# Storage and Retrieval: Memory, Search and Indexing

Reza Rawassizadeh

# Outline

- Java Memory Structure
- Algorithm Complexity
- Search Improvement Methods
- Bloom Filter

## Outline

- Java Memory Structure
- Algorithm Complexity
- Search Improvement Methods
- Bloom Filter

# Java Memory Management

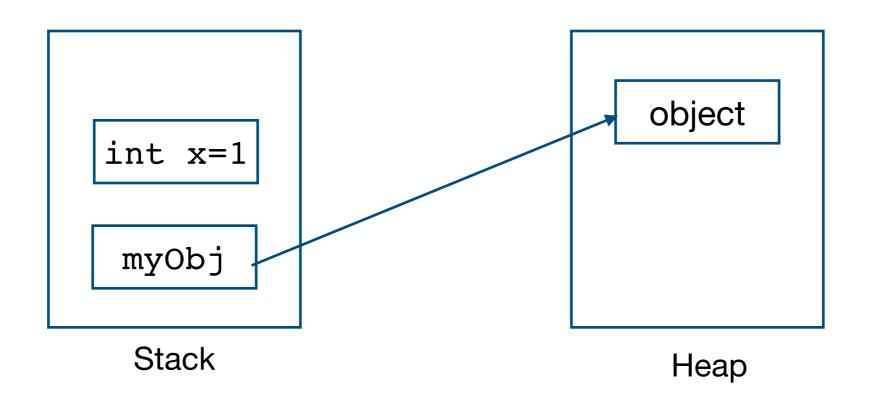
- Java has automatic memory management. It automatically performs garbage collection.
- By garbage we mean class objects which are instantiated, but not in use anymore. They occupy the memory. They are called garbage and the compiler should remove them.
- There is no guarantee that automatic garbage collection of java does not cause our code to raise OutofMemoryError.

# Memory Structure in Java

- Java divides memory into two parts, stack and heap.
- Stack: stores Java primitive types (int, char, ...) and holds a reference to heap objects.
- Java primitive types do not have reference to an object, their value directly stayed in stack memory.
- Heap: It is a part of the memory that <u>actual object</u> will be stored. In other words, the objects that their reference is located inside stack, hold their value inside the heap.

# Memory Structure in Java

TestClass myObj = new TestClass()



# Stack vs Heap

#### Stack

- The size of the stack is flexible and can changes as methods and functions create and delete local variables.
- Memory allocation (assignment and freeing) is automatic, without a need for code.
- Stack has size limits, which can vary according to the underlying operating system that hosts JVM.
- Variables inside the stack remain there as long as the function that created them is running.
- If stack space is full, Java throws java.lang.StackOverFlowError

#### Heap

- It is **not managed automatically** and we need to **free allocated memory by code**, when memory blocks are no longer needed.
- The heap is prone to memory leak problems, where memory is allocated to unused objects and will not be available to processes other than that.
- There is no size limit in the heap.
- Compared to stack, objects in the heap are much slower to access. It is also slower to write to the memory on the heap.
- If heap space is full, Java throws java.lang.OutOfMemoryError

# Java Memory Structure

- We have only one heap memory for each JVM process. Therefore, heap is a shared part of memory regardless of how many threads are running inside the Java.
- Usually we do not configure maximum stack and heap size.
   However, Java enables us to define them as follows:

-Xms<size> set initial Java heap size

-Xmx<size> set maximum Java heap size

-Xss<size> set java thread stack size

java -Xmx6g myApplication

# Memory Size Manipulation in Eclipse IDE

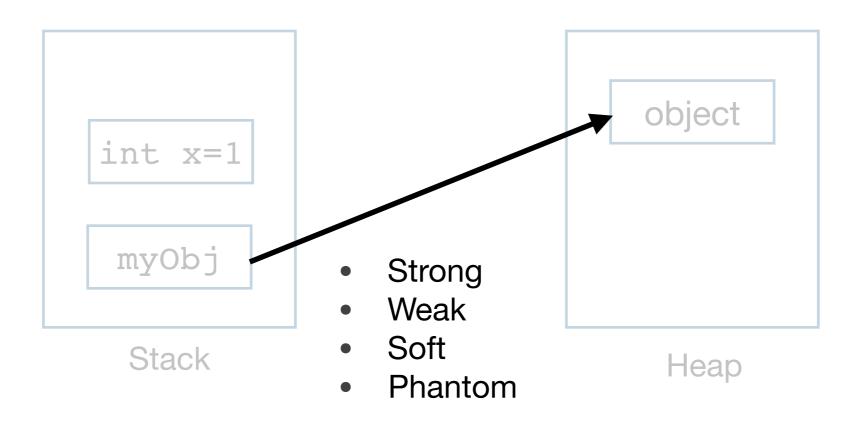
- Run —> Run Configurations —> Arguments —> VM arguments
- Enter Xmx6g and Xmx256m

Test the following code:

```
package edu.bu.met622.memory;
import java.util.Vector;

public class MemoryTest {
    public static void main(String[] args){
        Vector v = new Vector();
        while (true)
        {
            byte b[] = new byte[1048576];
            v.add(b);
            Runtime rt = Runtime.getRuntime();
            System.out.println( "free memory: " + rt.freeMemory() );
        }
    }
}
```

# Reference Types in Java



source: https://www.onlinetutorialspoint.com/java/reference-types-in-java-strong-soft-weak-phantom.html

# Memory References

• **Strong:** When there is a direct reference to an object and it is not eligible for garbage collection.

```
Test obj = new Test()
```

 Weak: When an object has neither strong nor soft reference, it is a weak reference. Weak references should be explicitly specified while referencing them.

```
// Strong Reference
Test a = new Test();
a.x();
// Creating Weak Reference to Test object to which 'a'is also pointing.
WeakReference<Test> weakref = new WeakReference<Test>(a);
```

• **Soft:** When an object is free for garbage collection, but it is not yet garbage collected, until JVM is running low on memory and looking for objects to remove.

```
// Marked for gc, but JVM might not do it immediately.
g = null;
```

• **Phantom:** Objects are eligible for GC, but JVM puts them in a queue called "**ReferenceQueue**". We don't know a phantom referenced object is dead or alive.

# Outline

- Java Memory Structure
- Algorithm Complexity
- Search Improvement Methods
- Bloom Filter

# Big O notation

Big O notation specifies the order of magnitude of performance rather than the exact performance. It also assumes the <u>worst-case response time</u>. If we write an algorithm that could take a while or be instantaneous, big O uses the longer one. It uses an *n* to reflect the number of operations or size we have.

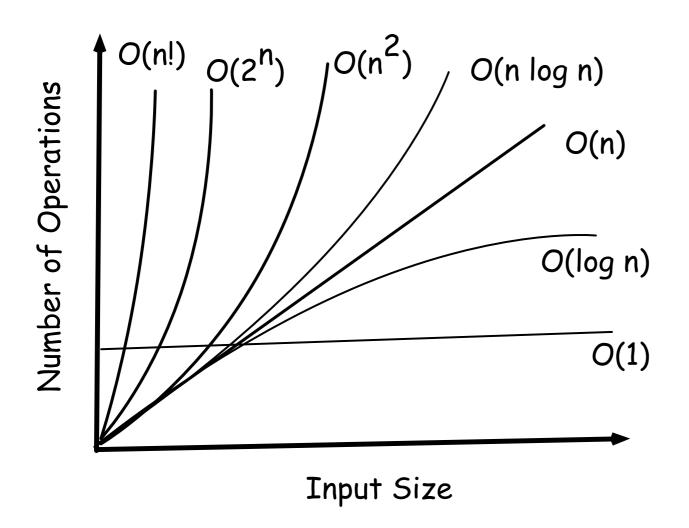
**O(1)**—constant time: It doesn't matter how large the data is, the answer will always take the same time to return.

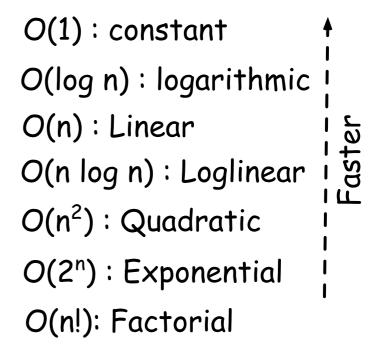
**O(n)**—**linear time:** The performance will grow linearly with respect to the size of the collection. Looping through a list and returning the number of elements matching "Panda" will take linear time.

**O(n log n)**—**logarithmic time:** A logarithm is a mathematical function that grows much more slowly than the data size. Binary search runs in logarithmic time because it doesn't look at the majority of the elements for large collections.

 $O(n^2)$ —n squared time: Code that has nested loops where each loop goes through the data takes n squared time. An example would be putting every pair of pandas together to see if they'll share an exhibit.

# Big O notation





### Outline

- Java Memory Structure
- Algorithm Complexity
- Search Improvement Methods
- BloomFilter

- Hash Tables
- Tree Structures
- Bit Manipulations & Compression
- Sliding Window
- MinHashing

- Suppose that we have a dataset composed of 1000 transactions and each transaction has 100 member (itemset).
- For the first transaction the algorithm should compare followings items together: {i<sub>1</sub>,i<sub>2</sub>}, {i<sub>1</sub>,i<sub>3</sub>}...{i<sub>1</sub>,i<sub>100</sub>}, {i<sub>2</sub>,i<sub>3</sub>}, {i<sub>2</sub>,i<sub>4</sub>},... {i<sub>2</sub>,i<sub>100</sub>}, ... Therefore, for single transaction we need comparisons. Assuming we have 1000 transactions, then this number of comparison will be extremely large. This method called **brute force**.

transaction	items		
1	i <sub>1</sub> , i <sub>2</sub> , , i <sub>100</sub>		
2	•		
3	•		
:			
1000	•		

- Hash Tables
- Tree Structures
- Bit Manipulations & Compression
- Sliding Window
- Minhashing

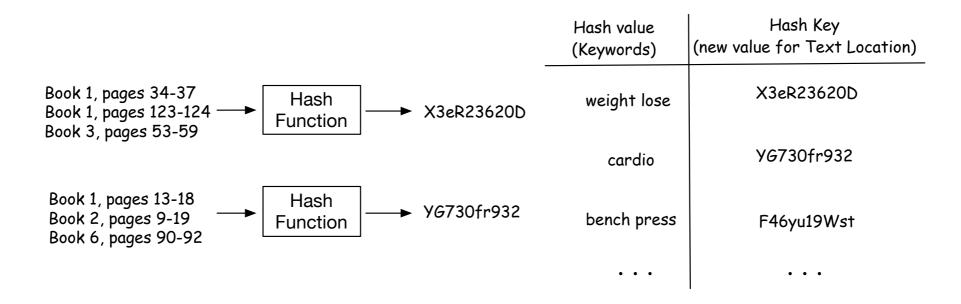
### Hash Table

A hash function is a function that maps the original data (value) to a smaller size data (key). Usually a hash function will be applied on a set of data (2D data) and as a result we get a 2D table, which is hash table.

- A gym coaching system.
- Reading books to coach us and answering our questions.
- To search books in a reasonable time it needs index.

Keyword	Text Location	
weight lose	Book 1, pages 34-37 Book 1, pages 123-124 Book 3, pages 53-59	
cardio	Book 1, pages 13-18 Book 2, pages 9-19 Book 6, pages 90-92	
bench press	Book 3, pages 101-102	
	• • •	

### Hash Function



Hash function usually converting the large strings into smaller strings with equal sizes.

You can say in this example we use hash function to compress the data. We could not say your argument is wrong, but it is more than compression, it also enables the system to rapidly access the data.

Hash table as a data structure that associates a key to a value to enable the algorithm very quickly lookup for the original data [McDowell '16].

Reading a record from hash table, adding a new record into hash table, or updating an existing record in the table all have O(1) complexity, in worst cases, when our hash function is not good, it has O(n) complexity.

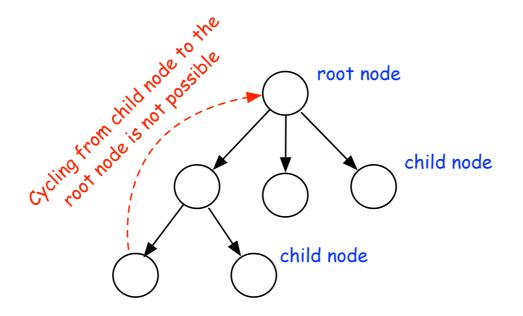
# BitCask Hash Table Example

- Bitcask is an implementation that supports <u>hash index</u>. It offers high-performance read and write.
- All information will be stored <u>inside memory</u>, but if there is a need to have a read from the disk, with <u>one single disk seek</u> it can read the required data from disk into memory.
- Bitcask is useful when we have lots of updates in our keyvalue pairs.
- You can look more about Bitcask here: <a href="https://">https://</a>
   docs.riak.com/riak/kv/2.1.4/setup/planning/backend/bitcask/

- Hash Tables
- Tree Structures
- Bit Manipulations & Compression
- Sliding Window
- Minhashing

### Tree Structure

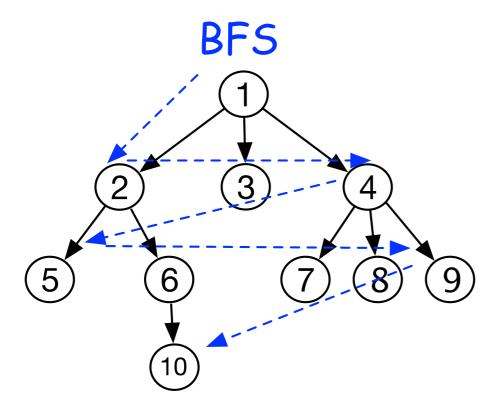
Tree is a sub type a graph data structure, which has a root and child nodes (but without cycle)



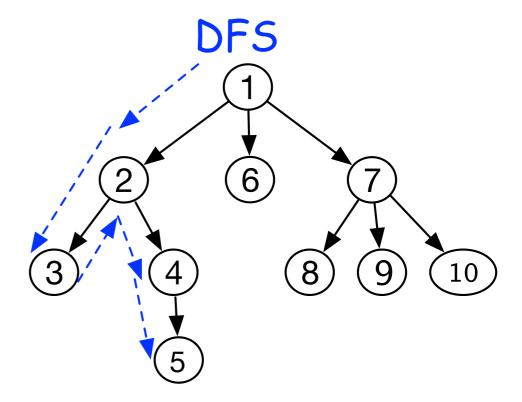
Tree structure and its elements. Note that, unlike graph, cycling is not possible in tree.

# Scanning the Tree

#### **Breadth first search**



#### **Depth first search**

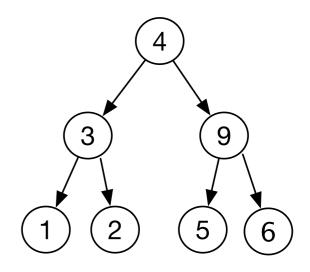


# Binary Tree

When each root node in the tree has only two child nodes it is called binary tree.

Binary search tree (BST) is a type of binary tree in which all nodes on its left size should be smaller that the nodes on the right side, i.e. all left nodes < all right nodes. Besides, in BST all nodes are stored as key/value pairs and keys are presented as values on node.

**BST**s are useful when the data objects (or keys) are having a **sort of order** inside the tree, because, when the algorithm intends to compare a new data object with the content of the tree, it checks **whether the new data object is smaller or larger than the root**. If it is **smaller** then, it goes and search the **left side of the tree**, otherwise, if it is greater it goes and search the right side of the tree.



An example of balanced binary tree, which is also balanced.

# Binary Tree

Searching an information in binary tree usually takes *O* (*log n*). Inserting a new key (data object) inside a binary tree is not extremely efficient, i.e. *O*(2n), and when the table is not empty it is *O*(n²), because it the algorithm should navigate through a correct branch to fit the new key into its correct position or perhaps update a node and its children structure. Therefore, it is good to consider using binary table when the structure of data is static and not changing.

A full binary tree, means that each node of the table as either zero or have two children (both figures are full binary tree)

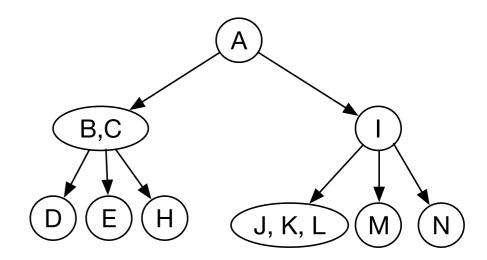
Unbalanced binary tree.

The advantage of **balanced binary tree** over BST is that their search cost and insert cost is guaranteed to be logarithmic *O(n log n)* 

### 2-3 Search Tree

It is not trivial to construct a balance tree. Therefore, in some implementation nodes could hold more than one keys. These types of trees are called **2-3 search trees.** When there is n keys in a node, it always has n+1 children.

They are not binary and balanced any more, but still keeping tree nodes on balanced depth. Besides, keys are ordered.



**2-3 search tree**, which some node hosts more than one key.

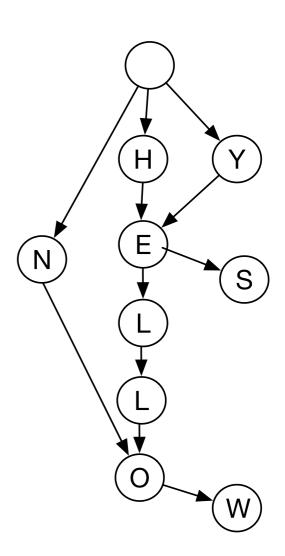
The good thing about 2-3 search tree is that search and insert cost both guaranteed to be *O(log n)* 

### **B-Tree**

- B-Tree (Balancing Factor Tree) is a type of a 2-3 search tree, in which a node can have more than two child.
- All of B-Tree leaves must be at the same depth.
- B-Tree has B parameter which is branching factor and following two rules are always applicable in B-trees:
  - (i)  $B \le \text{children per node} \le 2B$
  - (ii) *B-1* <= keys per node < 2*B* -1

### Trie, Prefix Tree, Radius Tree

- Trie nodes are assumed to be ordered from the root and the root node of the trie is always empty.
- Nodes in trie unlike other trees do not hold a key, they hold a partial key.
- Trie can be used to store words, the path from the root to the last child presents a word and each node stores a character.
- When we add more words (or information) into a trie the more its size grows, but it requires less time to find the right place for the newly inserted data object, because, as the tree is getting bigger, the tree holds more words.
- A more advanced form of tire is called patricia tree, where a node can have more than one keys (more than one character)



Trie can find the word in a dictionary in O(n) time, assuming n is the length of words (characters of words). Besides, it can insert word in O(n) time.

- Hash Tables
- Tree Structures
- Bit Manipulations & Compression
- Sliding Window
- Minhashing

# Data Compression and Bit Manipulation

The **bit** is the smallest unit of information in computer science and it can be either 0 or 1. Eight bit constitute a larger data called byte. 1024 bytes called kilo byte, 1024 kilo byte called mega byte and 1024 giga byte called tera byte,...

Hi = 0100100001101001, H= 01001000 and i= 01101001

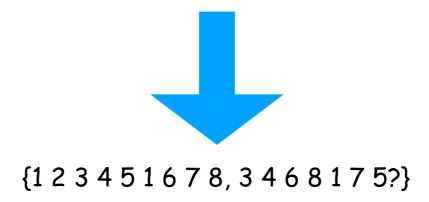
- The process of **data compression** is transforming the data from one format into another format which is *smaller* => *occupy less space* => *reduce the latency (because search execution time will be reduced)*.
- Usually this process is done on bit level and the data converted into a binary format, some bit manipulation will be done on the data, its size is reduced and then it gets smaller. Either the information will loose some of its data (lossy compression) or not lose any of its data (lossless compression).

## Data Compression Example

do not ask what XYZ can do for you, ask what can you do for XYZ?



An algorithm could create a dictionary and assign number to each word as follows: do=1, not=2, ask=3, what=4, XYZ=5, can=6, for =7, you=8



Lempel and Ziv compression [Ziv '78].

# Bitmap Index

- One useful concept with bitwise operation or compression is the use of Bitmap index.
- Bitmap indexes are useful for data with low cardinality. By cardinality here we mean the diversity of data is limited, for instance, gender could be either 'male' or 'female'.

	Exercise	Strength	Cardio	Burning Fat	Exercise	Strength
-	Treadmile	no	yes	high	Treadmile	0 1 11 Cardio
	Bench Press	yes	no	Low	Bench Press	1 0 00
	Dead Lift	yes	no	Medium	Dead Lift	1 0 01 Burning

(left) Different gym exercise training and this impact, (right) converted exercise data to bitmap.

# Huffman Encoding

- Huffman coding is popular a <u>lossless compression</u> technique.
- input:  $\{a, b, c, d, a, d, c, b, c, e, e, c, b, b, a, c, e\}$
- by default computers use ASCII codes (8 bits) to store each character, which means here we need  $16 \times 8 = 128$  bits to store this string of characters.
- Instead of using ASCII codes we can use three bits to present all four characters, something like followings, with occupies  $16 \times 3 = 48$  a = 000, b = 001, c = 010, d = 100, e = 101.
- Therefore, it is smaller that the original string. Here, we have only four unique characters, in a real-world case we have also lots of repetitive information, like words inside the text document, pixels inside a picture, etc. Huffman encoding can compress much better, than this simple approach (not using ASCII format).

# Huffman Encoding Steps

abecdeeaebdcdeabdecdeabcdedeabdcdeadbcddeedabbcddeea bbcddeabbcdeeabcddeabcddeabe

- 1- frequencies of words/terms/characters,... are written in-front of them as follows:  $\{a=12, b=15, c=11, d=24, e=20\}$
- Meaning, to store this text in ASCII code we will need 640 bit to store this text, because:

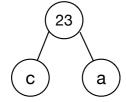
 $12 \times 8 + 15 \times 8 + 11 \times 8 + 24 \times 8 + 20 \times 8 = 640$ , but if we store this text with our three bit compression we will need  $12 \times 3 + 15 \times 3 + 11 \times 3 + 24 \times 3 + 20 \times 3 = 240$  bits. It is smaller than 640, but still we could make it also smaller (by using Huffman coding).

 Huffman encoding operates based on creating a <u>binary tree</u>, and assign values to each character based on their position inside the tree.

# Huffman Encoding

- First the algorithm orders characters based on their frequency, which will be as follows:  $\{c=11, a=12, b=15, e=20, d=24\}$ . Next, it takes the two data objects which have the <u>lowest frequency</u> and construct the two right most leaf nodes.
- The root node value for these two nodes are sum of the frequency of these two nodes, 11 + 12 = 23. (Fig a)

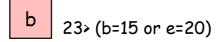
а

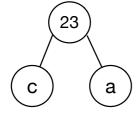


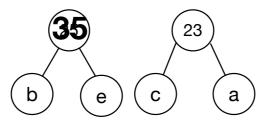
• Then we look for the next node which has the lowest frequency, i.e. b=15, and adds it to the tree as another node, but since it is a binary tree it adds it into a new branch and the new result root node will be 15+23=38 (Fig b.). On the other hand combining b and e results in smaller number so the algorithm choose b and e and makes a new branch.

$${c = 11, a = 12, b = 15, e = 20, d = 24}$$

а

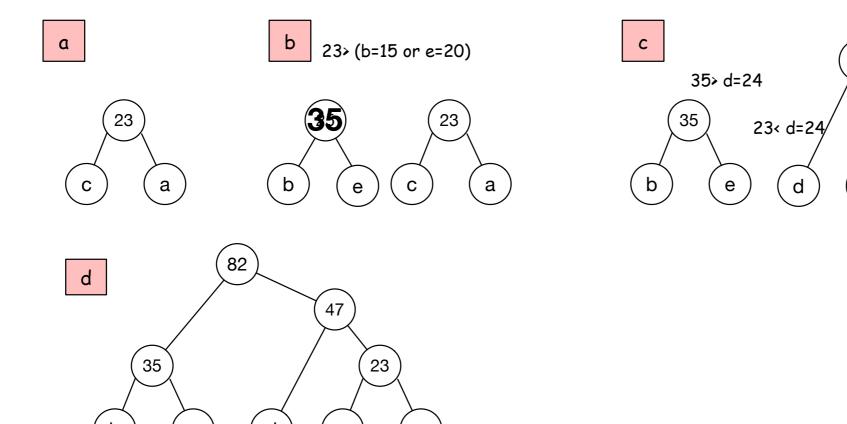






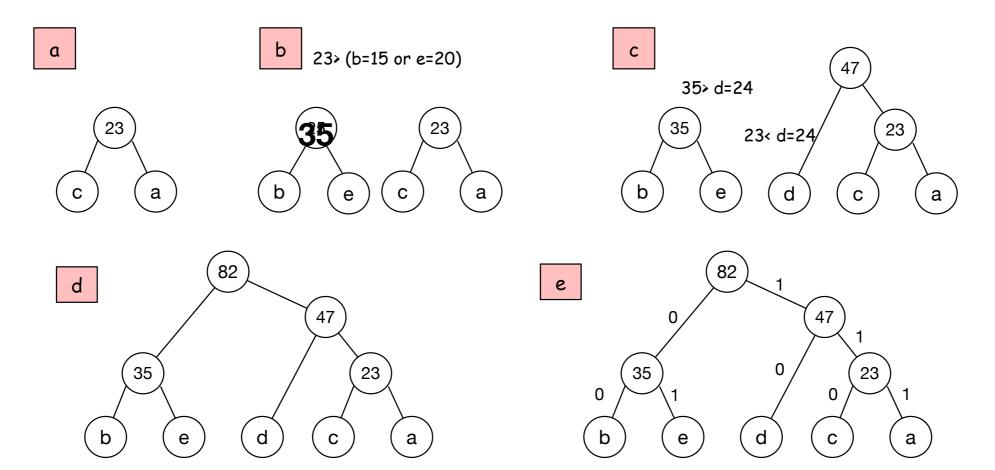
• Now, we should process d and 35 is larger than the 23. Therefore, the algorithm assigns it to the branch with lower frequency number and the new parent node will have value of 23+24= 47. There is no more data objects left to be added into the tree. Therefore, the algorithm connects both branches with the root value of 47+35 = 82 (Fig d).

$${c = 11, a = 12, b = 15, e = 20, d = 24}$$



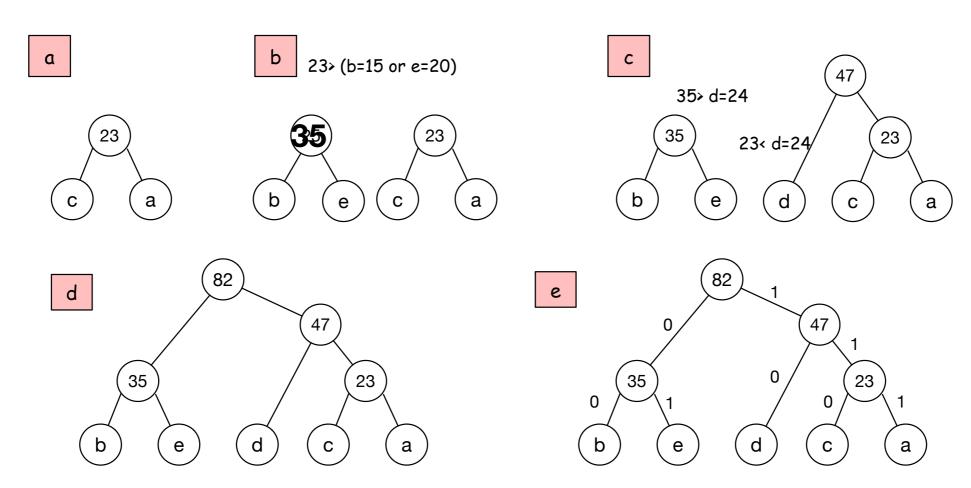
• When the tree is constructed the algorithm assigns 0 to all left branches and 1 to all right branches (Fig e). Now every character can be represented with a bit string started from root,  $\{b=00, e=01, d=10, c=110, a=111\}$ 

$${c = 11, a = 12, b = 15, e = 20, d = 24}$$



 You can realize that with this representation characters that are more frequent have smaller number of bits to present them and characters that are less frequent have larger number of bits.

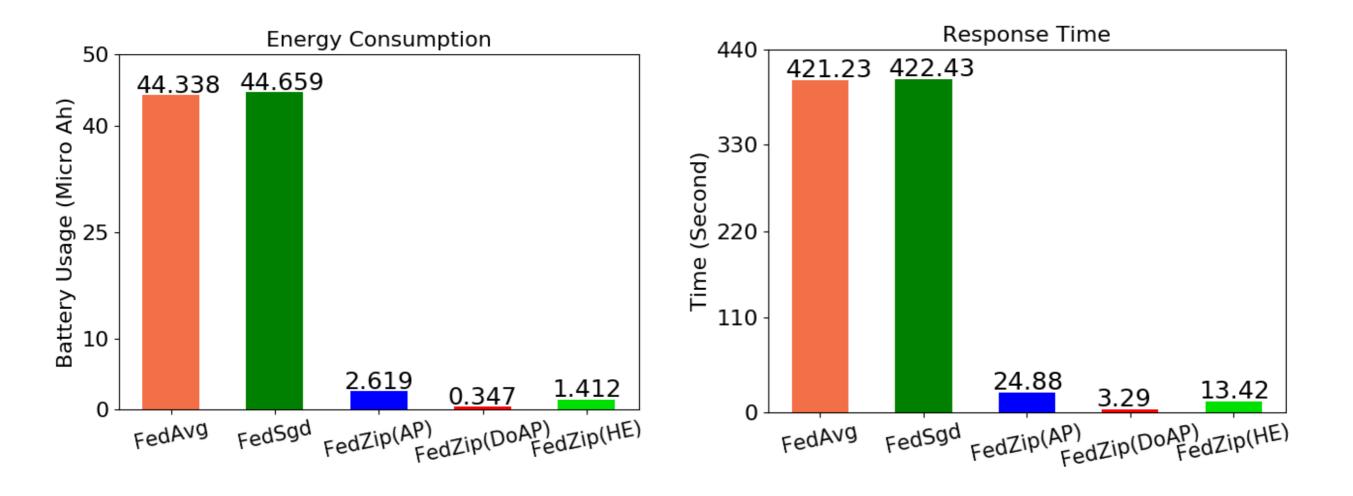
$${c = 11, a = 12, b = 15, e = 20, d = 24}$$



$$12 \times 3(111 = a) + 15 \times 2(00 = b) + 11 \times 3(110 = c) + 20 \times 2(01 = e) + 24 \times 2(10 = d) = 185$$

Since 185 is smaller than 240, it is more compressed. Besides, we need a small space to store the tree as well, which is too small and usually neglect able.

# How Huffman Encoding can make a revolution?



Malekijoo, A., Fadaeieslam, M. J., Malekijou, H., Homayounfar, M., Alizadeh-Shabdiz, F., & Rawassizadeh, R. (2021). FEDZIP: A Compression Framework for Communication-Efficient Federated Learning. arXiv preprint arXiv:2102.01593.

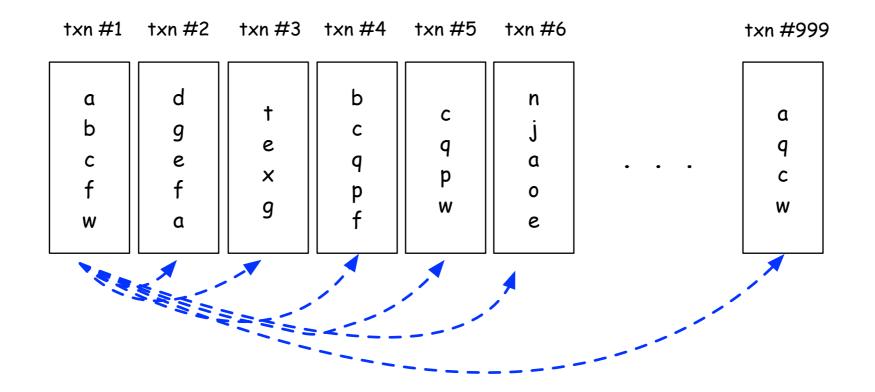
#### Java Examples

- A simple implementation: <a href="https://www.geeksforgeeks.org/">https://www.geeksforgeeks.org/</a>
   huffman-coding-greedy-algo-3/
- More detailed implementation: <a href="https://www.techiedelight.com/huffman-coding/">https://www.techiedelight.com/huffman-coding/</a>
- In other programming languages: <a href="https://rosettacode.org/wiki/Huffman\_coding">https://rosettacode.org/wiki/Huffman\_coding</a>

# Search Improvement Methods

- Hash Tables
- Tree Structures
- Bit Manipulations & Compression
- Sliding Window
- Minhashing

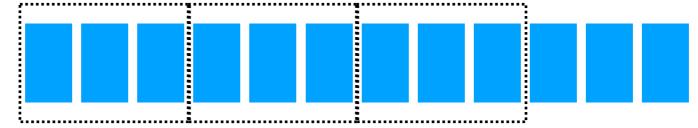
# Sliding Window



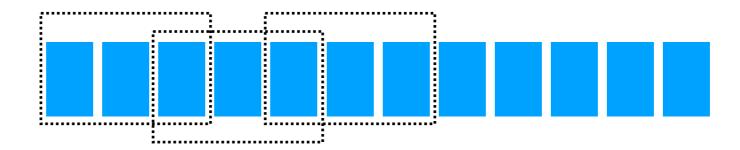
Comparing events of txn #1 with all other transactions to identifies its frequent itemsets. This is brute force comparison and it is not feasible.

# Sliding Windows

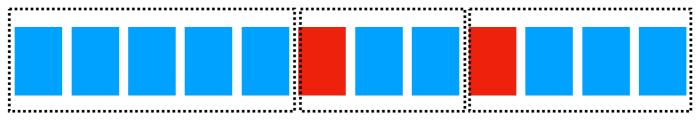
Disjoint Sliding Windows (windows are not overlapping)



Overlapping Sliding Windows(windows are overlapping)

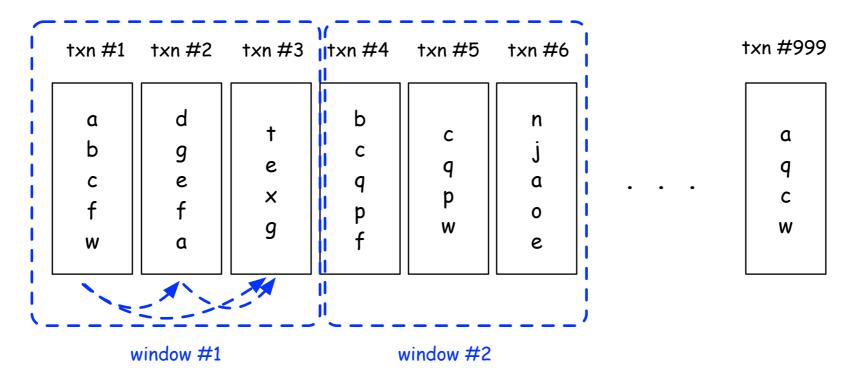


 LandMark Sliding Windows (size of the window depends on a encountering a landmark event)

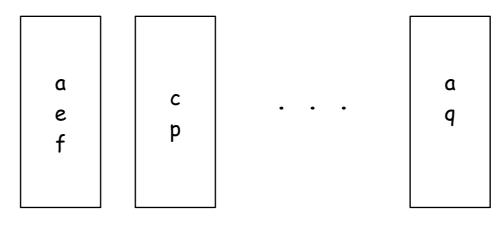


#### Sliding Window Example

#### Phase 1:



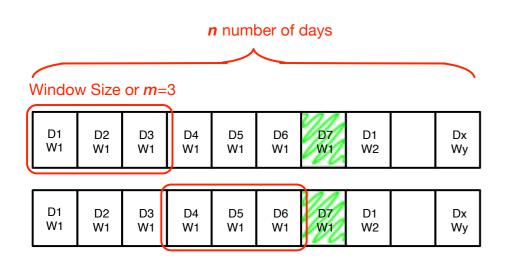
Phase 2:

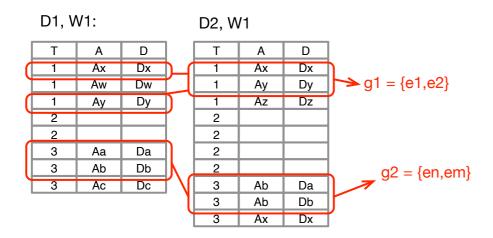


window #1 window #2

window # n÷(window size)

# Sliding Window Impact





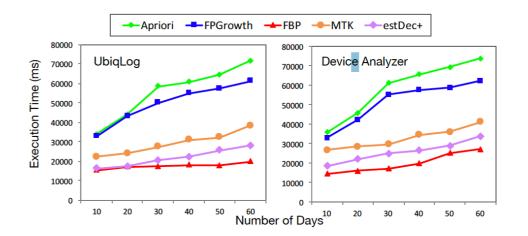


Fig. 6: Execution time comparision between FBP and other algorithms on the smartphone.

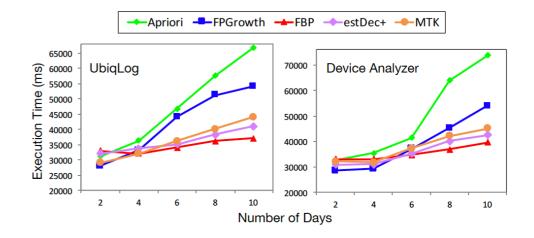


Fig. 7: Execution time comparision between FBP and other algorithms on the smartwatch.

Rawassizadeh, R., Momeni, E., Dobbins, C., Gharibshah, J. Pazzani, M. (2016) Scalable Mining of Daily Behavioral Patterns from Multivariate Temporal Data. In *IEEE Transactions on Knowledge and Data Engineering*. 28(11), 3098-3112. ACM Computing Review Notable Article of 2016.

# Search Improvement Methods

- Hash Tables
- Tree Structures
- Bit Manipulations & Compression
- Sliding Window
- Minhashing

- MinHash, which is widely in use to efficiently estimate similar sets of information objects. The information object could be image, time series (audio signal, heart rate) or anything. We can convert any information object into a set or vector and use Minhashing method to identify their similarities.
- Jaccard similarity is used to quantify the similarity between two sets of information and it is written as:

$$J(S_1, S_2) = \frac{S_1 \cap S_2}{S_1 \cup S_2}$$

 Minhash is using Jaccard. It maps each set of information into signature vectors which are vectors of fixed length. This enables the Jaccard to identify how similar are two sets without enumerating each of their elements.

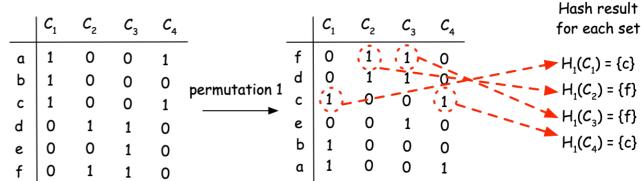
	Gym Member	ym Member   Exercises			
	Member 1	bench press, leg press, squat			
	Member 2	bicep curls, over head press			
_	Member 3	bicep curls, tricep curls, over head press			
_	Member 4	bench press, over head press, squat			

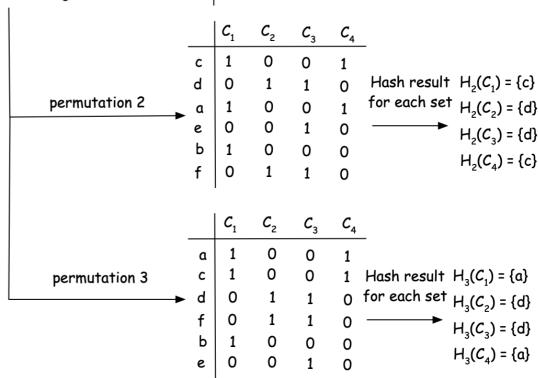
	Member	Member ;	Member 3	Member .
bench press	1	0	0	1
leg press	1	0	0	0
squat	1	0	0	1
bicep curls	0	1	1	0
tricep curls	0	0	1	0
over head press	0	1	1	1

• **Step 0:** The step before the first step, is converting our dataset into a boolean (0 or 1) matrix, and any matrix that includes lots of zeros, is called a sparse matrix.

**Step 1:** For the sake of simplicity, we rename columns as *C*s and rows as alphabets (*a*,*b*,*c*,...) in the matrix presented in the Table. Therefore, the result will look like the left side of Figure.

Then, the MinHash algorithm randomly permutes rows and as a result we will have a matrix as the right side of Figure. In this example we permuted the table three times (tree has been chosen arbitrary), but based on our signature vector size and dataset size we can create more permutations. The MinHash of each *C* (gym member) is the number of the row (fitness activity) with the first non-zero (i.e. 1) in the permuted order.





**Step 2:** Based on the hash values for three permutations in the Figure, we can write a signature  $S(\ )$ , for each set member as a set of its hash values, such as following:

$$S(C_1) = \{H_1(C_1), H_2(C_1), H_3(C_1)\} = \{c, c, a\}$$

$$S(C_2) = \{H_1(C_2), H_2(C_2), H_3(C_2)\} = \{f, d, d\}$$

$$S(C_3) = \{H_1(C_3), H_2(C_3), H_3(C_3)\} = \{f, d, d\}$$

$$S(C_4) = \{H_1(C_4), H_2(C_4), H_3(C_4)\} = \{c, c, a\}$$

In other words, we have used a hash function  $H(\ )$  that converts each set gym member into a signature (here is a single row name or fitness activity), in each permutation. The signature is the set of hash values for each permutation, but it is smaller than the original data and thus signatures fit into the memory better.

**Step 3:** The Jaccard function can compare two sets to each other but through their signatures only. It means that the Jaccard similarity uses the signature, instead of original data. For example:

$$J(C_1, C_2) = \frac{\{c, c, a\} \cap \{f, d, d\}}{\{c, c, a\} \cup \{f, d, d\}} = Null \text{ or }$$

$$J(C_2, C_3) = \frac{\{f, d, d\} \cap \{f, d, d\}}{\{f, d, d\} \cup \{f, d, d\}} = 1$$

We can conclude that member 1  $(C_1)$  and member 2  $(C_2)$  have no similarity and member 2  $(C_2)$  and member 3  $(C_3)$  are very similar.

In this example the number of data are too small, but in real world scenarios each set has many data objects and if we intend to compare the contents instead of signature it is not memory efficient.

# Java Examples of MinHashing

- https://mymagnadata.wordpress.com/2011/01/04/ minhash-java-implementation/
- https://massivealgorithms.blogspot.com/2014/12/mattsblog-minhash-for-dummies.html

#### Outline

- Java Memory Structure
- Algorithm Complexity
- Search Improvement Methods
- Bloom Filter

- It is an efficient data structure that tell us if a particular data existed in a set or not. Its output can tell us (i) the target data object does not exist in the set, or (ii) the target data object might exist in the set.
- It is memory efficient and fast, which is useful for many different types of application.
- Its base structure is a bit vector (each cell is a bit).

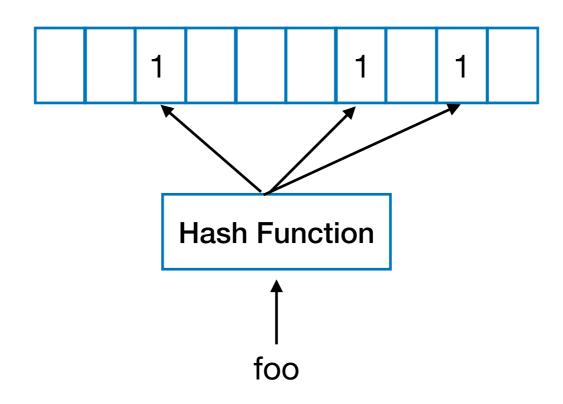
 When we add a data into the bit vector, it transfers the original data from a hash function into a bit vector and set some bits in its bit array. Then, later we can check whether the data existed inside Bloom filter, by checking the bits which are set to 1.

1. Empty bit vector



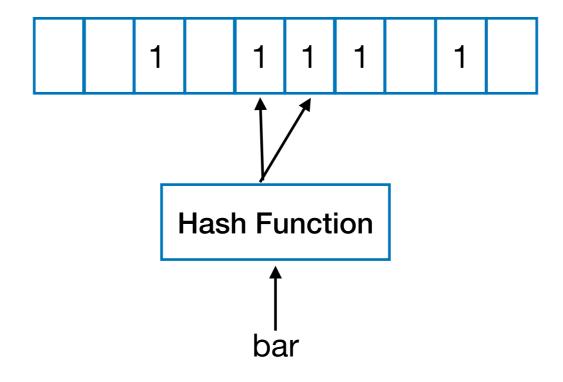
Database: —

2. We add a string, e.g. "foo" into the bloom filter



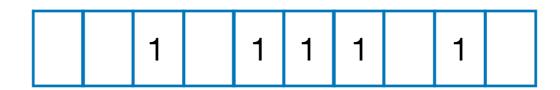
Database: foo

3. We add another string, e.g. "bar" into the bloom filter

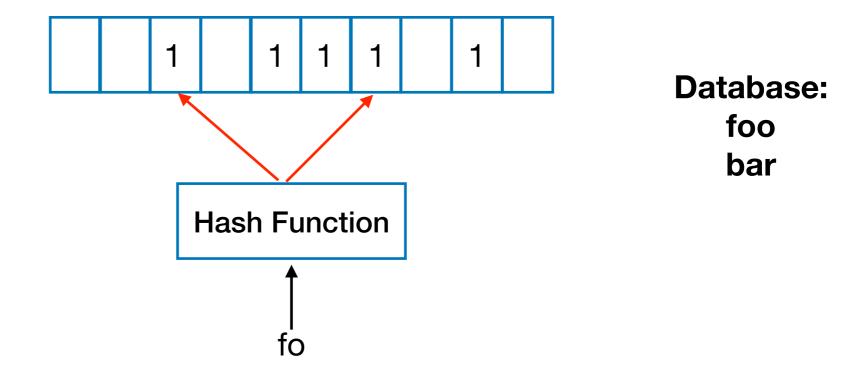


Database: foo bar

4. Now our bit vector includes both "bar" and "foo".



5. If we query for "foo", or even "fo" it uses the hash function to convert them to bit stream. Then the algorithm goes and check its bit vectors. If those bits are set to 1, then it returns "maybe" they exist in the Bloom filter structure.



6. If we query for "x", it again uses the hash function to convert it to a bit stream. Then the algorithm goes and check its bit vectors. If its related bits are not set to 1, then it returns no.

#### Bloom Filter Example

Here is the link: <a href="https://www.javamex.com/tutorials/collections/bloom\_filter\_java.shtml">https://www.javamex.com/tutorials/collections/bloom\_filter\_java.shtml</a>

Bloomfilter visualization

https://www.jasondavies.com/bloomfilter

#### References

- https://www.infoq.com/ presentations/lsm-append-datastructures/
- http://www.benstopford.com/ 2015/02/14/log-structuredmerge-trees/
- http://www.lucenetutorial.com/ lucene-query-syntax.html
- http://www.tutorialspoint.com/ lucene

