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Faculty of Natural Sciences and Technology I
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Workload-based Data Partitioning for Index Construction

Bachelor's Thesis

written by

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Acknowledgement

Abstract

Contents

Chapter 1

Introduction

Here is a citation [1].

- DBMS routinely use index structures for increased performance
- Index pre-configured or chosen by user
- Mostly no utilization of underlying data or workload distribution
- Except: learned indexes -> Related Work
- Motivation: different data structures for different query workloads (hash table?)
- For this, introduce concept of hybrid index structures
- Create partitions to create singular indexes and combine them
- Optimize partitions based on one/multiple metrics
- As motivation: GENE, starting point for generic search
- Introduce what is covered in what section of this thesis

Chapter 2

Related Work

This chapter covers work related to Workload-based Data Partitioning. I also introduce the index structures used as baselines in the evaluation.

The well-known B-tree is the first basic index structure used in the comparison [2].

Another index that was used is an ART Tree [3].

To cover the last index structure used in the comparison, we need to look at another class of index structures that only emerged recently. Learned index structures generally try to leverage recent progress in the field of Machine Learning to improve index performance.

RMI [4] and ALEX [5] use many small Machine Learning models to build a tree-like hierarchy. The segmentation happens through the given structure and training of the internal node's models.

FITing-Tree [6] tries to combine the flexibility of traditional index structures with learning by indexing linear data segments. The data partitioning is done by a single pass over the sorted data. The segmentation algorithm aims to determine the data segments' bounds so that the relation between keys and positions in the sorted array can be approximated by a linear function. A new segment is created if a point falls outside an error cone. Otherwise, the cone is adjusted by tightening the cone boundaries to ensure the error bounds within each segment.

The authors of the PGM-index [7], which I used as the third baseline in the evaluation, tried to improve upon the ideas of FITing-Tree. While their approach seemed reasonable, a disadvantage was the data segmentation. The authors note that the single-pass segmentation algorithm does not produce the optimal number of data segments, leading to more tree leaves and an increased lookup time. By reducing the segmentation to the problem of constructing a convex hull and allowing the index to be built recursively, they could increase the lookup time by xxxxx.

While learned index structures perform so well because they can adapt to the underlying data distribution, they do not consider the workload that will

be executed. While RMI and ALEX partition the data indirectly through their models, FITing-Tree and PGM explicitly use segmentation algorithms before building the index to determine the data that belongs in one segment. However, workload information might be beneficial to index construction, e.g. by indicating that certain data segments are not frequently requested. This is what's different in my work because I try to use the workload for data segmentation, not primarily the underlying data distribution.

1. *Hybrid/Adaptive Index Structures*

    - Adaptive Hybrid Indexes [8] for context and compacting/decompressing criteria
    - GENE [9] for the approach to look at indexes as logical components and combining them, generic search briefly to iterate over starting options and give our partitioning as a possible better starting point.

2. *Distributed (Database) Systems*

    Context: data partitioning in the sense that different partitions can be stored on different nodes of the distributed system

    - Schism [10] for their workload-centric approach to data partitioning

Chapter 3

Background

3.1 Hybrid Index Structures

- What are hybrid index structures?
- Advantages: optimize for subproblems, combine to one index
- challenges: correct combination of these structures (e.g. routing through data structure)

3.2 Partition and Partitioning functions

- Mathematical set theory definition of partition
- Adaption to key space/segments
- Partitioning functions for indexes
- Used in routing of through index

3.3 Numerical Differentiation

- Finite difference approximations
- Relation to true derivative (limes h -> 0)
- Consistency order of approximations
- Forward, Central, Backward finite difference approximations

Chapter 4

Approach and Algorithms

4.1 Approach

- Data generation
- Workload generation + parameters
- Partitioning (more details in section 4.2 and 4.3)
- Interface between Partitioning and Bulkloading
- (Informed) Bulkloading
- Benchmarking

4.2 Partitioning by Frequency

- Motivation: caching
- Idea from numerical approximations
- Algorithm

4.3 Partitioning by Purity

- Motivation: optimize index for different query types
- Algorithm

Chapter 5

Datasets and Workloads

This chapter deals with the used datasets and workloads

5.1 Datasets

- Generation procedure
- Used parameters for parameterized distributions

5.1.1 Synthetic Datasets

- uniform dense

5.1.2 Real-world Datasets

- SOSD datasets (osm, books, fb)

5.2 Workloads

5.2.1 Synthetic Workloads

- uniform sampling
- lognormal (because used in hybrid adaptive indexing paper)
- step workloads
- Proof of concept workload

5.2.2 Real-world Workloads

- Self-generated
- Are they representative (look into dbbench/YSCB)

- workloads especially OLTP often skewed (Identifying Hot and Cold Data in Main-Memory Databases, https://www.microsoft.com/en-us/research/wp-content/uploads/2013/04/ColdDataClassification-icde2013-cr.pdf)

Chapter 6

Evaluation

This chapter will deal with the evaluation of the experiments

6.1 Setup

- hardware
- index parameters like slot size, PGM epsilon etc.

6.2 Lookup Performance

6.2.1 Frequency Algorithm

6.2.2 Purity Algorithm

6.3 Role of Partitioning Parameters

- $window_size$, delta for frequency
- $window_size$ for purity (as of yet)

6.3.1 Frequency Algorithm

6.3.2 Purity Algorithm

Chapter 7

Conclusion and Future Work

- Previous results reproducable?
- What have we found?
- Does partitioning yield better lookup times?
- Is it beneficial to move leaves higher up in tree?
- Is it beneficial to use hybrid index structures (i.e. change layout/data structure in nodes)
- Best case/worst case considerations?
- Future Work: Combination of metrics
- Future Work: Look at more data structures other than BinarySearch-Leaves and Hashtables
- Future Work: What other workload metrics can be used for partitioning?

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Appendix A

Appendix