iBTune: Individualized Buffer Tuning for Large-scale Cloud Databases

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Alibaba
VLDB 2019
Outline

Background and Motivation

Algorithm and System

Deployment and Result
Background

The memory uses at Alibaba product environment

Buffer pool is the largest memory consumer

Table 1: Usage of different memory pools

<table>
<thead>
<tr>
<th>Memory Pool</th>
<th>buffer pool</th>
<th>insert buffer</th>
<th>log buffer</th>
<th>join buffer</th>
<th>key buffer</th>
<th>read buffer</th>
<th>sort buffer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. Size</td>
<td>29609.98M</td>
<td>8.00M</td>
<td>200.00M</td>
<td>0.13M</td>
<td>8.00M</td>
<td>0.13M</td>
<td>1.25M</td>
</tr>
<tr>
<td>Percent</td>
<td>99.27%</td>
<td>0.03%</td>
<td>0.67%</td>
<td>0.00%</td>
<td>0.03%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

Memory is bottleneck among the resources

SDDP: Self-Driving Database Platform
Motivation

Reduce memory (buffer pool) while guaranteeing SLA (response time).

- DBA manually uses a small number of BP sizes (10 configurations in our case).
- Each instance’s BP size might be different as the query workload is different.
- Manual tuning is not scalable for large cloud databases since each instance has different BP size.

CDF of individual BP sizes before and after the iBTune applies

**iBTune: Individualized Buffer Tuning for Large-scale Cloud Databases**
iBTune - Preliminary Attempt

Buffer pool (BP) size is sensitive to miss ratio: BP size is reduced from 188G to 80G when it’s hit ratio is from 99.968% to 99.950%

- **Challenge**: Heuristic method (such as shrinking 10% each time) does not work, since we have to try many times, which makes the system unstable and is unacceptable for mission-critical applications.

**Intuition**:
- Calculate BP based on hit ratio (miss ratio) to avoid restarting system multiple times
- Confirm whether the BP size meets the requirement of SLA
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iBTune – High level idea

- Practical function:
  \[ F1(t_{\text{miss\_ratio}}) = \text{New BP size} \]

- F1(t_{\text{miss\_ratio}}) = \text{New BP size} \checkmark

- F2(t_{\text{miss\_ratio}}) = \text{Response time} \leftarrow

- Apply new BP size

- DB instance

- Pairwise DNN

- Guarantee SLA

- Safe Response time (SLA)
Finding BP=f(miss ratio)

• A number of empirical measurements on real systems have shown power law popularity distributions and follow that:

\[ \frac{\log (mr_{target}) - \log (mr_{cur})}{\log (bp_{bptarget}) - \log (bp_{cur})} \approx -\alpha_i. \]

• Parameter \( \alpha \) is obtained from the workload, which is 1.2 in our case.

A large class of heavy-tailed requests with popularities following a power law distribution fits in our formulation.
Calculating tolerable miss ratio

- K-nearest-neighbors (DB instances)
- Find the nearest neighbors
  - Such as 6 in our case
  - Neighbor distance is calculated by similarity
- Calculate tolerable miss ratio
  - The weighted mean of the miss ratios of the k-nearest-neighbors

How to obtain k-nearest-neighbors?
Calculating similarity

• Features
  – RT
  – QPS
  – miss ratio
  – CPU usage
  – logical read
  – io read

The last three metrics are divided by QPS

Pearson correlation coefficients

<table>
<thead>
<tr>
<th></th>
<th>Raw</th>
<th>Div By QPS</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPU usage:</td>
<td>0.055</td>
<td>0.093</td>
</tr>
<tr>
<td>Logical read:</td>
<td>0.127</td>
<td>0.394</td>
</tr>
<tr>
<td>IO read:</td>
<td>0.017</td>
<td>0.117</td>
</tr>
</tbody>
</table>

Till now, we can get the k-nearest-neighbors and tolerable miss ratio and calculate the new BP size.
Predicting RT

Pairwise DNN: Predict the respond time (RT) based on the tolerable miss ratio

• Training
  – Input: two instances’ metrics + right instance’s RT
  – Output: Left instance’s RT
• Predicting
  – input: A instance’s metrics X 2 except miss ratio
  – Output: RT corresponding to tolerate miss ratio
• The granularity of metric is a day

The predicted RT is compared with the safe SLA (RT)
Predicting RT

Pairwise DNN: Predict the respond time (RT) based on the tolerable miss ratio

- **Training**
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- **Predicting**
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  - Output: RT corresponding to tolerate miss ratio

- The granularity of metric is a day

The predicted RT is compared with the safe SLA (RT)
Determine the safe RT for different applications

Group all the instances into different applications, and find the 95% percentile of the response times in each group as the corresponding safe limit for that application.
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System halt avoidance

Based on X-Paxos: high availability protocol implementation at Alibaba

1. Adjust backup node’s BP size
   It leads to 10~20 sec system halt to backup node, without affecting system service.

2. Switch master and backup after the backup node recovers

3. Monitor the new master for 24 hours

4. Switch

5. If the new master is abnormal, i.e., the number of slow SQLs increases, rollback will be triggered.

If the new master works fine during the following 24 hours, backup nodes’ BP will be adjusted.
Evaluation

- All results are from our product environment
- X-Engine: MySQL compatible database based on LSM-Tree storage engine
- With high performance Paxos implementation
- Pairwise DNN: 100K data samples

<table>
<thead>
<tr>
<th></th>
<th>Taobao</th>
<th>Tmall</th>
<th>Youku</th>
<th>Fliggy</th>
<th>Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>Select</td>
<td>5245/s</td>
<td>2815/s</td>
<td>1017/s</td>
<td>22930/s</td>
<td>120/s</td>
</tr>
<tr>
<td>Insert</td>
<td>4222/s</td>
<td>0</td>
<td>1/s</td>
<td>1520/s</td>
<td>10/s</td>
</tr>
<tr>
<td>Update</td>
<td>0</td>
<td>30/s</td>
<td>315/s</td>
<td>4/s</td>
<td>980/s</td>
</tr>
<tr>
<td>Delete</td>
<td>2708/s</td>
<td>0</td>
<td>10/s</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

1,000 sample instances scattered across different applications

iBTune has been deployed on 10,000 database instances
Memory saving: ~17%
Single instance

Performance before and after BP adjustment (45G->21G) during holidays and workdays:

- Red line is the time when BP size is adjusted
- Green lines show the holiday which is 7-days
- Predicted RT: only 3 points exceeded which is acceptable

The IO read metric is the real IO, since all our DB instances turn on direct IO
10 representative instances. The memory saving ranges from 50% to 10%, which strongly supports that a single number does not fit all. Instance 1 has a large increase in RT after the adjustment. We find that there is one query that consumes 99.97% of the total response time. The lookup value in WHERE condition changes for this query.
Conclusion & Future Work

• iBTune has been deployed on 10,000 database instances with memory saving: ~17%

• Future work
  – Cache preload
    • Backup node needs run SQLs to load data into cache after BP adjustment
    • Perform switching after preload
  – Buffer increase
    • Currently reply on DBA
    • Automatic increase buffer
  – Multiple parameters tuning
    • DBMS configure file
Thanks