- If we choose $\{1, 2, 3\}$, the S1 and S2 will both select an element from $\{1, 2, 3\}$
- If we choose $\{4, 5\}$, then S1 will sampling in $\{4, 5\}$ and S2 in $\{6, 7\}$
- $p(e_1 = e_2) = p_1(S_i) = 0.6$

Dependently Sampling Algorithm II

Algorithm

- $step_0$: $e_i = \text{Sample}(S_i)$
- $step_1$: randomly select a set from S_i and S_{d1}

S1

- $step_{21}$: if S_{d1}, $e_1 = \text{Sample}(S_{d1})$
- $step_{31}$: if S_i, $e_1 = e_i$

S2

- $step_{22}$: if S_{d1}, $e_2 = \text{Sample}(S_{d2})$
- $step_{32}$: if S_i, $e_2 = e_i$

Problem: $n_1 \neq n_2$

$n_1 > n_2$

$S_1 = \{1,2,3\} \cup \{4\}$; $S_2 = \{1,2,3\} \cup \{6,7\}$

- S_1 select $\{1,2,3\}$ with probability $p_1(S_i) = 0.75$
- Then S_2 select an element e from S_i with probability $p_2(e) = p_1(S_i) * \frac{1}{3} = 0.25 > 0.2$

$n_1 < n_2$

$S_1 = \{1,2,3\} \cup \{4,6\}$; $S_2 = \{1,2,3\} \cup \{7\}$

- S_1 select $\{4,6\}$ with probability $p_1(S_{d1}) = 0.4$
- Then S_2 select an element e from S_{d2} with probability $p_2(e) = p_1(S_{d1}) * \frac{1}{1} = 0.4 > 0.25$

Case1: n1 < n2

Problem

$$(p_1(S_i) = \frac{n_i}{n_1}) > (p_2(S_i) = \frac{n_i}{n_2}) \tag{4}$$

Approach

So in $step_1$, when select S_i, it should be changed S_{d2} in probability of p.

$$\begin{cases} p_2(S_i) = p_1(S_i) * (1 - p) = \frac{n_i}{n_2} \\ p_2(S_{d2}) = p_2(S_{d1}) + p_1(S_i) * p = 1 - \frac{n_i}{n_2} \end{cases} \tag{5}$$

$$p = 1 - \frac{n_1}{n_2} \tag{6}$$

Dependently Sampling Algorithm II

Algorithm

- *step*$_0$: $e_i = \text{Sample}(S_i)$
- *step*$_1$: randomly select a set from S_i and S_{d1}

S1

- *step*$_{21}$:if S_{d1}, e_1=Sample(S_{d1})
- *step*$_{31}$:if S_i, $e_1 = e_i$

S2

- *step*$_{22}$: if S_{d1}, e_2=Sample(S_{d2})
- *step*$_{32}$: if S_i:
  - let $S = S_{d1}$ in probability of $1 - \frac{n_1}{n_2}$
  - if S_{d1}, e_2=Sample(S_{d2})
  - if S_i, $e_2 = e_i$

Probability

$$p(e_1 = e_2) = p_1(S_i) * (\frac{n_1}{n_2}) = \frac{n_i}{n_2}$$

Case2: n1 > n2

Problem

$$(p_1(S_{d1}) = 1 - \frac{n_i}{n_1}) > (p_2(S_{d_2}) = 1 - \frac{n_i}{n_2}) \tag{7}$$

Approach

So in $step_1$, when select S_{d1}, it should be changed S_i in probability of p. The equation is

$$\begin{cases} p_2(S_i) = p_1(S_i) + p_2(S_{d1}) * p = \frac{n_i}{n_2} \\ p_2(S_{d2}) = p_2(S_{d1}) * (1 - p) = 1 - \frac{n_i}{n_2} \end{cases} \tag{8}$$

$$p = 1 - \frac{n1 * (n2 - n_i)}{n2 * (n1 - n_i)} \tag{9}$$

Dependently Sampling Algorithm II

Algorithm

- $step_0$: $e_i = \text{Sample}(S_i)$
- $step_1$: randomly select a set from S_i and S_{d1}

S1

- $step_{21}$:if S_{d1}, e_1=Sample(S_{d1})
- $step_{31}$:if S_i, $e_1 = e_i$

S2

- $step_{22}$: if S_{d1}:
  - let $S = S_i$ in probability of $1 - \frac{n1*(n2-n_i)}{n2*(n1-n_i)}$
  - if S_{d1}, e_2=Sample(S_{d2})
  - if S_i, $e_2 = e_i$
- $step_{32}$: if S_i, $e_2 = e_i$

Probability

$$p(e_1 = e_2) = p_1(S_i) = \frac{n_i}{n_1}$$

Why not shuffle $S_1 \cup S_2$

Probability

$p(e_1 = e_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|} < \frac{|S_1 \cap S_2|}{max(|S_1|,|S_2|)}$

randomly select in $S_1 \cup S_2$: "starvation"

if $|S_1| = 99, |S_2| = 1$, then $p(e \in S_1) = 0.99, p(e \in S_2) = 0.01$

So task2 may be starving

shuffle $S_1 \cup S_2$: offset

$S_1 = \{2, 3\}, S_2 = \{1, 2, 3\}$

{ 2,3}

{1,2,3}

{1,2,3}

Sampling Tree: there are two sets: S_1, S_2

- $A = S_1 \cap S_2$
- $B = S_1 - A$
- $A = S_2 \cap A$

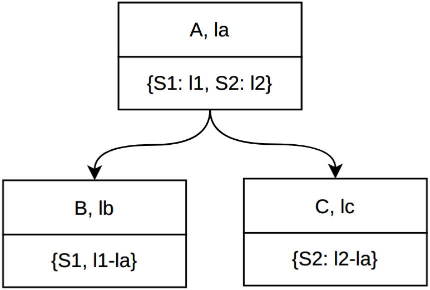


Figure: Sampling Tree

Sampling Tree: insert S_3

- $A \subset S_3$
- Insert $\{S_3 : l_3\}$ in A ascending order
- $S_3 = S_3 - A$
- Insert S_3 in subtree that has the largest intersection with S_3

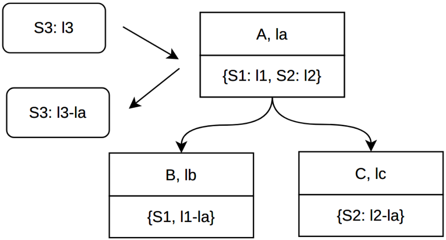


Figure: Sampling Tree

Sampling Tree: Insert S_3

- $B \not\subset S_3$
- Create new node: $D = S_3 \cap B$
- $E = B - D$
- $F = S_3 - D$

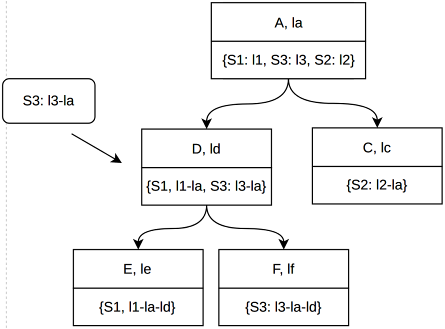


Figure: Sampling Tree

Sampling Tree: Delete S_3

- Delete S_3 in root
- Recursively let the subtree delete S_3
- Until reaching the leaf node, then delete it
- The corresponding parent node merges the child nodes

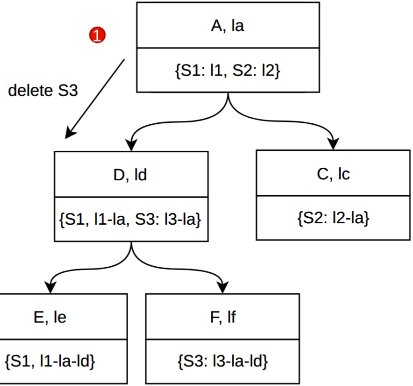


Figure: Sampling Tree

Sampling Tree: Sampling in root

- Split U into *parent* and *child*
  - $p < \frac{l_a}{l_1}, parent \cup \{S1\}$
  - ......
  - $p > \frac{l_i}{l_{i+1}}, child \cup \{S_i, S_{i+1}, \ldots\}$
- Sampling e in A, which represents the sampling result of *parent*
- Push down *child*
- Because $e \notin A$, so we need to push down e and the collection U_e containing it

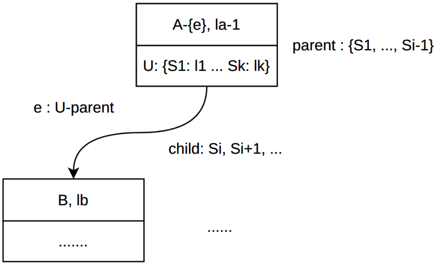


Figure: Sampling Tree

Sampling Tree: Sampling in child

- Split child into *parent* and *child*
- Sampling e in A, which represents the sampling result of *parent*
- Push down *child*
- Because $e \notin A$, so we need to push down e and the collection containing it
- if $U_e \subset U$, then add e in this node

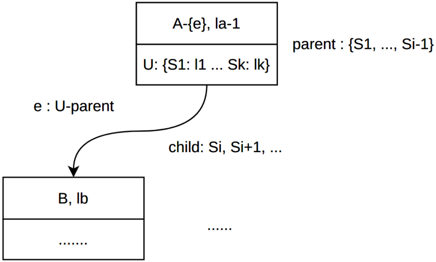
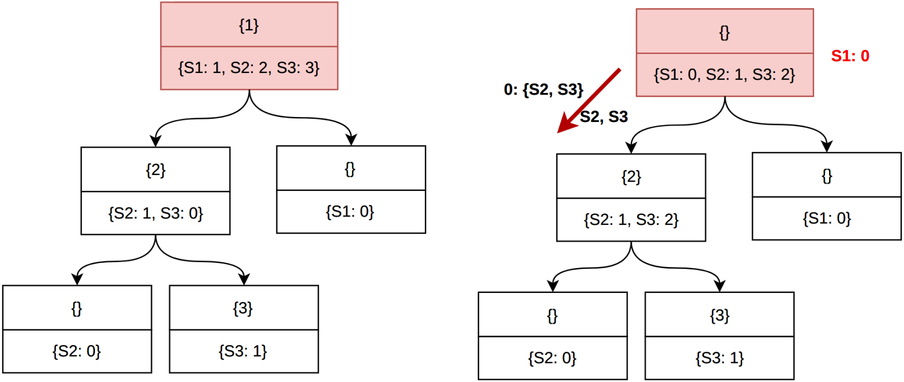
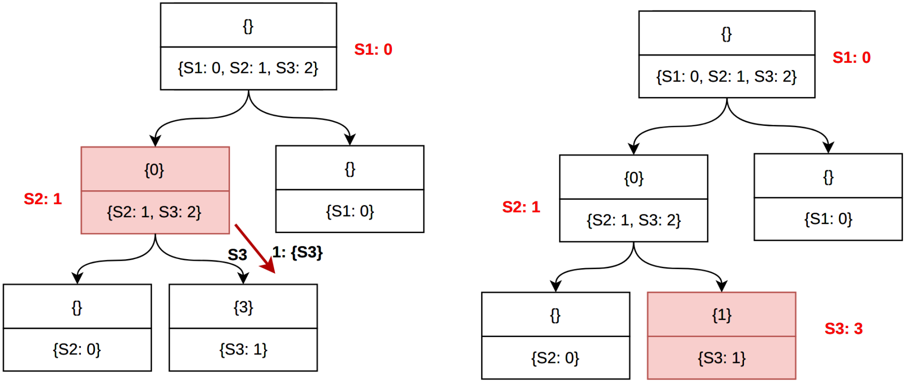


Figure: Sampling Tree

Example


{1}
{S1: 1, S2: 2, S3: 3}
{2}
{S2: 1, S3: 0}
{}
{S1: 0}
{}
{S2: 0}
{3}
{S3: 1}
{}
{S1: 0, S2: 1, S3: 2}
S1: 0
0: {S2, S3}
S2, S3
{2}
{S2: 1, S3: 2}
{}
{S1: 0}
{}
{S2: 0}
{3}
{S3: 1}

Example


{}
{S1: 0, S2: 1, S3: 2}
S1: 0
{0}
{S2: 1, S3: 2}
S2: 1
{}
{S1: 0}
S3
1: {S3}
{}
{S2: 0}
{3}
{S3: 1}
{}
{S1: 0, S2: 1, S3: 2}
S1: 0
{0}
{S2: 1, S3: 2}
S2: 1
{}
{S1: 0}
{}
{S2: 0}
{1}
{S3: 1}
S3: 3

Sampling Tree: randomly prove

Basis

1-path: $p(e) = \frac{1}{l}$

Induction

Assume for k-path, $p(e) = \frac{1}{l}$
For (k+1)-path, add a root node: $\{A : l_a\}$.
Case1: sampling in A

$$p(e) = p(A) * \frac{1}{l_a} = \frac{l_a}{l + l_a} * \frac{1}{l_a} = \frac{1}{l + l_a}$$

Case2: sampling in subtree

$$p(e) = (1 - p(A)) * \frac{1}{l} = \frac{l}{l + l_a} * \frac{1}{l} = \frac{1}{l + l_a}$$

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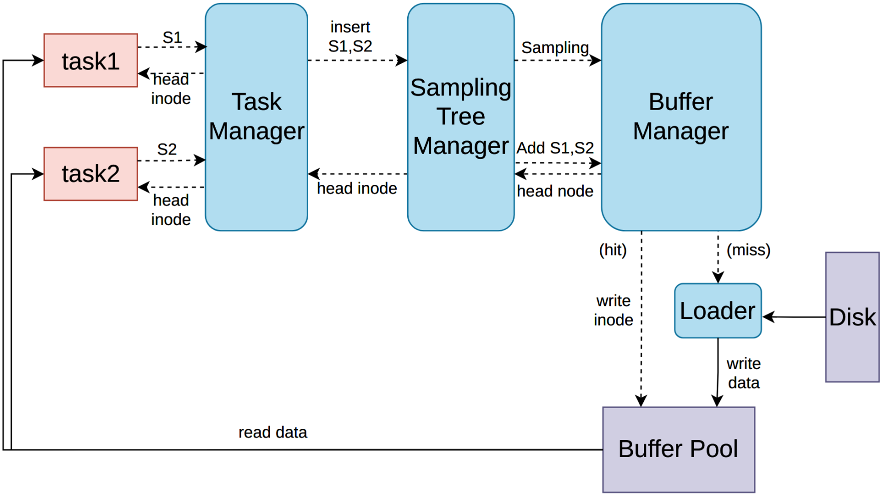
Architecture



Task Manager and Loader

Task Manager

- recieve task <task name, index set> and return head address
- send hearbeat

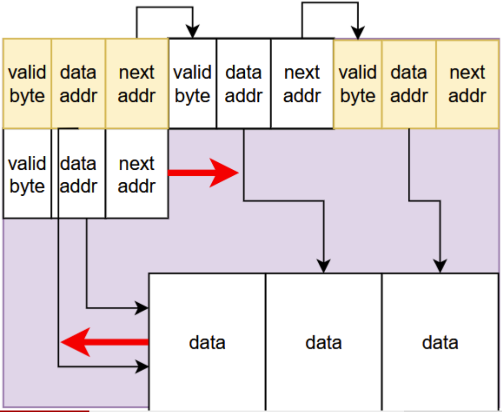
Loader

- process pool
- read data from disk and decode them
- write them in buffer pool

Buffer Pool: Data Structure

data

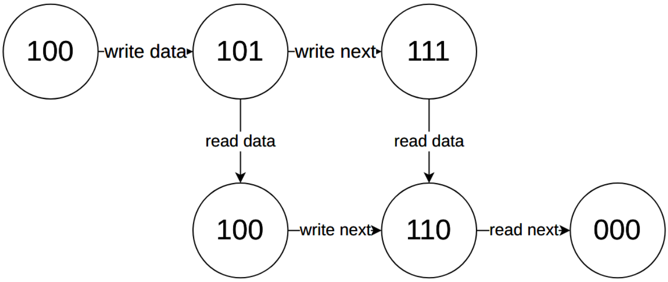
- There are two kinds of nodes: inode and datanode, and they are fixed size.
- Every task has a head inode address



Buffer Pool: Valid Byte

valid byte

- used bit: If the used bit is equal to 1, this inode is used
- next bit: If the next bit is equal to 1, the next addr is valid
- data bit: If the data bit is equal to 1, the data addr is valid



Buffer Pool Manager

- BM is responsible for maintaining three tables
- BM is responsible for freeing useless nodes

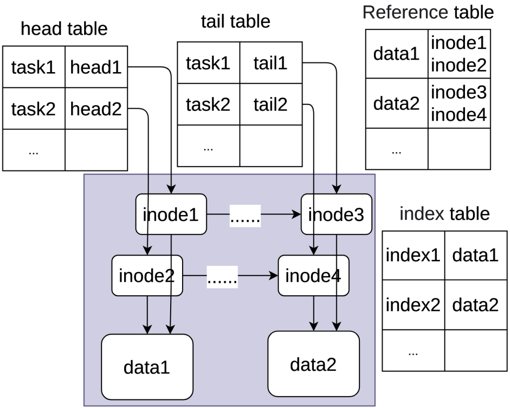


Figure: Sampling Tree

which data shound be free

Expection diff

The difference between
the number of times data has been quoted and
the number of times data should be quoted

Example

S1 = 1, 2, 3 , S2 = 1, 2
The Sampling result is S1: 3, S2: 2
$ExpectionDiff(3) = 1 - 1 = 0,$
$ExpectionDiff(2) = 2 - 1 = 1$

Answer

Choose the smallest Expection diff

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Hit rate Experiment

Assumption

There are two sets: S_1, S_2, and their length is n_1, n_2
The intersection set of them is S_i, whose length is n_i
$hitrate = \frac{hit}{n_i}$
$bufferSize = k$, which means that the buffer can have k datanode, and we ignore the size of the inode

Hit rate

Random replacement algorithm VS ExpectionDiff replacement algorithm

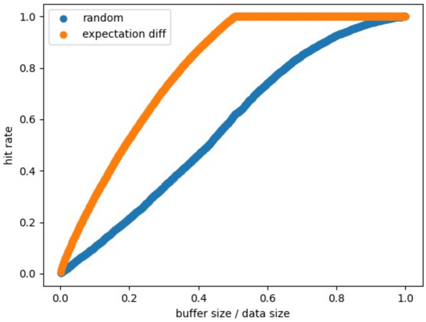

Figure:

Number of orphans

$p(e_1 = e_2 | e_2 \in S_i) = \frac{n_1}{n_2}$
Assume $p = \frac{n_1}{n_2}$

$$\begin{aligned} N &= \sum_{i=0}^{n_i} (1 - \frac{n_1 - i}{n_2 - i}) \\ &\geq \sum_{i=0}^{n_1} (1 - \frac{n_1 - i}{n_2 - i}) \\ &= \sum_{i=0}^{p*n_2} (1 - \frac{p * n_2 - i}{n_2 - i}) \\ &\approx \int_{i=0}^{p*n_2} (1 - \frac{p * n_2 - i}{n_2 - i}) \\ &= n_2 * (p - 1) ln^{1-p} \end{aligned} \tag{10}$$

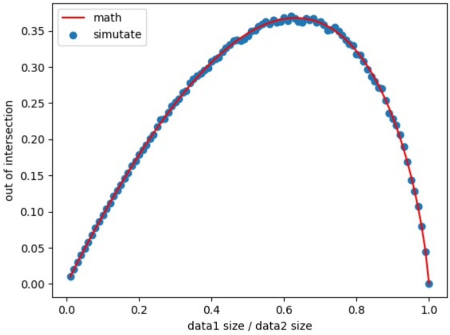

Figure:

Hit rate

$$buffer\_size = \frac{k}{n_2}$$

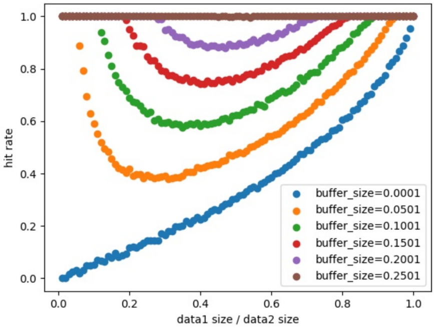

Figure:

Time Experiment

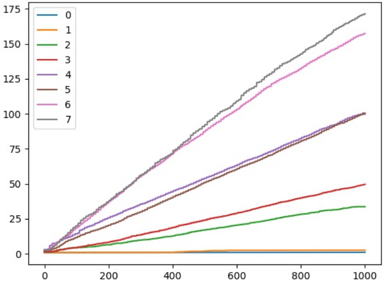

Figure: time

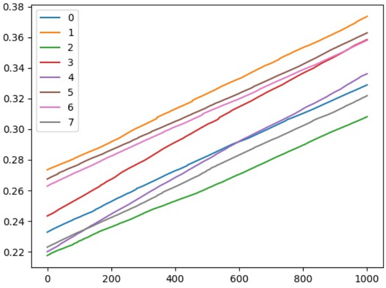

Figure: time with GlobalDataLoader

Correctness Experiment