Introduction
Theory
Our Implementation
Tests
Demonstration
Conclusion

An Implementation of Hypersuccinct Trees

Christopher Pack, Alexander Auras, Nathanael Stöhr, Charbono Lonyem Tegomo

> Lehrstuhl für theoretische Informatik Universität Siegen

> > January 27, 2022



Outline

- Introduction
- 2 Theory
 - Hypersuccinct Tree Code
- Our Implementation
 - Our hypersuccinct tree
 - Queries
- Tests
- Demonstration



Table of Contents

- Introduction
- 2 Theory
 - Hypersuccinct Tree Code
- Our Implementation
 - Our hypersuccinct tree
 - Queries
- 4 Tests
- Demonstration



Introduction

- We were tasked with creating an implementation of a hypersuccinct tree encoding, as described in [1].
- Additionally we add the possibility of huffman encoding for part of the tree, to provide an implementation of the encoding improvement mentioned in [2].
- Our result is a library that can encode trees in acceptable time, and is able to perform queries on those encoded trees in O(1), while offering huffman encoding for their Microtrees.

Table of Contents

- Introduction
- 2 Theory
 - Hypersuccinct Tree Code
- Our Implementation
 - Our hypersuccinct tree
 - Queries
- Tests
- Demonstration



The tree covering Algorithm

- Given a splitting size m, all resulting trees are at most of size 2m.
- The resulting subtrees at most share a single node, their root.
- Most subtrees' roots lie either directly below other subtree roots or share roots with other subtrees, and a dictionary of the root's children can be used to identify tree connections.
- Subtrees that do not lie directly at or below other roots require a special node, a Dummy, to represent their connection to its higher tree.



Demonstration

The tree covering Algorithm

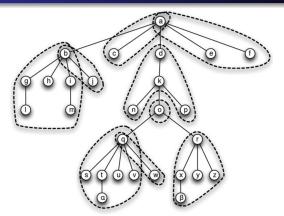


Figure: Example of Tree decomposition with m = 5 [1]



To fully decompose a tree for hypersuccinct encoding, [1] offers the following procedure:

- First decompose the entire tree into Minitrees with the size $\lceil Ig^2n \rceil$.
- Generate the FIDs and Dummys for their interconnections.
- Then decompose each Minitree into Microtrees with the size $\lceil \frac{lgn}{8} \rceil$.
- Generate the FIDs and Dummys for their interconnections.

Queries

As mentioned in [1], additional data needs to be saved in order to execute queries without needing to decode hypersuccinct trees.

- Additional query data is saved for each level of abstraction (Minitrees, Microtrees, individual nodes).
- To execute some queries, navigation on the FID and the Typevector is required.
 - As the definition of "Fully Indexable Dictionary" states, it is necessary to implement Rank and Select queries.
 - A possible efficient implementation is described in [3], which is implemented in an external library [4].



Table of Contents

- Introduction
- 2 Theory
 - Hypersuccinct Tree Code
- Our Implementation
 - Our hypersuccinct tree
 - Queries
- Tests
- Demonstration



Hypersuccinct nodes and trees

- Hypersuccinct nodes are tripels that represent their Minitree, Microtree, and Node within the Microtree.
- The Hypersuccinct_Tree class implements the encoding and offers the query functions.
- The Hypersuccinct Factory handles creating a hypersuccinct tree from possible sources.

The Hypersuccinct Factory

- The hypersuccinct factory encodes trees efficiently, making use of multiple threads with a multithreading library [5].
- Creates data for query execution.
- The hypersuccinct factory also creates hypersuccinct trees from an encoded file. Since an already encoded file is read, there is no processing for generating any data.

FIDs and specific issues

Bitvector	Bit							
	1	2	3	4	5	6	7	8
Minitree FID 0	1	1	0	1	0	0	1	1
Minitree TV 0	0	1	-	0	-	-	1	0
Minitree Nr.	0	3	0	1	1	1	5	2
Minitree FID 1	1	0	1	1	0	1	1	1
Minitree TV 1	0	-	1	1	-	1	1	0
Minitree Nr.	3	3	6	7	3	8	9	4

Figure: Indices for Minitrees

FIDs and specific issues

- To solve the discrepancies with FID and tree indices:
 - Bitvectors that denote the first Type 0 (Top) and Type 1 (Low) tree of every FID.
 - Bitvectors the denote their Top and Low FIDs for each Tree.
 - This is done for both Mini- and Microtrees, so 8 bitvectors in total.
- To solve the issue with identifying the correct low trees:
 - When identifying trees, we always take the top tree of the FID that the low index points to.
 - This is possible since each FID points to its first low tree, which points to its own FID, and other low FIDs have incremental indices by construction.



Minitrees and Lookuptable entries

- Minitrees and Lookuptable entries are structs that hold bitvectors.
- Minitrees hold all information for their Microtrees, all their query data and all their Microtree query data.
- Lookuptable entries hold information of their structure and a key for identification, as well as query data.

Simple Queries

Simple queries are such that require only one bitvector per abstraction. Their structure simply moves from one abstraction level to the next one to answer the query.

These simple queries are:

- getParent
- 2) degree
- 3) subtreeSize
- 4) depth
- 5) height
- leftmostLeaf
- rightmostLeaf
- 8) leafSize
- 9) levelSuccessor (Not implemented)
- 10) levelPredecessor (Not implemented)

Rank Queries

Rank queries are queries that return some sort of rank from the tree. These queries are all similar in structure, and need multiple bitvectors per level of abstraction, due to special cases. These rank queries are:

- 1) childRank
- leafRank
- 3) nodeRank (Not implemented)

Special cases: Rank

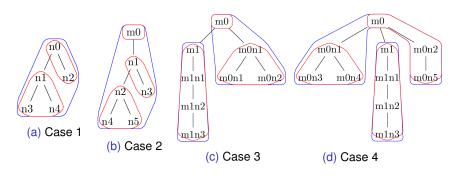


Figure: 4 Special Cases for Rank Queries

Special Cases: Rank

- We can use the FID to identify each special case.
 However, since rank queries do not provide an index in for the FID, the identification of the right position of the node in the FID is difficult, and we therefore need to provide an answer from the node indices alone.
- We need specific bitvectors that denote the rank of the first child of a tree for data to resolve these cases.
- We do not need two bitvectors in the lookup table. If Case 4 only has one Microtree in the higher Minitree, the respective lookuptable will already present the correct result for m0n2.



Child

This is a very unique query, as it is simpler than rank queries, since the index provided points to direct positions on the FIDs:

- We can identify the correct node by moving through the Minitree FID, then the Microtree FID and then the lookuptable entry.
- Dummy nodes can easily be skipped both at the end and the beginning of the query.

Helper Queries

These queries are purely used within other queries to take on some repeat tasks:

- 1) isDummyAncestorWithinMiniTree
- 2) isDummyAncestorWithinMicroTree
- 3) getParentForQuery

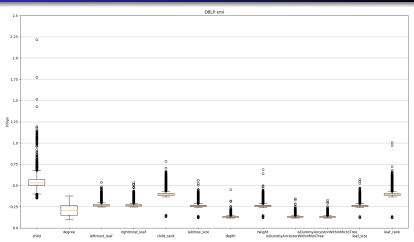
Table of Contents

- Introduction
- 2 Theory
- Hypersuccinct Tree Code
- Our Implementation
 - Our hypersuccinct tree
 - Queries
- Tests
- Demonstration



Introduction
Theory
Our Implementation
Tests
Demonstration
Conclusion

Query tests



Query tests

- All queries except *child* maintain an anverage runtime below $100\mu s$.
- The runtime of child actually increases with larger trees.
 We identified the reason for this being a simple getMinitree function, which is also used in multiple other queries.

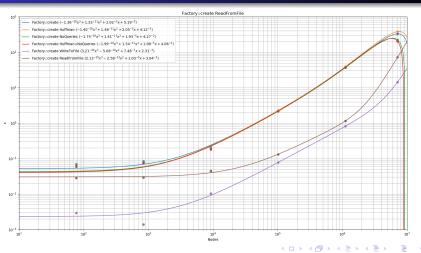
create, writing and reading

- The encoding process in create has been optimized as much as we think possible.
 - While the farzan-munro algorithm cannot be optimized with multithreading, the creation of Microtrees are individual tasks that can be parallelized.
 - Adding huffman encoding decreases efficiency slightly.
- Reading and writing files is straightforward and therefore much more efficient.
 - Writing just pushes every vector with Elias-Gamma encoding into a file.
 - Reading just decodes the vectors from the file. There is no handling of badly formatted vectors.



Introduction
Theory
Our Implementation
Tests
Demonstration
Conclusion

create, writing and reading



Introduction
Theory
Our Implementation
Tests
Demonstration
Conclusion

Space and Huffman

Tree Name	Normal	Huffman	Huffman + Lookuptable
TreeNath	52	23	24
TreeNath3	5196	2695	2706
TreeNath4	53369	31709	31732
TreeNath5	583289	345005	345029
XMark2	2004196	831572	831627
DBLP	3690039	593804	593842

Figure: Space for normal encoding and huffman encoding in byte

- Space reduction is fairly obvious.
- XMark2 is larger than DBLP with huffman due to having more evenly distributed tree structures.

Table of Contents

- Introduction
- 2 Theory
 - Hypersuccinct Tree Code
- Our Implementation
 - Our hypersuccinct tree
 - Queries
- Tests
- Demonstration



Introduction
Theory
Our Implementation
Tests
Demonstration
Conclusion

- Demonstration of program -

Conclusion

- We have created a library that can encode trees succinctly.
- Our tree encoding is space efficient and allows us to execute various queries in O(1).
- We offer huffman encoding for our tree, which saves space.
- The encoding process is optimized, can encode trees with more than 7 million nodes in less than 6 minutes.

References I

- A. Farzan and J. I. Munro, "A uniform paradigm to succinctly encode various families of trees," *Springer Science+Business Media*, 2012.
- J. I. Munro, P. K. Nicholson, L. S. Benkner, and S. Wild, "Hypersuccinct trees – a universally compressed data structure for binary and ordinal trees," 2021.
- R. Raman, V. Raman, and S. S. Rao, "Succinct indexable dictionaries with applications to encoding k-ary trees and multisets," *ACM Transactions on Algorithms (TALG)*, 2007.

References II



