GlobalDataLoader in Multi DeepLearning Task

Xie Jian

I2EC, ICS, NJU

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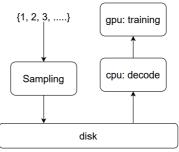


DataLoader in Pytorch

Data loading

Assume there is a task training in a dataset with index set

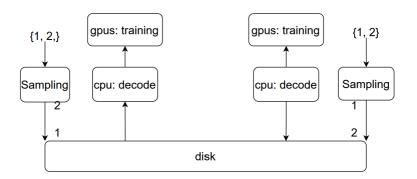
- Sampler sample some index randomly
- Worker read the data from disk
- CPU decode them
- GPU load them and training



Multi task loading data

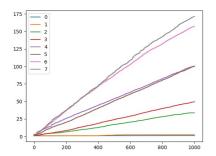
Problem

The data will be repeatedly read and processed by different tasks. Dose it matter?



Experiment

Multiple tasks with worker = 4, batch size = 32are trained at the same time with in a Tesla T4 with 16G memory. The server has 512g memory and 48 Intel(R) Xeon(R) Gold 5118 CPU.



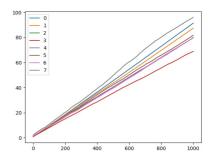


Figure: data loading time

Figure: data training time

Idea

idea

Avoid repeatedly reading and processing:

- After shuffle, the data should be read in a similar order
- And there are a global DataLoader to read the same data only once

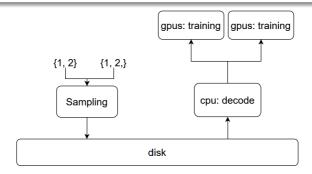


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Sampling: problem description

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:

$$p(e_1) = \frac{1}{|S_1|}$$
 $p(e_2) = \frac{1}{|S_2|}$
 $Maximize(p(e_1 = e_2))$ (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 $S_{d2} = S_2 - S_i$.

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

Algorithm

- *S*₁:
 - $step_{11}$: randomly select a set from S_i and S_{d1}
 - $step_{12}$: if the set is S_{d1} , randomly select a element e_1 from S_{d1}
 - $step_{13}$: if the set is S_i , randomly select a element e_1 from S_i
- *S*₂:
 - $step_{21}$: randomly select a set from S_i and S_{d2}
 - $step_{22}$: if the set is S_{d2} , randomly select a element e_2 from S_{d2}
 - $step_{23}$: if the set is S_i , randomly select a element e_2 from S_i

Probability

$$p(e_1) = \frac{1}{n_1}, p(e_2) = \frac{1}{n_2}$$

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

Dependently Sampling Algorithm I

Insight

The $step_{13}$ is same as $step_{23}$ (randomly select an element e from S_i).

Example

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

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



Dependently Sampling Algorithm I

Algorithm

- *S*₁:
 - $step_{11}$: randomly select a set from S_i and S_{d1}
 - $step_{12}$: if the set is S_{d1} , randomly select a element e_1 from S_{d1}
 - $step_{13}$: if the set is S_i , go to $step_3$
- *S*₂:
 - $step_{21}$: randomly select a set from S_i and S_{d2}
 - $step_{22}$: if the set is S_{d2} , randomly select a element e_2 from S_{d2}
 - $step_{23}$: if the set is S_i , go to $step_3$
- step₃: randomly select a element e from S_i

Probability

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



Dependently Sampling Algorithm I

Insight

The $step_{11}$ and $step_{21}$ 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 $\{6,7\}$
- $p(e_1 = e_2) = p_1(S_i) = 0.6$



Problem

Algorithm

- $step_1$: randomly select a set from S_i and S_{d1}
- *S*₁:
 - $step_{12}$: if the set is S_{d1} , randomly select a element e_1 from S_{d1}
 - $step_{13}$: if the set is S_i , go to $step_3$
- *S*₂:
 - $step_{22}$: if the set is not S_{d1} , randomly select a element e_2 from S_{d2}
 - $step_{23}$: if the set is S_i , go to $step_3$
- step₃: randomly select a element e from S_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

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

$\mathsf{Approach}$

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

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

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

Dependently Sampling Algorithm II

$\mathsf{Algorithm}$

- $step_1$: randomly select a set S from S_i and S_{d1}
- *S*₁:
 - $step_{12}$: if the S is S_{d1} , randomly select a element e_1 from S_{d1}
 - $step_{13}$: if the S is S_i , go to $step_3$
- *S*₂:
 - $step_{22}$: if the S is S_{d2} , randomly select a element e_2 from S_{d2}
 - $step_{23}$: if the S is S_i
 - randomly let $S = S_{d1}$ in probability of $1 \frac{n_1}{n_2}$
 - if S is S_{d2} , randomly select a element e_2 from S_{d2}
 - if S is S_i , go to $step_3$
- step₃: randomly select a element e from S_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

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

Approach

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

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

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

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Dependently Sampling Algorithm II

Algorithm

- $step_1$: randomly select a set S from S_i and S_{d1}
- *S*₁:
 - $step_{12}$: if the S is S_{d1} , randomly select a element e_1 from S_{d1}
 - $step_{13}$: if the S is S_i , go to $step_3$
- *S*₂:
 - $step_{22}$: if the S is S_{d2} , randomly select a element e_2 from S_{d2}
 - randomly let $S = S_i$ in probability of $1 \frac{n1*(n2-n_i)}{n2*(n1-n_i)}$
 - if S is S_{d2} , randomly select a element e_2 from S_{d2}
 - if S is S_i , randomly select a element e_2 from S_i
 - $step_{23}$: if the S is S_i , go to $step_3$
- $step_3$: randomly select a element e from S_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

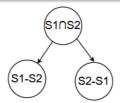
shuffle $S_1 \cup S_2$: offset

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



Sampling Tree: two sets

- case1: Both randomly sample in $S_1 \cap S_2$
 - $p_1 < \frac{n_i}{n_1}$ $p_2 < \frac{n_1}{n_2}$
- case2: For S_1 , sample in $S_1 \cap S_2$. For S_2 , sample in $S_2 S_1$
 - $p_1 < \frac{n_i}{n_1}$ $p_2 > \frac{n_1}{n_2}$
- case3: For S_1 , sample in $S_1 S_2$. For S_2 , sample in $S_2 S_1$
 - $p_1 > \frac{n_i}{n_1}$

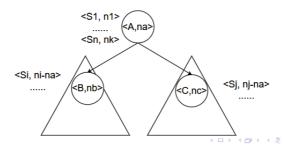


Sampling Tree: n sets

Algorithm: parent node

There are two sets: S_{child} , S_{parent} .

- $p_1 < \frac{n_a}{n_1}, S_{parent} = S_{parent} \cup S_1$
 -
- $p_j > \frac{n_{j-1}}{n_j}, S_{child} = S_{child} \cup S_j$
- $p_{j+1} < \frac{n_{j-1}}{n_{j+1}}, S_{parent} = S_{parent} \cup S_{j+1}$



Prove

Basis: For two sets $\{S_1, S_2\}$:

$$p(e_1) = \frac{1}{|S_1|}, p(e_1) = \frac{1}{|S_2|}$$

$$p(e_1 = e_2) = \frac{1}{\max(|S_1|, |S_2|)}$$
(10)

Induction:

If $\{S_1, S_2, ... S_k\}$ satisfies:

$$\forall i, p(e_i) = \frac{1}{|S_i|}$$

$$\forall i, j, p(e_i = e_j) = \frac{1}{\max(|S_i|, |S_j|)}$$
(11)

then $\{S_1, S_2, ... S_k, S_{k+1}\}$ sets is also satisfies



Induction

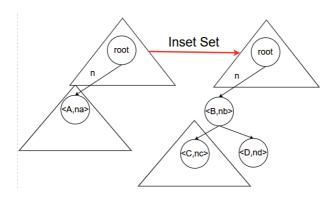
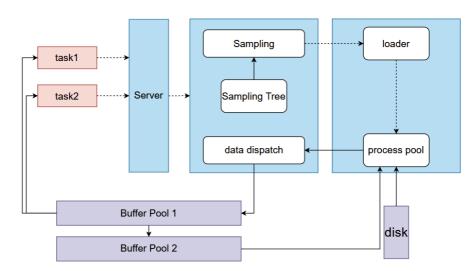


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Architecture



Server and Loader

Server

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

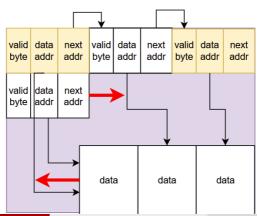
Loader

- check Buffer Pool2
- if miss, read from disk

Buffer Pool: Data Structure

data

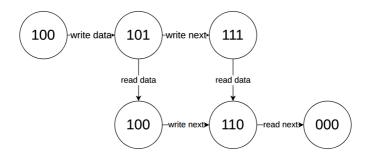
- There are two kinds of nodes: inode and datanode, and they are fixed size.
- Every task has a head inode address



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: Evict

inode

if used bit is equal to 0, then it can be evited

data node

if all reference nodes of datanode is unused, then it can be evited to Buffer Pool2

Buffer Pool 2

LRU

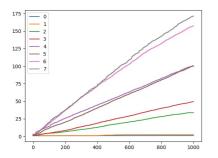


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Experiment



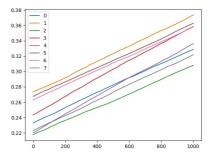


Figure: time

Figure: time with GlobalDataLoader