

# Graph Algorithms in DROP

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**Priority Queue**

**Overview**

1. Conception behind a Priority Queue: A *priority queue* is an abstract data type like a regular queue or stack, but where additionally each element has a *priority* associated with it. In a priority queue, an element with a high priority is served before an element with a low priority. In some implementations, if two elements have the same priority, they are served according to the order in which they were enqueued, while in other implementations, ordering of elements with the same priority is undefined.
2. Implementation Backing a Priority Queue: While priority queues are often implemented with heaps, they are conceptually different from heaps. A priority queue is a concept liker a list of a map; just as a list can be implemented using a linked list or an array, a priority queue can be implemented using a heap or a variety of other methods such as an unordered array.

**Operations**

1. Basic Operations of Priority Queue: A Priority Queue must at least support the following operations (Wikipedia (2020)):
   1. Is Empty: Check whether the queue has no elements.
   2. Insert with Priority: Add an element to the queue with an associated priority.
   3. Pull Highest Priority Element: Remove the element from the queue that has the highest priority, and return it.
      1. This is also known as *pop element off*, *get maximum element*, or *get front (most) element*.
      2. Some conventions reverse the order of the priorities, treating lower values to be higher priority, so this may be known as *get minimum element*.
      3. This may instead be specified as separate *peek at highest priority element* and *delete element* functions, which can be combined to produce *pull highest priority element*.
2. Peeking and Finding Minimum/Maximum: In addition, *peak* – in this context often called *find-max* or *find-min* – which returns the highest priority element but does not modify the queue, is very frequently implemented, and nearly always executes in  time. This operation and its performance are crucial to many applications of priority queues.
3. Advanced Operations of Priority Queue: More advanced implementations may support mor complicated operations, such as *pull lowest priority element*, inspecting the first few highest and lowest priority elements, clearing the queue, clearing sub-sets of the queue, performing a batch insert, merging two or more queues into one, incrementing priority of any element, etc.
4. Stacks and Queues Modeled as Priority Queues: Stacks and queues may be modeled as particular kinds of priority queues. As a reminder, this is how stacks and queues behave:
   1. Stacks => Elements pulled in the *last-in* *first-out* order.
   2. Queues => Elements pulled in the *first-in* *first-out* order.

In a stack, the priority of each inserted element monotonically increases; thus, the last element inserted is always the first retrieved. In a queue, the priority of each element monotonically decreases; thus, the first element inserted is always the first element retrieved.

**Implementation**

1. Naïve Implementation: There are a variety of simple, usually inefficient, ways to implement a priority queue. They provide an analogy to help one understand what a priority queue is. For instance, one can keep all elements in an unsorted list. Whenever the highest priority element is requested, search through all the elements for the one with the highest priority. In the big- notation, this corresponds to insertion time and pull time due to search.
2. Heap Based Priority Queue Implementation: To improve performance, priority queues typically use a heap as their backbone, giving performance for inserts and removals, and to build initially from a set of elements. Variants of the basic heap data structure such as pairing heaps or Fibonacci heaps can provide better bounds for some operations (Cormen, Leiserson, Rivest, and Stein (2009)).
3. Binary Search Tree Based Implementation: Alternatively, when a self-balancing binary search tree is used, insertion and removal also take time, although building trees from existing sequences of elements takes time; this is typical where one might already have access to the data structures, such as with third-party or standard libraries.
4. Priority Queues and Sorting Algorithms: From a computational standpoint, priority queues are congruent to sorting algorithms. The section below on the equivalence between priority queues and sorting algorithms describes how efficient sorting algorithms can create efficient priority queues.

**Specialized Heaps**

1. Functionality Provided by Specialized Heaps: There are several specialized heap data structures that either provide additional operations of outperform heap-based implementations for specific types of keys. This section supposes that the set of possible keys is
2. Bucket Queue for Integer Priorities: In the case of integer priorities, when only insert, find min, and extract min are needed, a bucket queue can be constructed as an array of linked lists plus a reference *top*, initially . Inserting an item with key appends the item to the element of the linked list, as well as updated

both in constant time. *Extract-min* deletes and returns one item from the list with index *top*, then increments if needed until it points again to a non-empty list; this takes in the worst case. These queues are useful for sorting the vertexes of a queue by their degree (Skiena (2010)).

1. van Emde Boas Priority Queue: A van Emde Boas tree supports *minimum*, *maximum*, *insert*, *delete*, *search*, *extract-min*, *extract-max*, *predecessor*, and *successor* updates in time, but has a space cost for small queues of about where is the number of bits in the priority queue (van Emde Boas (1975)). The space can be significantly reduced with hashing.
2. Fusion Tree Based Priority Queue: The Fusion tree by Fredman and Willard (1994) implements the *minimum* operation in time and *insert* and *extract-min* operations in time. However, as they clearly state, the algorithm has theoretical interest only, since the constant factors involved in the execution time preclude practicality.
3. Optimization for multiple Peek Operations: For applications that do many *peek* operations for every *extract-min* operation, the time complexity for peek actions can be reduced to in all tree and heap implementations by caching the highest priority element after every insertion and removal. For insertion, this adds at most a constant cost, since the newly inserted element is compared only with the previously cached minimum element. For deletion, this adds at most an additional *peek* cost, which is typically cheaper than the deletion cost, so overall time complexity is not significantly impacted.
4. Monotone Priority Queues: Monotone priority queues are specialized queues that are optimized for the case where no item is ever inserted that has a lower priority – in the case of *min-heap* - than any item previously extracted. This restriction is met by several practical applications of priority queues.

**Summary of Running Times**

1. Catalog of Running Times: Listed below are the time complexities of various heap data structures. Function names assume a *min-heap*.

|  |  |  |  |
| --- | --- | --- | --- |
| **Operation** | **find-min** | **delete-min** | **References** |
| Binary |  |  | * Cormen, T., C. E. Leiserson, R. Rivest, and C. Stein (2009) |
| Leftist |  |  |  |
| Binomial |  |  | * Cormen, T., C. E. Leiserson, R. Rivest, and C. Stein (2009) |
| Fibonacci |  | (Amortized Time) | * Fredman, M. L., and R. E. Tarjan (1987) * Cormen, T., C. E. Leiserson, R. Rivest, and C. Stein (2009) |
| Pairing |  | (Amortized Time) | * Iacono (2014) |
| Brodal |  |  | * Brodal (1996a) |
| Rank-pairing |  | (Amortized Time) | * Haeupler, B., S. Sen, and R. E. Tarjan (2011) |
| Strict Fibonacci |  |  | * Brodal, G. S., G. Lagogiannis, and R. E. Tarjan (2012) |
| 2-3 heap |  | (Amortized Time) | * Takaoka, T. (1999) |

|  |  |  |  |
| --- | --- | --- | --- |
| **Operation** | **insert** | **decrease-key** | **meld** |
| Binary |  |  |  |
| Leftist |  |  |  |
| Binomial | (Amortized Time) |  | ( is the size of the larger Heap) |
| Fibonacci |  | (Amortized Time) |  |
| Pairing |  | (Amortized Time) |  |
| Brodal |  |  |  |
| Rank-pairing |  | (Amortized Time) |  |
| Strict Fibonacci |  |  |  |
| 2-3 heap | (Amortized Time) |  |  |

1. Pairing and Brodal Queues – Additional Notes: For pairing queues, the *decrease-key* operation has a lower bound of (Fredman (1999)) and an upper bound of (Pettie (2005)). For Brodal queues, Brodal and Okasaki later describe a persistent variant with the same bounds except for *decrease-key*, which is not supported. However, heaps with elements can be constructed bottom-up in (Goodrich and Tamassia (2005)).

**Using a Priority Queue to Sort**

1. Priority Queue vs. Sorting Algorithm Equivalence: The semantics of priority queue naturally suggest a sorting method: insert all the elements to be sorted into a priority queue, and sequentially remove them: they will come out in sorted order. This is actually the procedure used by several sorting algorithms, once the layer of abstraction provided by the priority queue is removed. This sorting method is equivalent to the following sorting algorithms laid out in the table below.
2. Heap-Based Priority Queue Implementation:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Name** | **Priority Queue Implementation** | **Best** | **Worst** | **Average** |
| Heapsort | Heap |  |  |  |
| Smoothsort | Leonardo Heap |  |  |  |
| Selection Sort | Unordered Array |  |  |  |
| Insertion Sort | Ordered Array |  |  |  |
| Tree Sort | Self-balancing Binary Search Tree |  |  |  |

**Using a Sorting Algorithm to Make a Priority Queue**

1. Thorup’s Lemma on Priority Queues: Thorup (2007) presents a general deterministic linear space reduction from priority queues to sorting implying that if one can sort up to keys in time per key, then there is a priority queue supporting *delete* and *insert* in and *find-min* in constant time.
2. Implication of the Thorup’s Priority Queue Lemma: The lemma states that, if there is a sorting algorithm that can sort in time per key, where is some function of and the word size, then one can use the given procedure to create a priority queue when pulling the highest priority element in time, and inserting new elements – and deleting elements – in time. For example, if one has a sorting algorithm, one can create a priority queue with pulling and insertion.

**Applications – Bandwidth Management**

1. Priority Queue in Traffic Management: Priority queues can be used to manage limited resources such as bandwidth on a transmission line from a network router. In the event of outgoing traffic queuing due to insufficient bandwidth, all other queues can be halted to send traffic from the highest priority queue upon arrival. This ensure prioritized traffic – such as real-time traffic, e.g., an RTP steam of a VoIP connection – is forwarded with the least delay and the least likelihood of being rejected due to a queue reaching its maximum capacity. All other traffic can be handled when the highest priority queue is empty. Another approach used is to send disproportionately more traffic from higher priority queues.
2. Priority Queues in Network Standards: Many modern protocols for local area networks also include the concept of priority queues at the media access control (MAC) sub-layer to ensure that high-priority applications such as VoIP and IPTV experience lower latency than the other applications which can be served with the best-effort service. Examples include IEEE 802.11e – an amendment to IEEE 802.11 which provides quality of service – and ITU-T G.hn, a standard for high-speed local area network using existing home wiring – power lines, phone lines, and coaxial cables.
3. User/Network Level Priority Control: Usually, a limitation policer is set to limit the bandwidth that the traffic from the highest priority queue can take, in order to prevent high priority packets from choking off all other traffic. This limit is usually never reached due to high level control instances such as Cisco Call Manager, which can be used to inhibit calls which would exceed the programmed bandwidth limit.

**Applications – Discrete Event Simulation**

Another use of the priority queues is to manage events in a discrete event simulation. The events are added to a queue with their simulation time used as a priority. The execution of the simulation proceeds by repeatedly pulling the top of the queue and executing the event thereon.

**Application – Dijkstra’s Algorithm**

When the graph is stored in the form of an adjacency list or a matrix, a priority queue can be used to extract the minimum efficiently when implementing the Dijkstra’s algorithm, although one needs the ability to alter the priority of a particular vertex in the priority queue efficiently.

**Application – Huffman Coding**

Huffman coding requires one to repeatedly obtain the two lowest coding trees. A priority queue is one method of achieving this.

**Application – Best-First Search Algorithm**

Best-first search algorithm, such as the A\* algorithm, find the shortest path between two vertexes or nodes in a weighted graph, trying out the most promising routes first. A priority queue – also known as a *fringe* – is used to keep track of the unexplored routes; the one for which the estimate – a lower bound on the case of A\* - of the total path length is smallest is given the highest priority. If memory limitations make the best-first search impractical, variants like SMA\* algorithms can be used instead, with a double-ended priority queue to allow removal of low priority items.

**Application – ROAM Triangulation Algorithm**

1. Dynamic Triangulation of a Terrain: The Real-time Optimally Adapting Meshes (ROAM) algorithm computes the dynamically changing triangulation of a terrain. It works by splitting triangles where more detail is needed and merging them where less detail is needed. The algorithm assigns each triangle in the terrain a priority, usually related to the error reduction if the triangle would be split.
2. Separate Queues for Split/Merge: The algorithm uses two priority queues – one for triangles that can be split and another for triangles that can be merged. In each step, the triangle from the split queue with the highest priority is split, or the triangle from the merge queue with the highest priority is merged with its neighbors.

**Application – Prim’s Algorithm for Minimum Spanning Tree**

Using *min-heap* priority queue in Prim’s algorithm to find the minimum spanning tree of a connected and undirected graph, one can achieve a good running time. This *min-heap* priority queue uses the *min-heap* data structure that supports operations such as *insert*, *minimum*, *extract-min*, and *decrease-key* (Cormen, Leiserson, Rivest, and Stein (2009)). In this implementation, the weight of the edges is used to determine the priority of the vertexes. Lower the weight, higher the priority, and higher the weight, lower the priority.

**Parallel Priority Queue**

Parallelization can be used to speed up priority queues. There are different methods to parallelize priority queues. The easiest approach is to parallelize individual operations such as *insert* and *extract-min*. Another method allows concurrent access of multiple processes to the same priority queue. The last method uses operations that work on elements, instead of just one element. For example, *extract-min* will remove the first elements with the highest priority.

**Parallelize Individual Operations**

1. Speed-up achieved using Multiple Processors: An easy way to parallelize priority queues is to parallelize individual operations. This means that the queue works like a sequential one, but individual operations are sped up several processors. The maximum speed up for this technique is limited by because there are sequential implementations for priority queues whose slowest operation runs in , e.g., binomial heap.
2. Operations Executable in Time: The operations *insert*, *extract-min*, *decrease-key*, and *delete* can be executed in constant time in Concurrent Read, Exclusive Write (CREW) PRAM with processors, where is the size of the priority queue (Brodal (1996b)). In the following, the queue is implemented as a binomial heap. After every operation, only three trees of the same order are allowed, and the smallest tree of order is smaller than all roots of trees of higher order.
3. *insert*: A new binomial tree with order , is inserted. Then two trees of the same order get linked to a tree of order if there are three trees of order . The tree with the smallest root in order is not involved in this procedure. Each processor executed this step for trees in one order. So can be run in .
4. *extract-min*: The minimal element is the smallest element of the tree of order . To make sure that the new minimum is in order too, for each order

the tree is split in two trees of order . As each processor executes the step for one order, this step can be executed in parallel in . After this step, a parallel link is executed. So, two trees of order are joined to a tree of order if at least three trees of order exist. This is executable in parallel, so *extract-min* can be run in constant time.

1. *delete* and *decrease-key*: The concept behind constant time *insert* and *extract-min* can be extended to achieve a constant time for *delete* as well. The *decrease-key* operation can then be implemented as a *delete* followed by an *insert*. Thus, the *decrease-key* operation is also a constant time operation.
2. Benefits and Drawbacks of the Approach: The advantage of this type of parallelization of the priority queue is that it can be used like a sequential one. But the maximum speed-up is only . This speed-up is further limited in practice because there is additional effort for communication between different processors.

**Concurrent Parallel Access**

1. Benefits offered by Concurrent Access: If a priority queue offers concurrent access, multiple processors can perform operations concurrently on that priority queue. However, this raises two issues.
2. Challenges encountered due to Concurrent Access: First of all, the definition of the semantics of the individual operations is no longer obvious. For example, if two processes want to extract the element with the highest priority, should they get the same element or different ones? This restricts parallelism to the level of the program using the priority queue. In addition, because multiple processors have access to the same element, this leads to contention.
3. CRCW Implementation using a Skip-List: The concurrent access to a priority queue can be implemented on a Concurrent Read, Concurrent Write (CRCW) PRAM model. In the following, the priority queue is implemented as a skip-list (Sundell and Tsigas (2005), Linden and Jonsson (2018). In addition, an atomic synchronization primitive, CAS, is used to make the skip-list lock free.
4. Structure of the Skip-List: The nodes of a skip-list consist of a unique key, a priority, an array of references for each level, to the nodes, and a *delete* mark. The *delete* mark marks of the node is about to be deleted by a processor. This ensures that the other processors can react to their deletion appropriately.
5. Skip-List Insertion - Step #1: First, a new node with a key and a priority is created. In addition, the node is assigned a number of levels, which dictate the size of the array references.
6. Skip-List Insertion - Step #2: Then a search is performed to find the correct position to insert the new node. The search starts from the first node and from the highest level. The skip-list is traversed down to the lowest level until the correct position is found.
7. Skip-List Insertion - Step #3: During the search, for every level, the last traversed node will be saved as a parent node for the new node at that level.
8. Skip-List Insertion - Step #4: In addition, the node to which the reference, at that level, of the parent node points towards, will be saved as the successor node of the new node at that level. Afterwards, for every level of the new node, the references of the parent will be set to the new node.
9. Skip-List Insertion - Step #5: Finally, the references, for every level, of the new node will be set to the corresponding successor nodes.
10. *extract-min*: First, a skip-list is traversed until a node is reached whose *delete* mark is not set. The *delete* mark is then set to true for that node. Finally, the references to the parent nodes of the deleted node are updated.
11. Conflict due to Concurrent Access: If the concurrent access to a priority queue is allowed, conflicts may arise between two processes. For example, a conflict arises if one process is trying to insert a new node, but at the same time another process is about to delete the predecessor of the same node (Sundell and Tsigas (2005)). There is a risk that a new node is added to the skip-list, yet is no longer reachable.

**K-Element Operations**

1. Simultaneous Operations on Elements: For this type of parallelization, new operations are introduced, that operate on elements simultaneously instead of only one. The new operation *k\_extract-min* then deletes smallest elements of the priority queue and returns those.
2. Layout of the Parallelization Infrastructure: The queue is parallelized on distributed memory. Each processor has its own local memory, and a local, sequential, priority queue. The elements of global, parallel priority queue are distributed across all processors.
3. Insertion into the Local Queues: A *k\_insert* operation assigns elements uniformly randomly to the processors which insert the elements into their local queues. Note that single elements can still be inserted into the queue.
4. Local vs Global Queue Elements: Using this strategy, the global smallest elements are in the union of the local smallest elements of every processor, with high probability. Thus, each processor holds a representative part of the global priority queue.
5. Application in *k\_extract-min* Operation: The above property is used when *k\_extract-min* is executed, as the smallest elements each are removed and collected in a result set. The elements in the result set are still associated with their original processor. The number of elements removed from each local queue depends on and the number of processors (Sanders, Mehlhorn, Dietzfelbinger, and Dementiev (2019)).
6. Iterative Parallel Selection of Elements: By parallel selection, the smallest elements of the result set are determined. With high probability, these are the global smallest elements. If not, elements are again removed from each local queue, and put into the result set. Now these elements can be returned. All other elements of the result set are inserted back into their local queues.
7. Running Time of *k\_extract-min* Operation: The running time of *k\_extract-min* is where

and is the size of the priority queue (Sanders, Mehlhorn, Dietzfelbinger, and Dementiev (2019)).

1. Improving the Local Processor Performance: The priority queue can be further improved by not moving the remaining elements of the result set directly back into the local queues after a *k\_extract-min* operation. This saves moving elements back and forth all the time between the result set and the local queues.
2. Caveat Underlying *K\_element* Merge: By removing several elements at once, a considerable speedup can be achieved. But not all algorithms can use this kind of priority queue. Dijkstra’s algorithm can work on several nodes at once, for example. The algorithm takes the node with the smallest distance from the priority queue and calculates new distances for all its neighbors. If nodes are taken out, working at one node could change the distance of another of the nodes. So, using operations destroys the label setting property of the Dijkstra’s algorithm.

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**Binary Heap**

**Overview**

1. Binary Tree Based Data Structures: A *binary heap* is a heap data structure that takes the form of a binary tree. Binary trees are a common way of implementing priority queues (Cormen, Leiserson, Rivest. And Stein (2009), Wikipedia (2020)), and were introduced as a structure for heap-sort (Williams (1964)).
2. Binary Heap Property - Shape Constraint: A binary heap is defined as a binary tree with two additional constraints. First, the shape property states that a binary heap is a *complete binary tree*, i.e., all levels of the tree, except possibly the last, i.e., the deepest, one are fully filled, and if the last level of the tree is not complete, the nodes of that level are filled from the left to the right.
3. Binary Heap Property - Key Comparison: The heap property states that the key stored in each node is either greater than or equal (), or less than or equal to (), then keys in the node’s children, according to some total order.
4. Min vs Max Binary Heaps: Heaps where the parent key is greater than or equal to () the child keys are called *max-heaps*; those where it is less than or equal to () are called *min-heaps*.
5. Efficient Algorithms for Insertion/Removal: Efficient logarithmic time algorithms are known for the two operations needed to implement a priority queue on a binary heap; inserting an element, and removing the smallest of the largest element from a *min-heap* or a *max-heap*, respectively.
6. In-place Heap-Sort Algorithm: Binary heaps are also commonly employed in the heapsort sorting algorithm, which is an in-place algorithm because binary heaps can be implemented as an implicit data structure, storing keys in an array, and using their relative positions within that array to represent child-parent relationships.
7. Time Complexity using Big- Notation:

|  |  |  |
| --- | --- | --- |
| **Operation** | **Average** | **Worst Case** |
| Space |  |  |
| Search |  |  |
| Insert |  |  |
| Delete |  |  |
| Peek |  |  |

**Heap Operations**

Both insert and remove operations modify the heap to conform to the shape property first, by adding or removing the end of the heap. Then the heap property is restored by traversing up or down the heap. Both operations take time.

**Insert**

1. Binary Heap Insertion Algorithm Steps: To add an element to the heap, an *up-heap* operation must be performed – this is also known as *bubble-up*, *percolate-up*, *sift-up*, *trickle-up*, *swim-up*, *heapify-up*, or *cascade-up* – by following the steps below:
   1. Add an element to the bottom level of the heap at the most left.
   2. Compare the added element with its parent; if they are in the correct order, stop.
   3. If not, swap the element with its parent and return to the previous step.
2. Tim Complexity of Insertion Operation: The number of operations required depends only on the number of levels the new element must rise to satisfy the heap property, thus the insertion operation has a worst-case complexity of and an average case complexity of .

**Extract**

1. Alternate Names for Extract Operation: The procedure for deleting the root from the heap – effectively extracting the maximum element in a *max-heap* or the minimum element in a *min-heap* – and restoring properties is called *down-heap* – also known as *bubble-down*, *percolate-down, sift-down, sink-down, trickle-down, heapify-down, cascade-down*, and *extract-min/max*.
2. Steps involved in the Extract Operation:
   1. Replace the root of the heap with the last element on the last level.
   2. Compare the new root with its children; if they are in the correct order, stop.
   3. It not, swap the element with one of its children and return to the previous step. Swap with its smaller child in a *min-heap* and its larger child in a *max-heap*.
3. Fulfillment of the Heap Property: The downward moving node is swapped with the *larger* of its children in a *max-heap* – in a *min-heap*, it would be swapped with its smaller child, until it satisfies the heap property in its new position.
4. Worst-Case Time Complexity: In the worst-case, the new root has to be swapped with its child on each level until it reaches the bottom of the heap, meaning that the delete operation has a time complexity relative to the height of the tree, or .

**Building a Heap**

1. Williams’ Method for Heap Construction: Building a heap from an array of elements can be done by starting with an empty heap, then successively inserting each element. This approach, called Williams’ method after the inventor of the binary heaps, is easily seen to run in time; it performs insertions at cost each. In fact, this procedure can be shown to take time in the worst case, meaning that is also asymptotic lower bound on the complexity (Cormen, Leiserson, Rivest, and Stein (2009)). In the average case, averaging over all the permutations of inputs – the method takes linear time (Hayward and McDiarmid (1991)).
2. Floyd’s Method for Heap Construction: However, Williams’ method is sub-optimal. A faster method – due to Floyd (Hayward and McDiarmid (1991)) – starts by arbitrarily putting elements on a binary tree and respecting the shape property – the tree could be represented by an array – as shown below. Then starting from the lowest level and moving upwards, shift the root of each subtree downward as in the deletion algorithm until the heap property is satisfied.
3. Bottom up Heapification of the Input: More specifically, if all subtrees starting at some height have already been heapified – here the bottom-most level corresponds to zero – the trees at height can be heapified by sending their root down along the path of maximum valued children when building *max-heap* – and minimum valued children when building *min-heap*. This process takes swap operations per node. In this method, most of the heapification takes place at the lower levels.
4. Cost of Heapifying the Subtrees: Since the height of the heap is , the number of nodes at height is less than

Thus, the cost of heapifying all the subtrees is

This uses the fact that converges.

1. Worst Case Count of Comparisons: Th exact values of the above, i.e., the worst-case number of comparisons during the heap construction, is known to be equal to (Suchenek (2012)), where is the sum of all the digits of the binary representation of , and is the exponent of in the prime factorization of . Note that this does not mean that sorting can be done in linear time because building the heap is the first step in the heapsort algorithm.
2. Average Case Count of Comparisons: The average case is more complex to analyze, but it can be shown to asymptotically approach comparisons.
3. Input Array Bottom-up Heapification: The *max-heap* builder function can be constructed using the details specified above to convert an array that stores a complete binary array with nodes to a *max-heap* by repeatedly heapifying it in a bottom up manner. This is based on the observation that the array of elements is indexed by are all leaves of the tree – assuming that the indexes start from – thus, each one is a one-element heap. Thus, the *max-heap* builder would run *max-heapify* on each of the remaining nodes.

**Heap Implementation**

1. Array Based Binary Tree Implementation: Heaps are commonly implemented with an array. Any binary tree can be stored in an array, but because a binary heap is always a complete binary tree, it can be stored compactly. No space is required for references; instead, the parent and the children of each node can be found by arithmetic on array indexes.
2. Binary Heap as an Implicit Data Structure: These properties make the heap implementation a simple example of an implicit data structure or an Ahnentafel list. Details depend on the root position, which may in turn depend on the constraints of the programming language used for then implementation, or the programmer preference. Specifically, sometimes the root is placed at in order to simplify the arithmetic.
3. Indexes of Parents/Children #1: Let be the number of elements in the heap and be an arbitrary valid index of the array storing the heap. If the tree is at index , with valid indexes through , then each element at index has:
   1. Children at indexes and
   2. Parent at index
4. Indexes of Parents/Children #2: Alternatively, if the tree is at index 1, with valid indexes through , then each element at index has:
   1. Children at indexes and
   2. Parent at index
5. Use in Heapsort/Priority Queue: This implementation is used in the heapsort algorithm where it allows the space in the input array to be re-used to store the heap, i.e., the algorithm is done in-place. The implementation is also useful for use as a Priority Queue where use of a dynamic array allows for the insertion of an unbounded number of items.
6. Implementation of Up-heap and Down-heap: The up-heap/down-heap operations can be stated in terms of an array as follows: Suppose that the heap-property hold for indexes The sift-down function extends the heap property to . Only index

can violate the heap property. Let be the index of the largest child of – for a *max-heap*, or a smallest child for a *min-heap* – within the range . If no such index exists because

then the heap property holds for the newly extended range and nothing needs to be done. By swapping the values and the heap property for position is established. At this point, the only problem is that the heap property may not hold for index . The sift-down function is applied tail recursively for index until the heap property is established for all the elements.

1. Implementation of Sift-down Operation: The sift-down function is fast. In each step it only needs two comparisons and one swap. The index value where it is working doubles on each iteration, so that at most steps are required.
2. Memory Management for Big Heaps: For big heaps and for virtual memory, storing elements according to the above scheme is insufficient; almost every level is in a different page. B-heaps are binary heaps that keep sub-trees in a single page, reducing the number of pages accessed by up to a factor of (Kamp (2010)).
3. Merging Two Equal Sized Heaps: The operation of merging two heaps takes for equal sized heaps. The best that can be done in terms of an array implementation is simply concatenating the two heap arrays and building the heap of the result.
4. Merging Two Different Sized Heaps: A heap on elements can be merged with a heap on elements using key comparisons, or, in the case of a reference based implementation, in time (Sack and Strothotte (1985)).
5. Splitting a Heap into Two: An algorithm for splitting a heap on elements into to heaps of and elements, respectively, based on a new view of heaps as an ordered collection of sub-heaps, was presented in Sack and Strothotte (1990). This algorithm requires comparisons. This view presents a new and a conceptually simple algorithm for merging heaps.
6. Heap Implementations Optimized for Merging: When merging is a common task, a different heap implementation is recommended, such as binomial heaps, which can be merged in .
7. Binary Tree Data Structure Implementation: Additionally, a binary tree can be implemented using a traditional binary tree data structure, but there is an issue of finding an adjacent element in the last level of the binary heap when adding an element. This element can be determined algorithmically or by extra data to the nodes, called *threading* the tree – instead of merely storing references to the children, the in-order succession of the nodes is stored as well.
8. *Min-max* and *Min-max-median* Heaps: It is possible to modify the heap structure to allow the extraction of both the smallest and the largest elements in time (Atkinson, Sack, Santoro, Strothotte (1986)). To do this, the rows alternate between *min-heap* and *max-heap*. The algorithms are roughly the same, but in each step, one must consider the alternating rows with alternating comparisons. The performance is roughly the same as a normal single-direction heap. This idea can be generalized to a *min-max-median* heap.

**Derivation of Index Equations**

1. Relation between Roots and Nodes: In an array-based heap, the children and the parent of a node can be located via a simple arithmetic on the node’s index. This section derives the relevant equation for heaps with their root at index , with additional notes on heaps with their roots on index .
2. Defining the Level of a Node: To avoid confusion, the *level* of a node is defined as its distance from the root, such that the root itself occupies level .

**Child Nodes**

1. Deriving Index for Right Child: For a general node located at index beginning from , the index of the right child will first be derived, i.e.,
2. Number of Nodes in a Layer: Let node be located in level , and note that any level contains exactly up to nodes. Furthermore, there are exactly nodes contained in layers up to and including layer . Because the root is stored at , the node will be stored at index .
3. Last Node of a Layer: Putting the above observations together yields the following expression for the index of the last node in layer :
4. Indexes for Left/Right Children: Each of these nodes must have exactly children, so there must be nodes separating ’s right child from the end of its layer

Since the left child of any node is always child before its right,

1. Root Node Located at : If the root node is located at index instead of , the last node at each level is instead at index Using this throughout yields

and

for heaps with their root at .

**Parent Node**

Every node is either the left or the right child of its parent, so either of the following is true:

Therefore, the expression for the parent index is

**Related Structures**

1. Swapping the Child Nodes: Since the ordering of the siblings in a heap is not specified by the heap property, a single node’s two children can be freely interchanged unless doing so violates the shape property. Note, however, that in the common array-based heap, simply swapping the children might also necessitate moving the children’s subtree nodes to retain the heap property.
2. Special Case of -array Heap: The binary heap is a special case of the -array heap in which

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**Binomial Heap**

**Overview**

A *binomial heap* is a data structure that acts as a priority queue but allows pairs of heaps to be merged together. It is important as an implementation of the mergeable heap abstract data type – also called meldable heap – which is a priority queue supporting merge operation. It is implemented as a heap similar to binary heap, but using a special structure that is different from the complete binary trees used by binary heaps (Vuillemin (1978), Cormen, Leiserson, Rivest, and Stein (2009), Wikipedia (2019)).

**Definition**

1. Trees in a Binomial Heap: A binomial heap implemented as a set of *binomial trees* – as opposed to a binary heap, which has the shape of a single binary tree – whose trees are recursively defined as follows (Cormen, Leiserson, Rivest, and Stein (2009)):
   1. A binomial tree of order zero is a single node.
   2. A binomial tree of order has a root node whose children as roots of binomial trees of order – in that order.
2. Rationale behind the Heap Layout: A binomial tree of order has nodes, and height . The name comes from the shape: a binomial tree of order has nodes at depth , a binomial coefficient. Because of its structure, a binomial tree of order can be constructed from two trees of order by attaching one of them as the left-most child of the other root of the tree. This feature is central to the *merge* operation of a binomial heap, which is its major advantage over conventional heaps (Brown (1978), Cormen, Leiserson, Rivest, and Stein (2009)).

**Structure of a Binomial Heap**

1. Properties of the Binomial Heap: A binomial heap is implemented as a set of binomial trees that satisfy the *binomial heap properties* (Cormen, Leiserson, Rivest, and Stein (2009)):
   1. Each binomial tree in a heap obeys the *minimum-heap property*; the key of a node is greater than equal to the key of its parent.
   2. There can be only either *one* or *zero* binomial trees of each order, including the zero order.
2. Rationale behind the Binomial Heap Property: The minimum heap property ensures that the root of each binomial tree contains the smallest key in the tree. It follows that the smallest key in the entire heap is one of the roots (Cormen, Leiserson, Rivest, and Stein (2009)).
3. Representing the Trees in the Heap: The second property implies that a binomial heap with nodes consists of at least binomial trees. The numbers and the orders of these trees are completely determined by the number of nodes ; there is one binomial tree for each non-zero bit in the binary representation for the number . For example, the decimal number is in binary, , thus a binomial heap with nodes will consist of three binomial trees of order , , and (Brown (1978), Cormen, Leiserson, Rivest, and Stein (2009)).
4. Items with Distinct Keys: The number of distinct ways that items with distinct keys can be arranged into a binomial heap equals the largest odd divisor of . For

these numbers are (sequence in the ). If the items are inserted into a binomial heap in a uniformly random order, each one of these arrangements is equally likely (Brown (1978)).

**Implementation**

1. Tree Roots in a Linked List: Because no operation requires random access to the roots of the binomial trees, the roots of the binomial tree can be stored in a linked list, ordered by the increasing order of the tree.
2. Linked List of Sibling Nodes: Because the number of children for each node is variable, it does not work well for each node to have separate links to each of its children; instead, it is possible to implement this tree using links from each node to its highest ordered child in the tree, and to its sibling in the next smaller order after that. These sibling pointers can be interpreted as next pointers in a linked list of children of each node, but with opposite order from the linked list of roots; from the largest to the smallest order, rather than vice versa.
3. Ease of Linking Equi-Ordered Trees: This representation allows two trees of the same order to be linked together, making a tree of the next larger order, in constant time (Brown (1978), Cormen, Leiserson, Rivest, and Stein (2009)).

**Merge**

1. Merging Trees of Same Order: The operation of *merging* two heaps is used as a sub-routine in most other operations. The basic subroutine within this procedure merges pairs of binomial trees of the same order. This may be done by comparing keys at the roots of the two trees, which are the smallest keys in both trees. The root node with the larger key is made into a child of the root node with the smaller key, increasing its order by one (Brown (1978), Cormen, Leiserson, Rivest, and Stein (2009)).
2. Simultaneously increasing Root List Traversal: To merge two heaps more generally, the lists of roots of both heaps are traversed simultaneously in a manner similar to that of the merge algorithm, in a sequence from the smaller orders of trees to the larger orders.
3. Merging Trees with Unique/Non-Unique Orders: When only one of the two heaps being merged contains a tree of order , this tree is moved to the output heap. When both of the two trees contain a tree of order , the two trees are merged into one tee of order so that the minimum heap property is satisfied. It may later become necessary to merge this tree with some other tree of order in one of the two input heaps.
4. At most Three Trees Examined: In the course of the algorithm, it will examine at most three trees of any order, two from the heaps merged, and one composed of two smaller trees (Brown (1978), Cormen, Leiserson, Rivest, and Stein (2009)).
5. Analogy with Binary Carry Propagation: Because each binomial tree in a binomial heap corresponds to a bit in the binary representation of its size, there is an analogy between merging of two heaps and the binary addition of the *sizes* of the two heaps, from right to left. Whenever a carry occurs during an addition, this corresponds to a merging of the two binomial trees during the merge (Brown (1978), Cormen, Leiserson, Rivest, and Stein (2009)).
6. Running Time of Merge: Each tree has an order of at most , and therefore, the running time is (Brown (1978), Cormen, Leiserson, Rivest, and Stein (2009)).

**Insert**

1. Insertion using *Create* and *Meld*: *Inserting* a new element into a heap can be done by simply crating a new heap containing only this heap element and then merging it with the original heap. Because of the merge, a single insertion takes time.
2. Speed-up Using Amortized Merge: However, this can be sped up using a merge procedure that shortcuts the merge after it reaches a point where only one of the merged heaps has trees of larger order. With this speed up, across a series of consecutive insertions, the total time for insertions is . Another way of stating this is that, after logarithmic overhead for the first insertion in the sequence, each successive *insert* has an *amortized* time of , i.e. constant, per insertion (Brown (1978), Cormen, Leiserson, Rivest, and Stein (2009)).
3. Worst Case Insertion Time: A variant of the binomial heap, the skew binomial heap, achieves constant worst-case insertion time by using forests whose tree sizes are based on the skew binary system rather than on the binary system (Brodal and Okasaki (1996)).

**Find Minimum**

1. Minimum Element Among the Roots: To find the *minimum* element of the heap, one finds the minimum among the roots of the binomial trees. This can be done in time, as there are just tree roots to examine (Cormen, Leiserson, Rivest, and Stein (2009)).
2. Updating Root in Time: By using a reference to the binary tree that contains the minimum element, the time for this operation can be reduced to time. The reference may be updated when performing any operation other than finding the minimum. This can be done in per update, without raising the overall asymptotic running time of any operation.

**Delete Minimum**

1. Merging Subtrees of Minimum Element: To *delete the minimum element from the heap*, first locate the element, then remove it from the root of its binomial tree, and obtain a list of subtrees, which are each themselves binomial trees. Transform the list of subtrees into a separate binomial heap by re-ordering them from the smallest to the largest order. Then merge this range with the original heap.
2. Time for Delete Minimum: Since each root has at most children, creating this heap takes. Merging heap takes time , so the entire delete minimum operation takes time (Cormen, Leiserson, Rivest, and Stein (2009)).

**Decrease Key**

1. Maintaining the Minimum Heap Property: After *decreasing* the key of an element, it may become smaller than the key of its parent, violating the minimum heap property. In such a case, the element is exchanged with its parent, and possibly also with its grand-parent, and so on, until the minimum heap property is no longer violated.
2. Specific Representations Demanded by Decrease-Key: Each binomial tree has at most height, so this takes time (Cormen, Leiserson, Rivest, and Stein (2009)). However, this operation requires that the representation of the tree include references from each node to its parent tree, somewhat complicating the implementation of other operations (Brown (1978)).

**Delete**

To *delete* any element from the heap, decrease its key to negative infinity – or equivalently to some vale lower than any element in the heap – and then delete the minimum value from the heap (Cormen, Leiserson, Rivest, and Stein (2009)).

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**Soft Heap**

**Overview**

1. Operations Supported by Soft Heap: A *soft heap* is a variant on the simple data structure that has constant amortized time for 5 types of operations. This is achieved by carefully corrupting, i.e., increasing, the keys of at most a certain of values in the heap. The constant time operations are:
   1. => Create a new soft heap
   2. => Insert an element into a soft heap
   3. => Combine contents of two soft heaps into one, destroying both
   4. => Delete an element from a soft heap
   5. => Get the element with the minimum key in the soft heap
2. Constant Time Delete Operation Bound: Other heaps such as Fibonacci heaps achieve most of the bounds without any corruption, but cannot provide a constant-time bound on the critical operation. The amount of corruption can be controlled by the choice of a parameter , but the lower this is set, the more time insertions require - - for an error rate .
3. Specific Guarantee offered by Soft Heap: More precisely, the guarantee offered by soft heap is the following: for a fixed between and , at any point in time there will be at most corrupted keys in the soft heap, where is the number of elements so far. Note that this does not guarantee that only a fixed percentage of keys *currently* in the heap are corrupted; in an unlucky sequence of insertions and deletions, it can happen that all the elements in the heap will have corrupted keys. Similarly, there are no guarantees that in a sequence of elements extracted from the heap with and , only a fixed percentage will have corrupted keys; in an unlucky scenario only corrupted elements are extracted from the heap.
4. Core Idea behind the Construct: The soft heap was designed by Chazelle (2000). The term *corruption* in the structure is the result of what Chazelle calls *car-pooling* in a soft heap. Each node in the structure contains a linked list of keys and one common key. The common key is a upper bound on the values of the keys in the linked list. Once a key is added to the linked list, it is considered corrupted and its value is never again used in any of the operations; only the common keys are compared. This is what makes the soft heaps *soft*; one cannot be sure whether any particular value put into it will be corrupted. The purpose of these corruptions is to lower the information entropy of data, enabling the data structure to break-through the information barrier regarding heaps.

**Applications – Selection Algorithm**

1. Design of Deterministic Algorithms: Despite their limitations and unpredictable nature, soft heaps are useful in the design of deterministic algorithms. They have been used to achieve the best complexity to date for finding a minimum spanning tree. They can also be used to easily build an optimal selection algorithm, as well as *near-sorting* algorithms, which are algorithms that place every element near its final position, a situation in which the insertion sort is fast.
2. Use in the Selection Algorithm: One of the simplest examples is the selection algorithm. Say that one wants to find the largest set from a group of numbers. First, one chooses an error rate of ; that is, at most of the keys inserted will be corrupted. Now, all elements are inserted into the heap – the original values are called the *correct* keys, and the values stored in the heap are called the *stored* keys. At this point, at most keys are corrupted, that is, for at most keys are the *stored* key larger than the *correct* key, for all others the stored key equals the correct key.
3. Repeated Deletion of the Minimum Element: Next, the minimum element is deleted from the heap times, and this is done according to the *stored* key. As the total number of insertions made is still , there are still at most corrupted keys remaining in the heap. Accordingly, at least

keys remaining in the heap are not corrupted.

1. Runtime for the Selection Algorithm: Let be the element with the largest correct key among the elements removed. The stored key of is possibly larger than its correct key – if was corrupted – and even this larger value is smaller than all the keys of the remaining elements in the heap, as the minimum keys are being removed. Therefore, the correct key of is smaller than the remaining uncorrupted elements in the soft heap. Thus, divides the elements somewhere between and 66%/33%. The set is then partitioned about using the partition algorithm from quicksort, and the same algorithm is applied again to either set of numbers less than or the set of numbers greater than , neither of which can exceed elements. Since insertion and deletion requires amortized time, the total deterministic time is

Using the master theorem for divide-and-conquer, this becomes

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**The Soft Heap: An Approximate Priority Queue with Optimal Error Rate**

**Abstract**

1. Functionality Provided by Soft Heap: Chazelle (2000a) introduces a simple variant of a priority queue, called a *soft heap*. The data structure supports the usual operations; insert, delete, meld, and findmin.
2. Breaking the Information-Theoretic Bound: Its novelty is to beat the logarithmic bound on the complexity of a heap in a comparison-based model. To break this information-theoretic barrier, the entropy of the data structure is reduced by artificially raising the values of certain keys.
3. Error Rate and Implied Complexity: Given any mixed sequence of operations, a soft-heap with an error rate - for any

ensures that, at any time, at most of its items have their keys raised. The amortized complexity of each operation is constant, except for insert, which takes time.

1. Data Structures used by Soft Heap: The soft-heap is identical for any value of in a comparison-based model. The data structure is purely reference based. No arrays are used and no numeric assumptions are made on the keys.
2. *Car Pooling* Groups of Data: A key idea behind soft heap is to move items across data structures not individually, as is customary, but in groups, in a data-structuring equivalent of *car-pooling*. Keys must be raised as a result, in order to preserve the heap-ordering of the data structure.
3. Application Usage of Soft Heap: The soft heap can be used to compute exact or approximate medians and percentiles optimally. It is also useful for approximate sorting and for computing minimum spanning trees of general graphs.

**Introduction**

1. Soft-heap as a Priority Queue Variant: Chazelle (2000a) designs a simple variant of priority queue called a *soft-heap*. The data structure stored items in a heap with keys in a totally ordered universe, and supports the following operations.
2. Create : Create a new empty soft-heap .
3. Insert : Add a new item to .
4. Meld : Form a new soft-heap with items stored in and .
5. Delete : Remove an item from .
6. Findmin : Return an item in with the smallest key.
7. Motivation behind Corruption of Keys: The soft heap may, at any time, increase the value of certain keys. Such keys, and by extension, the corresponding items, are called *corrupted*. Corruption is entirely at the discretion of the data structure and the user has no control over it. Naturally, findmin returns the minimum *current* key, and may or may not be corrupted. The benefit is speed: during heap updates, items travel together in packets in form of *car-pooling*, in order to save time.
8. Reducing Entropy of Data Stored: From an information-theoretic point of view, corruption is a way to decrease the entropy of the data stored in the data structure, and thus, facilitate its treatment. The entropy is defined as the logarithm, in base two, of the number of distinct key assignments, i.e., entropy of the uniform distribution over key assignments. To see the soundness of this idea, push it to its limit, and observe that if every key was corrupted by raising its value to , then the set of keys would have zero entropy, and all operations can be performed in constant time. Interestingly, soft heaps show that entropy need not drop to zero for the complexity to become constant.
9. Soft Heap Time Complexity Lemma: Beginning with no prior data, consider a mixed sequence of operations that includes inserts, For any

a soft heap with error rate supports each operation in constant amortized time, except for inserts, which takes time. The data structure never contains more than corrupted items at any time. In a comparison-based model, these bounds are optimal.

1. Actual Numbers of Items Corrupted: Note that this does not mean that only items are corrupted in total through the sequence of operations. In fact, it is not difficult to imagine a scenario where are items are eventually corrupted; for example, insert items and keep deleting the corrupted ones. Despite this apparent weakness, the soft heap is optimal – and perhaps even mor surprising – useful. The data structure can be implemented on a pointer machine; no arrays are used, and no numeric assumptions on the keys are required.
2. Soft Heap as a Modified Binomial Queue: Soft heaps capture three distinct features, which are useful to understand at the outset. First, on setting

no corruption is allowed to take place and the soft heap behaves like a regular heap with logarithmic insertion time. Unsurprisingly, soft heaps include standard heaps as special cases. In fact, as will be seen, soft heap is nothing but a modified binomial queue (Vuillemin (1978)).

1. Soft Heap as a Median Finder …: More interesting is the fact that soft-heaps implicitly feature the median-finding technology. To see why, set to be a small constant; insert keys and then perform findmins, each followed by a delete. This takes time. Among the keys deleted, the largest one is away from the median of the original keys. To obtain such a number in linear time deterministically, as Chazelle (2000a) does, typically requires a variant of the median-finding algorithm of Blum, Floyd, Pratt, Rivest, and Tarjan (1973).
2. … but it is more than that: The previous remark should not lead one to think that a soft-heap is simply a dynamic median-finding data structure. Things are more subtle. Indeed, consider a sequence of inserts of keys in decreasing order, inter-mixed with findmins, and set

Despite the high value of the error rate , the findmins must actually return the minimum key at least half the time. The reason is that at most keys inserted can ever be corrupted. Because of the decreasing order of the insertions, these uncorrupted keys must be reported by findmin right after their insertion, since they are minimum at that time. The requirement to be correct half the time dooms any strategy based on maintaining medians or near-medians for the purpose of findmin.

**Applications**

1. Overview of Soft Heap Uses: Soft heaps are useful for computing minimum spanning trees and percentiles, for finding medians, for near sorting, and generally for situations where approximate rank information is sought. Some examples below.
2. Usage in Minimum Spanning Trees: The soft-heap was designed with a specific application in mind, the minimum spanning tree. It is a key ingredient in what is currently the fastest deterministic algorithm (Chazelle (2000b)) for computing the minimum spanning trees of a graph. Given a connected graph with vertexes and weighted edges, the algorithm finds a minimum spanning tree in time where is the classical functional inverse of Ackermann’s function.
3. Usage in Dynamic Rank Maintenance: Another simpler application is the dynamic maintenance of percentiles. Suppose one wishes to maintain the grade point average of students in a college, so that at any time one request the name of a student with a GPA in the top percentile. Soft heaps support such operations in constant amortized time.
4. Computing Selection in Linear Time: Soft heaps give an alternate method for computing medians in linear time – or generally performing linear time selection (Blum, Floyd, Pratt, Rivest, and Tarjan (1973)). Suppose one wants to find the largest element in a set of numbers. Insert numbers into the soft heap with error rate . Next call findmin and delete times. The largest number deleted has rank between and . After computing this rank, one can remove therefore at least numbers from consideration. On recurses over the remainder in the obvious fashion. This allows finding the largest element in time proportional to
5. Usage in Weak Near Sorting: A fourth application of soft heaps is approximate sorting. A weak version of near sorting requires that given distinct numbers, the algorithm should output them in a sequence whose number of inversions is at most instead of zero for exact sorting. As it turns out, this follows directly by inserting numbers into a soft heap with error rate and then deleting the smallest keys repeatedly. The number of inversions of the deleted number of is the number of keys deleted earlier whose original values are larger than . But must have been in a corrupted during those particular earlier deletions. The total number of keys in a corrupted state, counting over all deletions, is at most , and so the number of inversions is also bunded by .
6. Usage in Strong Near Sorting: A stronger version of near sorting requires that in the output sequence the rank of no number differs from its true rank in sorted time by mor than .It is shown below how the soft heap enables that in time. In particular, the lemma below provides simple linear algorithm for this strong form of near-sorting with, say error in rank. Of course, the result itself is not new. It can be derived trivially from repeated mean computation. The idea is that it is done using soft heaps.
7. Strong Near Approximation Sorting Lemma: For an

a soft-heap may be used to near-sort numbers in time ; this means that the rank of any number in the output sequence differs from its true rank by at most .

1. Insertion followed by Minimum Finding: Since the running time sought is , it may be assumed that between a large constant and . Given numbers, assumed to be distinct for simplicity, insert them into a soft heap and delete the item returned by findmin until the heap is empty.
2. Dividing Findmins across Time Slices: Using a soft heap with error rate , at most numbers are corrupted at any given time. The sequence of -paits – findmin and delete – is divided into time intervals each consisting of pairs; without loss of generality, it is assumed that
3. Items Deleted/Corrupted during the Interval: Let be the set of items deleted during , and let be the subset of that includes only items that were at some point uncorrupted during . It is assumed that items are time-stamped when first corrupted.
4. Smallest Uncorrupted Key in : Finally, let be the smallest original key among the items of , and let be the corresponding item; for convenience, set

and

Given an item

whose original key lies in one defines

The following are some simple facts.

1. Bound on Cardinality of :

because at most items are corrupted at the beginning of .

1. Range of the Original Keys: The ’s appear in increasing order, and the original key of any item in lies in . Since is uncorrupted during , it’s original key is at most the current – and hence, original – key of any item deleted during .
2. Upper Bound on the Corruption *Distance*:

Given

let be the interval that contains the original keys of . As just observed, the original key of is less than , and therefore

To avoid being selected by findmin, the item must have been in a corrupted state during the deletion of , for any

if such a exists. The total number of items in a corrupted state during the deletions of is at most , and therefore so is the sum of distances

over all such items . It follows that

hence the claim.

1. Bounds on Original Keys in an Interval: The number of items whose original keys fall in is less than . Indeed, suppose that the item does not belong to . It cannot be selected by findmin and deleted before the beginning of , since was not corrupted yet. By the time was deleted, the item in question must have been corrupted, and it cannot have been deleted yet. So, there can be at most such items. Thus, the total number of items with original keys in is at most
2. Origin of the Bound: Next, for each item

the search for which interval contains its original key can be done in time by sequential search. From the above lemma, this means that in post-processing time, the set of original keys have been partitioned into disjoint intervals, each containing between and keys. So, in time, any number can be output in a position of at most off its rank. Replacing by completes the proof.

**The Data Structure**

1. Soft Queue as a Modified Binomial Tree: Recall that a binomial tree of rank is a rooted tree of nodes; it is formed by the combination of two binomial trees of rank where the root of one becomes the new child of the other root (Vuillemin (1978)). A soft heap is a sequence of modified binomial trees of distinct ranks, called *soft queues*. The modifications come in the following two ways.
2. Master Tree and Rank Invariance: A soft queue is a binomial tree with sub trees possibly missing, somewhat like tees of a Fibonacci heap (Fredman and Tarjan (1987)) after a few deletions. The binomial tree from which is derived is called its *master tree*. The *rank* of a node is the number of children in the corresponding node in then master tree. Obviously, it is an upper bound on the number of children in . The following *rank invariance* is therefore enforced: the number of children of the root should be no smaller than
3. Items in a Soft Queue Node: A node may store several items, in fact a whole *item-list*. The of denotes the common value among all of the current keys in the ; it is an upper bound on the original keys. The soft-heap is heap-ordered with respect to , i.e., the of a node does not exceed the of any of its children. Fixing an integer parameter

all corrupted items are required to be stored at nodes of rank greater than .

1. Structure of the Item-List: Turning to the actual code, an item list is a list of singly-linked items with one field indicating the original value of the key.
2. Structure of the Soft Queue: A node of a soft queue indicates its and its rank in the master tree. References and give access to the children. If there are none, the references are NULL. Otherwise, the node is the parent of a soft-queue of rank one less – pointed to by – and the root of a soft queue of rank one less – pointed to by . This is a standard artifice to represent the high degree nodes as sequences of degree-2 nodes. To facilitate the concatenation of item-lists a reference to the tail of the list is also provided.
3. Top Structure of the Heap: The top structure of the heap consists of a doubly linked list consists of a doubly linked list called the *head-list*; each *head* has two extra references; one - – points to the root of a distinct queue, and another - – points to the root of the minimum among all for

It is required that

By extension, the rank of a queue – resp. heap – refers to the rank of its root – resp. . It is stored in the head as the integer variable .

1. Initialization of the Soft Heap: The soft heap is initialized by creating two dummy heads as global variables; gives access to the head-list, while , of infinite rank, represents the end of the list. The functions and create and initialize a new head and a new node in the trivial manner. The third global variable is the parameter

**Soft Heap Operations**

This section discusses a minor variant of the data structure, whose implementation is slightly simpler. It is straightforward to modify the data structure into a full-fledged soft heap. First, the variant bypasses create operation and integrates with insert. Also, note that the operation delete can be implemented in *lazy* style by simply marking the item to be deleted accordingly. Then, actual work is required only when *findmin* returns an item that is marked as deleted. For this reason, the discussion of and is skipped altogether, and instead the focus is on . It is obvious from this how to modify the data structure to accommodate and separately.

**Inserting an Item**

To insert a new item, an uncorrupted one node queue is created, and melded into the heap.

**Melding Two Heaps**

1. Breaking Down Lower-Rank Heap: Consider melding two heaps and . This section begins with a quick review, and then discusses the actual implementation of the algorithm.
2. Inserting a Queue into Heap: To meld a queue of rank into, the algorithm looks for the smallest index such that

The dummy head *tail* ensures that always exists. If

the head is inserted right before instead. Otherwise, the two queues are melded into one of rank by making the root with a larger key a new child of the other root.

1. Case of Pre-existing Rank: If

a new conflict arises. The process is repeated as long as necessary like a carry propagation in binary addition.

1. Updating the *ckey suffix\_min* Head: Finally, the suffix\_min references between and the last visited head are updated. When melding not just a single queue but a while heap, the last step can be done at the very end in just one pass through . The gist of the code for melding a soft queue into a soft heap is provided below.
2. Heap Rank corresponding to Queue: Let be a reference to the soft queue to be melded into the soft heap. First, the *head-list* is scanned to locate the point at which the melding proper can begin. This leads to the first head of rank at least that of which is denoted by . To facilitate the insertion of the new queue, the preceding head - – is retained.
3. Carry Propagation to Handle Pre-existing Ranks: If there is already a queue of the same rank as , the carry propagation is performed as discusses earlier. When merging two queues, the variables and are used to specify which of the two queues end up at/below the. A new node pointing to and is created. Its is inherited from the and its rank is one plus that of the , i.e., . Finally, the is updated to point the next element down the .
4. Insertion of the New Queue: The new queue can be inserted into the list of heads. Chazelle (2000a) uses a trick; if a carry has actually taken place, the head pointed to by is unused now and so can be recycled as the head of a new queue. Otherwise, a new head is created. is inserted between and ; all the heads in between can now be discarded. The call to restores the references.
5. Updating the Queue References: Prior to calling it is assumed that all references are correct, except for those between and . A simple walk from back to updates all the references.

**DeleteMin**

1. Pointing to Empty Item-List: The reference at the beginning of the points to the head with the minimum – corrupted or not. The trouble is that the item-list at that node might be empty. In that case, the item-list must be filled with items taken lower down in the queue pointed to by . To do that, one calls the function which replaces the empty item-list by another one. If necessary, this process is iterated until the new item-list at the root is not empty.
2. Migrating Items up the Root: Taking an argument the node at which the sifting takes place, the function attempts to move items up the tree towards the root. This is a standard operation in classical heaps. Typically, there is a single recursive call in the procedure and the computation tree is a path. The twist is the call to the recursion tree twice occasionally, in order to make the recursion tree branching, i.e., truly a tree. This simple modification causes item-lists to collide on the way up, which is resolved by concatenating them.
3. Invoking the Secondary Recursion: The loop condition for the second recursion is what makes the soft heap special. Without it, would be indistinguishable from the standard operation of a binomial tree. The loop condition holds if:
   1. the recursive loop has not yet been executed during this invocation of , i.e., branching is at most binary;
   2. the rank of exceeds the threshold of and it is either odd or it exceeds the rank of the highest-ranked child of by at least two.
4. Purpose behind the Recursion Criterion: The rank condition ensures that no corruption takes place too low in the queue; the parity condition is there to keep the branching from occurring too often; finally, the last condition ensures that branching occurs frequently enough. The variable implements the car-pooling in the concatenation

The cleanup is intended to prune the tree of nodes that have lost their item-lists to ancestors and whose keys have been set to .

1. Sift #1 - Ensuring is NULL: The at is worthless and it is effectively emptied at the beginning. The node is tested to see if it is a leaf. If so, it is bottomed out by setting its to , i.e., a large integer which will cause the node to stay at the bottom of the queue. If is not a leaf, then neither nor are NULL. In fact, this is a general statement; both are NULL or neither one is. This might change temporarily inside a call to but it is restored before the call ends.
2. Sift #2 - Maintaining Heap Ordering: The new item-list at might now have a large which violated heap ordering. If so, a rotation is performed by exchanging the children and .
3. Sift #3 - Update Node Contents: Once the children of are in place, the various references of are updated. In particular, the item-list of is passed on to , and so is its . Recall that while is truly a child of in the soft queue, the node is a child of only in the binary tree implementation of the queue.
4. Sift #4 - Secondary Recursion Criterion: Next in line, the most distinctive feature of soft-heaps; the possibility of sifting twice, i.e., of creating a branching process in the recursion tree for . If the secondary recursion condition is satisfied, meaning that the rank of is off and large enough, the is re-done.
5. Sift #5 - Heap Order Restoration: As a result of the sifting, another rotation may be required to restore heap ordering.
6. Sift #6 – Item-List Concatenation: The item-list at should now be concatenated with the one at , unless of course, it is empty or no longer defined. The latter case occurs when is at both and . Note that this could not happen after the previous .
7. Sift #7 - Terminal Cleanup: The queue is cleaned up by removing the nodes with infinite . is *not* updated since it is defined with respect to master tree. Note that this is where the rank and the number of children can be made to differ. In fact, for any node , the ranks of its children in the binary tree are always ensured to be equal, i.e.,
8. DeleteMin #1 - Child Node Count: The function returns the item with the smallest and deletes it. The reference takes us to the smallest , which is precisely what is wanted, unless of course, the corresponding item list is empty. In that case, invoked – perhaps more than once – to bring items back to the root. But first, the check for the rank invariance violation must be done. Indeed, the previous sifting may have caused the loss of too many children of the root, and hence a violation of the invariant. The number of children is therefore counted – alternatively, a field could be added to keep track of this number.
9. DeleteMin #2 - Rank Invariance Verification: The advantage of detecting a rank invariance violation so late in the game is that fixing it now is much easier since the root’s item-list is empty. If the rank invariance is violated, i.e.,

the queue is removed, and the head-list and references are updated. The root is *dismantled* by re-melding back its children.

1. DeleteMin #3 - Item List Sifting: If the rank invariance holds, the item-list is refilled at the root by calling .
2. DeleteMin #4 - Deleting Minimum Key: The minimum-key item can now be deleted.

**Complexity Analysis**

1. Soft Queue Master Tree Correspondence: This section proves that the soft-heap meets all its claims using a few simple lemmas. Consider a mixed sequence of operations including inserts. To begin with, the correspondence between a soft queue and its master tree must be explained. When no deletion takes place, the equivalence is obvious, and it is trivially preserved through the inserts and the melds. During sifting, the principal observation is that and always remain identical. Enforcement of this equality is what can cause a discrepancy between the rank and the number of children. But it allows viewing a rotation as an exchange between soft queues of the same rank, albeit with missing sub-trees. The corresponding master trees have the same rank, they are isomorphic, and therefore a rotation has no effect in the correspondence. Similarly, the clean-up prunes away sub-trees, with no consequence on the queue/master-tree correspondence.
2. Missing Leaves of the Master Tree: The interesting aspect of this correspondence is that the leaves of the master tree that are missing from the soft queue correspond to items that have migrated upward to join the item-lists of nodes of positive rank. Such items can never appear again in the leaves of any soft-queue. Note that dismantling a node by re-melding its children does not contradict this statement since it merely reconfigures the soft heap.

**The Error Rate**

1. Relation between and the Error Rate: To achieve the desired error rate, one sets
2. Vertex Item Cardinality Lemma:
3. Operations Impact on Item List Size: Until the first call to , all item lists have size one, and the inequality holds. Afterwards, simple inspection shows that all operations have no impact on the lemma’s inequality, or sometimes a favorable one, e.g., . All of them, that is, except for , which could potentially cause a violation. Here it is shown that this is not the case, and the lemma’s inequality is proven by induction.
4. Sift Impact on Item List Size: If calls itself recursively via only once, meaning that the loop condition is not satisfied, then the item list of – after possible rotation – migrates to a higher ranking node by itself, and the lemma holds by induction. Otherwise, the item-list at becomes the union of two item lists associated with after each call to .
5. Impact of Sift Recursion #1: For the second sift recursion to happen, must exceed , and one of two conditions must hold: either is odd, or it exceeds . In the first case, after the recursive call, the rank of is strictly less than , and by induction, the size of either one of the item-lists of is at most

Note that the disappears because

1. Impact of Sift Recursion #2: In the other case, the size of either one of the item-lists of is at most

This time, the disappears because and the rank of are both even, and so

In sum, the size of the union is at most , which proves the lemma.

1. Soft Heap Corrupted Item Bound Lemma: The soft heap contains at most corrupted items at any given time.
2. Binomial Tree Node Set Cardinality: The lemma proof starts with a simple observation. If is the node set of a binomial tree, then

This follows from the inequality

where is the rank of the binomial tree. A proof by induction is immediate and can be omitted here.

1. Bound of Master Tree Node Count: Recall that the ranks of the nodes of a queue is derived from the corresponding nodes in the master tree . So, the set – respectively - of nodes of rank greater than in – respectively - is such that

Within , the nodes of number a fraction at most of all leaves. Summing over the master trees, it may be found that

1. Master Tree Corrupted Item Bound: There is no corrupted item at any

so, by the Vertex Item List Cardinality Lemma, their total number does not exceed

Each forms a binomial tree by itself, where the rank of node becomes . So, using

and

the sum in is at most

**The Running Time**

1. Big- for Meld and Shift: Only meld and shift need to be looked at, all other operations being trivially constant-time. Assigning one credit per queue accounts for the carry propagation during the meld. Indeed, two queues of the same rank combine into one, which releases one credit to pay for the work. Updating references can take time, however.
2. Modeling Melds using Binary Tree: Specifically, carries aside, the cost of melding two soft heaps and is at most the smaller rank of the two, up to a constant factor. The entire sequence of the soft heap melds can be modeled as a binary tree . A leaf denotes a one-item heap, its cost is . An internal node denotes the melding of two heaps.
3. Meld Cost using Node Count: Since heaps can grow only though melds, the added size of the master heap in the soft heap at is proportional to the number of descendants in . The cost of the node , i.e., of the meld, is where and are the right children of – this uses the fact that the rank of the soft queue is exactly the logarithm of the number of nodes in its master tree. A simple recurrence, e.g., see Hoffman, Mehlhorn, Rosenstiehl, and Tarjan (1986), shows that adding together all these costs gives a total melding cost that is linear in the size of , i.e., .
4. Accounting for Dismantle-Induced Melds: For the analysis to be correct, no node dismantling should ever take place. This can be easily amended, however, to cover the general case. For the purposes of the analysis, re-meldings are assumed to be caused not by dismantlement of heap melds, but by queue melds. The benefit is to leave the tree unchanged. The dismantle-induced melds associated with the node of re-configure the soft heap at by removing some of its nodes and restoring the rank invariant. This can only decrease the value of , so the previous analysis remains correct.
5. Analysis of the Node Dismantlement Costs: Of course, the queue melds associated with node must now be accounted for. Dismantling node causes no more than queue melds. By the violation of the rank invariant, node has at least one missing child of

In the master tree there are at least leaves at or below that child, and all have disappeared from the soft queue. So, the dismantle-induced melds can be charged against these leaves, thereby concluding that melding takes time.

1. Consolidated Cost of Sift #1: Finally, it is shown that the cost of all calls to sift is . Consider any decreasing sequence of integers. An integer is called good if it is odd or if its successor is less than . Clearly, any sub-sequence of size two contains at least one good integer. Now consider a computation tree corresponding to an execution of . By examining the sequence of ranks along any root-to-leaf path, the previous observation leads to the conclusion that along any path size at least , at least one branching must occur, and not necessarily many more than that, because no branching occurs at rank and below. It follows that, excluding the update of references, the running time is , where is the number of times the loop-condition succeeds.
2. Consolidated Cost of Sift #2: It is easy to see, by induction, that if is the root of a sub-tree with fewer than two finite ’s below, the computation tree of is of constant size. Conversely, if the sub-tree contains at least two finite ’s at distinct nodes, then if the loop condition is satisfied at , both calls of the form bring finite ’s to the root, and the two non-empty item-lists are thus concatenated. There can be at most such merges, therefore

and the claim holds.

1. Cost of Updating References: The cost of updating references after each call to has been ignored so far. Maintaining the rank invariant makes the cost of updating negligible. Indeed, each update takes time proportional to the rank of the queue. If the rank invariant holds, the updating time is dominated by the itself, and is already accounted for. Otherwise, the root is dismantled, which, as just seen, releases leaves against which the update cost may be charged. By the Soft Heap Corrupted Bound Item Lemma, the number of corrupted items is bounded by . Setting

proves the Soft Heap Complexity Lemma, except for the optimality claim.

1. Algorithm Modification under Storage Constraints: The storage is linear in the number of insertions , but not necessarily in the number of items present. If storage is a premium, here is a simple fix. As soon as the number live items falls below, say , the soft-heap is entirely re-configured. All uncorrupted items are r-inserted, and separately, all corrupted items are strung together into a single item-list, whose key is set to . The time taken for re-configuring the heap can be charged to the deleted elements. Regarding corruption, re-configuration merely doubles the number of insertions, and so the number of corrupted items after user requested insertions will be at most . So, it suffices to replace by to achieve an error rate of . The modified soft heap is optimal in storage, and as shown below, in time.

**Optimality**

1. Proof of Soft-Heap Time Complexity Lemma: To complete the proof of the soft-heap time complexity lemma, this section shows that the soft-heap is optimal. Without loss of generality, one can assume that lies between a large constant and , and that is an integer .
2. True Rank of a Selection: Apply the Sting Near Approximation Sorting Lemma to distinct numbers, and pick out every element in the output sequence. By the near-sortedness of the output, the chosen subsequence is already sorted. It partitions the set of numbers into disjoint intervals, within with one can easily locate the other numbers in linear time, each number being at most a constant number of intervals off its enclosing interval. From this, in particular, the true rank of the selected numbers is derived.
3. Partitioning of the Selection: By using linear selection-finding within each interval, the largest element can be easily retrieved, for

Thus, the set of numbers can be partitioned into disjoint intervals of size .

1. Computation Height of the Comparison-Based Tree: Let

A standard counting argument shows that any comparison-based tree for performing this computation is of height at least

1. Optimality of Amortized Complexity: So, the entire algorithm requires time, but it involves operations on a soft-heap with error rate , followed by -time post-processing. It follows that the amortized complexity of the soft-heap is optimal.

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**A Simpler Implementation and Analysis of Chazelle’s Soft Heaps**

**Introduction**

1. An Approximate Meldable Priority Queue: Chazelle (2000a, 2000b) devised an approximate meldable priority queue data structure, called *soft heaps*, and used it to obtain the fastest known deterministic comparison-based algorithm for computing minimum spanning trees (Chazelle (2000a, 2000c)) as well as some new algorithms for selection and approximate sorting problems.
2. Origin of the Corrupted Elements: If elements are inserted in a collection of soft heaps, then up to of the elements still contained in these heaps, for a given *error parameter* , may be *corrupted*, i.e., have their keys artificially raised. Note that here is the number of elements inserted into the heaps, not the current number of elements in the heaps, which may be considerably smaller.
3. Soft Heap Operations Amortized Time: In exchange for allowing these corruptions, each soft heap operation is performed in amortized time.
4. Optimal Deterministic Comparison Based Algorithm: Soft heaps are also used by Pettie and Ramachandran (2002, 2008) to obtain an optimal deterministic comparison-based algorithm for finding minimum spanning trees, with a yet unknown running time, and for obtaining a randomized linear time algorithm for a problem that uses only a small number of random bits.
5. Heaps used in Chazelle’s Algorithm: Chazelle’s soft heaps are derived from the *binomial heaps* data structure in which each priority queue is composed ot a collection of *binomial trees*.
6. Heaps used by Kaplan and Zwick: Kaplan and Zwick (2009) describe a simpler and more direct implementation of soft heaps in which each priority queue is composed of a collection of standard *binary trees*.
7. No Clean-up Operations Required: Their implementation also has the advantage that no *clean-up* operations similar to the ones used in Chazelle’s implementation are required.
8. Unified Potential-Based Amortized Analysis: They also present a concise and unified potential-based amortized analysis of their new implementation.

**Soft Heaps**

1. Operations Supported by Soft Heaps: Soft heaps are approximate meldable priority queue data structures that support the following operations.
2. : Generate and return a new soft heap containing a single element whose original key is .
3. : Insert an element , with original , into the soft heap .
4. : Delete element from the soft heap currently containing it.
5. : Meld two soft heaps and , destroying them in the process, and return the melded heap.
6. : Return an element with the smallest *current* *key* in the soft heap and delete it from .
7. Elements with Minimal Current Key: It is important to note that operation returns an element with the smallest *current* key contained in . The current key of an element may be *larger* than its *original* key , which is never changed by the implementation. Elements whose current keys are larger than their original keys are said to be *corrupted*. The user has no control as to which elements become corrupted.
8. Corrupted Elements Upper Bound Count: If soft heaps were allowed to corrupt all elements their implementation would be trivial, but they would be useless. A surprisingly useful data structure is obtained if one requires that at most of the elements still contained in the soft heaps are corrupted, where is the total number of elements inserted into the soft heaps, and

is a pre-specified *error parameter*.

1. Operations that Insert or Delete: Note that an element is inserted into a soft-heap by either the or the operation. Also note that the corrupted elements that were removed from the soft heap by the operations are not counted.
2. Description of the Soft Heap Algorithm: Following Chazelle (2000b), this chapter describes an implementation of soft heaps with error parameter in which the amortized cost of and operations is and the amortized cost of all other operations is .

**Implementation**

This section describes the implementation of all soft heap operations, except for the operation which is added later. It is to be noted that many of the operations listed in Chazelle (2000b) do not use operation.

**The Data Structure**

1. Collection of Binary Trees: Each soft heap priority queue is composed of a collection of binary trees. A node of a binary tree may have a left child and a right child .
2. Rank and Children of Binary Trees: Every node in a binary tree has an integer *rank* denoted by , associated with it. The rank of a node never changes. If is a node of rank , then the ranks of and , of they exist, are . The rank of a tree is defined as the rank of its root.
3. Binary Tree Node Target Size: Each node has a *target size* associated with it. Let

where is the desired error rate. The target size of a node of rank is , where

The choice of in the definition of is arbitrary. Any constant strictly between and would do. Thus

which implies that

etc. It is easy to prove that

for

1. Actual Size of Each Node: Each node has a list of elements . The number of elements in is *roughly* – this will be more precise below.
2. Keys of the Binary Node: A node also has a key which is an upper bound on the keys contained in , and

then is corrupted. The data structure behaves as if the key of is artificially raised to . Using the terminology of the introduction, if is an element of , then is the current key of .

1. Heap Ordering of the Trees: Each tree is *heap-ordered* with respect to the values, i.e., if is a node and exists, then

Similarly, if exists, then

1. Priority Queue as a Sequence of Trees: A priority queue is composed as a sequence of trees, at most one of each rank. The rank is defined to be largest rank of a tree in . The trees composing are arranged in a linked list in which the trees appear in an increasing order of rank. points to the with the smallest rank belonging to .
2. Structure of the Binary Tree: If is a tree contained in a priority queue , then is the root node of , is the tree following in the linked list of , and is the tree preceding in the list. Both and may be NULL.
3. The Reference Member: Finally, if is a tree, then points to the tree whose root has the smallest among all the trees that follow in the linked list of . In this case, trees that appear earlier are preferred.

**The Sift Operation**

1. Purpose of the Sift Operation: As in Chazelle’s implementation, the keystone of soft heaps’ operation is the operation. As indicated earlier, the number of elements in should be about . If the number of elements in drops below , and is not a leaf, then operation is used to add more elements to .
2. Ensuring Existence of Left Child: A works as follows. By exchanging and , if necessary, it is ensured that exists, and that

if exists. Recall that is not a leaf.

1. Car-pooling of Child List: Then, using what Chazelle refers to as a *data structures version of car-pooling*, all elements of are moved to . This can be done in constant time by concatenating the lists and .
2. Left Child is now Empty: is the new ; this leaves the list empty.
3. Recursive Invocation of Operation: If is a leaf, it is simply removed from the tree by setting it to NULL. Otherwise is recursively called to replenish .
4. Criteria for the Run: Finally, if the number of elements in is still below and is still not a leaf, the operations are performed again.
5. maintains the Heap Order: It is easy to check that operations maintain the heap order. It is shown below that if is not a leaf after a operation, then

**The Combine Operation**

1. Combining Nodes of Same Rank: The second most important operation in the implementation of the soft heaps is the operation. A takes two root nodes and of the same rank, say , and combines them into a single tree of rank . This is done by generating a new node and setting to , to , and to empty. A is then performed to move enough elements into . The is, of course, instrumental in the implementation of the and the operations, as explained below.
2. Structural Changes to the Tree: Note that no re-balancing of the binary tree occurs. The only structural changes performed on the trees are:
   1. Discarding a leaf, done in
   2. Combining two trees of rank into a larger tree of rank by allocating a new root – this is done in .

**The Operation**

1. Purpose of : An operation updates the references of and all the trees that precede in the linked list of trees. Such an operation is performed when , where

is changed, e.g., by a operation, when is a new tree added to the list of trees, or when the tree following in the list is deleted.

1. Operational Sequence of the Update: An operation traverses the list of trees backward from . If is a tree such that was already set to its correct value, the is set to , if

or to

**The Operation**

A operation receives an element and returns a priority queue composed of a single tree containing a single node of rank .

**The Operation**

1. Purpose of the Operation: A receives two priority queues and and returns a new priority queue obtained by merging and .
2. Melding Linked Lists of Queues: Melding and is done in a fairly straightforward way. The linked lists of trees of and are combined, keeping a non-decreasing order of rank.
3. Two Trees of the Same Rank: Next, if two consecutive trees and in the list above have the same rank, they are combined using operation and the combined tree replaces them in the list.
4. Three Trees of the Same Rank: If three consecutive trees , , and in the list above have the same rank, then is left alone, while and are replaced by .
5. Updating Suffix Min of the Final Tree: Finally, if is the last tree in the list affected by these operations, and is performed to update the references.
6. Time Required by Meld: If

then it is easy to perform operation in time.

**The Operation**

To add an element to a priority queue , one uses to generate priority queue containing a single element and then melds this priority queue with .

**The Operation**

1. Purpose of the Operation: An operation returns an element with a minimum *current* key contained in . If is contained in , then the current key of is .
2. Root with the Smallest Key: The implementation of is extremely simple. Let

and

Thus is the root of a tree of with the smallest .

1. Invoking and Updating as Needed: An arbitrary element is returned from . Note that is never empty. If the number of elements in drops below , is called to replenish , and then updates the references.

**Correctness**

1. Minimal Current Key Extraction Lemma: An always returns an element of with a minimal current key.
2. Mandatory Maintenance of Heap Order: All elements inserted into are contained in the list of nodes that are part of the trees forming . All operations performed on soft heaps maintain heap order. Thus, elements with the smallest current key in a tree always reside at the root of the tree.
3. Guaranteed Pointing to the Smallest Key: An operation uses the reference to the first tree in to access a tree whose root has a minimal , and returns an element contained in , which is guaranteed to be non-empty. This element has a minimal key, as is required.
4. Bounding the Count of Corrupted Elements: The next two lemmas will be used to bound the number of corrupted elements.
5. Bounding the Size of Nodes Lemma: If is a node of rank at most , then

If is a non-leaf of rank

then

1. Size of a Rank Node: First, if is a node of rank at most , then

If becomes empty, then brings exactly one element into .

1. Nodes with Rank : Suppose now that

If drops below adds elements to until either

or until becomes empty.

1. Inductive Proof for Upper Bound #1: The next step is to prove by induction that

If

the claim is obvious. It is shown now that if the claim holds for all vertexes of rank , then it also holds for vertexes of rank .

1. Inductive Proof for Upper Bound #2: Let be a node of rank . New elements are added to only when

A operation concatenates to , where is a child of . As is of rank , it follows by induction that

Thus

as claimed.

1. Nodes in a Rank Lemma: If elements are inserted into soft heaps, then the number of nodes of rank is at most .
2. Proof of the above Lemma: Proof is done by induction on . A node of rank is generated only when a new element is inserted – using a operation – into a soft heap. Thus, the number of elements of rank is at most as claimed. An element of rank is generated only when two roots of rank are combined.
3. Bound of Corrupted Elements Lemma: If elements are inserted into soft heaps, then the total number of corrupted elements contained in the heaps, at any given time, is at most .
4. Nodes containing the Corrupted Elements: Each node of rank at most contains a single element. Thus, all corrupted elements belong to nodes of rank greater than .
5. Count of Nodes and Elements: By the Nodes in a Rank Lemma, the number of nodes in a rank is at most . By the Node Size Bounds Lemma, a node of rank

contains at most

elements.

1. Total Count of Corrupted Elements: As

the number of corrupted elements is at most

**Amortized Analysis**

1. Potentials Assigned to Heaps/Trees: Kaplan and Zwick (2009) assign potentials to heaps, trees, and nodes. A heap of rank has a potential of . A tree whose root is has a potential of where is the number of elements deleted from since the last operation, or since the creation of .
2. Potentials Assigned to Root/Leaf Nodes: If is a root node of rank , then has a potential of . If is a non-root node, it has a potential of .
3. Amortized Analysis of Operation: This section starts with an analysis of . Suppose that is a node of rank , that is a child of , and that the elements of are moved to .
4. Case where Child is a Leaf: If

then is a leaf, and disappears as a result of this operation. The unit potential released by the disappearance of pays for this operation.

1. Car-pooling of Non-leaf Children’s Elements: If, on the other hand

and hence

the unit cost of the operation is split among the elements participating in the *car-pool*. The charge for each element is at most

1. Cumulative Cost of Car-pooling: An element is charged at most once at each rank, thus its total *travel expenses* are
2. Potential Change due to Combine: The next operation considered is a operation which combines two nodes of rank , rooted at and , into a tree of rank rooted at . The potentials for both and decrease from to , releasing units of potential.
3. Costs Incurred during the Operation: One of these units pay for the constant cost of the operation, units are assigned to , one unit is used to increase the potential of the heap containing the newly formed tree, if it is now the tree with the largest rank.
4. Accounting of the Combine Costs: The remaining units are used, if needed, to pay for an ensuing operation. Note that
5. Meld Operation - Merging of Tree Lists: A operation receives two heaps of ranks and respectively. Suppose that

The operation first merges that lists of and , effectively destroying . This takes time, which is paid for by the released potential of .

1. Zero Amortized Cost for Component Operations: The subsequent operations pay for themselves and for the ensuing operation. If no operations are performed, the potential released by the destruction of pays for the operation.
2. Amortized Cost of : Finally, the amortized cost of operations are bounded. An operation locates an element with minimal current key in constant time.
3. Case where No Sifting is Required: Suppose that is a root node containing . If after deleting from one still has

or if

and is a leaf, then no further action is taken.

1. Incrementing the Deleted Element Count: Note, however, that , the number of elements deleted from since the last operation, is increased by , and the potential of the tree whose root is is increased by . This total cost of

is charged to , which would never be charged again.

1. Case when Sifting is Required: If

and is not a leaf, then a is performed.

1. Potential of Tree before : As is not a leaf, it must have had at least elements in its list after the previous operation. Thus

and the potential of the tree, prior to the operation, is at least

where

1. Bounding of the above Potential: It is not difficult to verify that for every

one has

Indeed for

one has

For

one has

and thus

For

one has

as

for

1. Amortized Operation: This decrease of at least in the potential of the tree pays for the operation that follows the operation.
2. Clean-up after the Last Leaf: Finally, if the root node is a leaf, and is the last element in , then and the tree rooted at are removed. The units of potential of are more than enough to pay for the operation performed after the removal of .
3. Inserting an Element into the Heap: When an element is inserted into a soft heap, a new heap, a new tree, and a new node are created. The heap, of rank , is assigned one potential unit, the tree zero units, while the new node, of rank , is assigned units.
4. Costs Incurred during the Elements’ Lifetime: During its lifetime, at most potential units are charged to to pay for its movements. Finally, an additional units are charged to when it is deleted.
5. Bounds on the Total Costs Incurred: On charging then one unit of actual work involved in inserting into a soft heap of its own, and the potential units assigned to this heap to , one gets that the total charge for , from its insertion until its deletion, is at most
6. Amortized Heap Operations Cost Lemma: The amortized cost of inserting an element into a soft heap with error rate is . The amortized cost of all other operations is .

**Adding a Delete Operation**

1. Amortized Analysis of Operation: The next item to consider is the implementation of the operation. One option, used by Chazelle (2000b), is to implement the operations in a *lazy* manner. Deleted elements are simply marked as such.
2. Chazelle’s Lazy Implementation of : If an operation returns an element marked as deleted, the operations is simply called again until a non-deleted element is returned.
3. Drawback of Lazy : The drawback of such an implementation is that it is not space optimal, and the space used by deleted elements cannot be reclaimed immediately. This can be fixed by re-building the data structure when more than half the elements are deleted.
4. Direct Implementation of the Operation: The operation is implemented directly as follows. is deleted from the linked list currently containing it. This can be easily done in constant time, using the forward and the backward references of in the list, without knowing the identity of .
5. Extraction of the Node containing the Element: The node can be retrieved using a union-find data structure, but this is too expensive in the current context. It is assumed, however, that the first element in the linked list knows to which list it belongs to.
6. Node after Deletion of the Element: If is the last remaining element of , a operation can be initiated to bring new elements into . If is a leaf, it is removed from the data structure. To implement this, however, a reference to the parent of in the tree needs to be maintained.
7. Ghost Elements in the List: For each node , one keeps a number that gives the number of elements in , including *ghost* elements that were deleted from of from lists that were appended from . One may thus have
8. Running Count of all Elements: When is appended to , one does

is not decremented when an element is deleted from , as it is not known when that happens.

1. Maintaining Count through the Operations: In fact, values should be maintained through all the implementations. All occurrences of discussed earlier should be replaced by , and values should be updated when the lists are created and moved.
2. Ghost Element Impact on Amortized Analysis: A moment’s reflection shows that the amortized analysis of the previous section remains valid. Some of the operations are charged to ghost elements, i.e., elements that were already deleted, but this is legal.

**Comparison with Chazelle’s Implementation**

1. Simplified Binary-Tree Soft Heap: The main difference between Kaplan and Zwick (2009) implementation and the Chazelle (2000b) implementation is that the former uses *binary* trees, whereas Chazelle’s implementation uses *binomial* trees. Kaplan and Zwick (2009) believe that their implementation is simpler and more intuitive, as argued in this section.
2. Binarization Inherent in Binomial Trees: Chazelle’s binomial trees are *binarized*. Each binomial tree is represented as a binary tree, with each node of the binomial tree corresponding to a *left* path in the binary tree. Thus, only root nodes, or nodes that are right children of their parents, have elements and keys associated with them. In the binary trees of Kaplan and Zwick (2009), all nodes play the same role.
3. Use of Partial Binomial Trees: The trees in Chazelle’s implementation are actually *partial* binomial trees, as tree nodes that remain without elements are deleted. In a standard binomial tree, a node of rank has exactly children. In Chazelle’s partial binomial trees, a node of rank may have less than children. If the number of children of an empty root node of rank drops below , Chazelle resorts to a *clean-up* operation that breaks the tree into a collection of trees. This slightly complicates the implementation and makes the analysis somewhat subtler. No such complications arise in the Kaplan and Zwick (2009) implementation.
4. Explicit Control of Element Count: Another important difference is that Kaplan and Zwick (2009) explicit control the number of elements contained in the list of a node of rank . They believe that this makes their implementation more intuitive and the analysis more transparent.
5. Space Efficient Implementation of : The way Kaplan and Zwick (2009) implement the operation is also different from the way suggested by Chazelle. Their implementation is automatically space efficient, without the need for periodic re-buildings.
6. Simplified and Unified Amortized Analysis: These changes in the implementation enable them to present a simplified and unified amortized analysis.

**Concluding Remarks**

1. Worst-Case Efficient Implementation: This chapter presented a simpler implementation of Chazelle’s soft heaps. It would be interesting to find additional applications of this data structure. It would also be interesting to know whether the soft heap operations can be implemented in *worst-case* time.
2. Reducing the Number of Comparisons: In the implementation presented, the amortized number of *comparisons* made for each element inserted into soft heaps is . It is possible to reduce this number to by maintaining references only for trees of rank greater than, say, , and keeping the values of the roots of the trees of rank at most in a small priority queue.
3. Case of no Corrupted Elements: It is interesting to point out that if one sets

in the construction above, i.e.,

for every node , a standard meldable priority queue data structure in which no corruptions occur is obtained. Each operation is performed in amortized time, where is the number of elements inserted into the priority queues. This may be viewed as an alternative to the celebrated *binomial heaps* data structure of Vuillemin (1978) (see also Cormen, Leiserson, Rivest, and Stein (2009)).

1. Efficient Comparison Based Selection Algorithms: As noted by Chazelle (2000a, 2000b), soft heaps give rise to a new linear-time median selection algorithm, very different from the algorithms of Blum, Floyd, Pratt, Rivest, and Tarjan (1973), Schonhage, Paterson, and Pippenger (1976), and Dor and Zwick (1999). It would be interesting to explore the possibility of using soft heaps to obtain an algorithm that finds the median of elements using less than comparisons. The best lower bound on the number of comparisons needed to find the median is currently for a fixed but tiny

(Dor and Zwick (2001)).

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**Spanning Tree**

**Overview**

A *spanning tree* of an undirected graph is a subgraph that includes all of the vertexes of , with minimum possible number of edges (Wikipedia (2020)). In general, a graph may have several spanning trees, but a graph that is not connected will not contain a spanning tree. If all of the edges of are also edges of a spanning tree of , then is a tree and identical to , that is, a tree has a unique spanning tree and that is itself

**Applications**

1. Use in Path Finding Algorithms: Several path-finding algorithms, including Dijkstra’s algorithm and the A\* search algorithm, internally build a spanning tree as an intermediate step in solving the problem.
2. Use in Cost Minimization Problems: In order to minimize the cost of power networks, wiring connections, piping, automatic speech recognition, etc., people often use algorithms that gradually build a spanning tree – or many such trees – as intermediate steps in the process of finding the minimum spanning tree (Graham and Hell (1985)).
3. Use in Link-State Protocols: The internet and many other telecommunications networks have transmission links that connect nodes together in a mesh topology that includes some loops. In order to avoid *bridge loops* and *routing loops*, many protocols design for such networks – including Spanning Tree Protocol, Open Shortest Path First, Link-State Routing Protocol, Augmented Tree-Based Routing, etc. – require each router to remember a spanning tree.
4. Graph Embeddings with Maximum Genus: A special kind of tree, the Xuong tree, is used in topological graph theory to find graph embeddings with maximum genus. A Xuong tree is a spanning tree such that, in the remaining graph, the number of connected components with an odd number of edges is as small as possible. A Xuong tree and an associated maximum genus embedding can be found in polynomial time (Beineke and Wilson (2009)).

**Definitions**

A tree is a connected, undirected graph with no cycles. It is a spanning tree of a graph if it spans – that is, it includes every vertex of – and is a subgraph of , i.e., every edge in the tree belongs to . A spanning tree of a connected graph can also be defined as a maximal set of edges that contains no cycle, or as a minimal set of edges that connect all vertexes.

**Fundamental Cycles**

Adding just one edge to the spanning tree will create a cycle; such a cycle is called a *fundamental cycle*. There is a distinct fundamental cycle for each edge not in the spanning tree; thus, there is a one-to-one correspondence between fundamental cycles and edges not in the spanning tree. For a connected graph with vertexes, and spanning tree will have edges, and thus, a graph of edges and one of its spanning trees will have fundamental cycles. For any given spanning tree, the set of all fundamental cycles forms a cycle basis, a basis for the cycle space (Kocay and Kreher (2004)).

**Fundamental Cut-sets**

1. Motivation behind the Fundamental Cut-set: Dual to the notion of a fundamental cycle is the *fundamental cut-set*. By deleting just one edge of the spanning tree, the vertexes are partitioned into two disjoint sets. The fundamental cut-set is defined as the set of edges that must be removed from the graph to achieve the same partition. Thus, each spanning tree defines a set of fundamental cut-sets, one for each edge of the spanning tree (Kocay and Kreher (2004)).
2. Duality between Cut-sets and Cycles: The duality between fundamental cut-sets and fundamental cycles is established by noting that the cycle edges not in the spanning tree can only appear in the cut-sets of the other edges of the cycle; and *vice versa*; edges in a cut-set can only appear in those cycles containing the edge corresponding to the cut-set. This duality can be expressed using the theory of matroids, according to which the spanning tree is the base of a graphic matroid; a fundamental cycle is the unique circuit within the set formed by adding one element to the base, and fundamental cut-sets are defined in the same way as the dual matroid (Oxley (2006)).

**Spanning Forests**

1. Competing Definitions of Spanning Forests: In graphs that are not connected, there can be no spanning tree, and on must consider *spanning forests* instead. Here, there are two competing definitions:
   1. Some authors consider a spanning forest to be the maximal acyclic subgraph of a given graph, or equivalently, a graph consisting of a spanning tree in each connected component of the graph (Bollobas (1998), Mehlhorn (1999)).
   2. For other authors, a spanning forest is a forest that spans all of the vertexes, meaning only that each vertex in the graph is a vertex in the forest. Under this definition, even a connected graph may have a disconnected spanning forest, such as a forest in which each vertex forms a single-vertex tree (Cameron (1994)).
2. Full versus Maximal Spanning Forest: To avoid confusion between these two definitions, Gross and Yellen (2005) suggest the term *full spanning forest* for a spanning forest with the same connectivity as a given graph, while Bondy and Murthy (2008) instead call this kind of forest a maximal spanning forest.

**Counting Spanning Trees**

The number of the spanning trees of a connected graph is a well-studied invariant.

**In Specific Graphs**

1. When is a Tree: In some cases, it is easy to calculate directly. If is a tree itself, then
2. is a Cycle Graph: When is a cycle graph with vertexes, then
3. is Complete with Vertexes: For a complete graph with vertexes, Cayley’s formula (Aigner and Ziegler (1998)) gives the number of spanning trees as .
4. is Complete Bipartite: If is a complete bipartite graph then

(Hartsfield and Ringel (2003)).

1. is an n-dimensional Hyper-cube: For an n-dimensional hyper-cube graph, the number of spanning trees is

(Harary, Hayes, and Wu (1988)).

**In Arbitrary Graphs**

1. Arbitrary Graph Spanning Tree Count: More generally, for any graph , the number can be calculated in polynomial time as a determinant of a matrix derived from the graph, using Kirchoff’s matrix-tree theorem.
2. Kirchoff’s Matrix-Tree Theorem Method: Specifically, to compute , one constructs a square matrix in which both the rows and the columns are indexed by vertexes of . The entry in row and column is one of three values:
   1. The degree of vertex if
   2. if vertexes and are adjoint, OR
   3. if vertexes and are different from each other but not adjacent.

The resulting matrix is singular, so its determinant is zero. However, deleting a row and a column for an arbitrarily chosen vertex leads to a smaller matrix whose determinant is exactly .

**Deletion-Contraction**

1. The Deletion-Contraction Recurrence Formula: If is a graph or a multi-graph, and is an arbitrary edge of , then the number of spanning trees of satisfies the *deletion-contraction recurrence*

where is the multi-graph obtained by deleting , and is the contraction of by (Kocay and Kreher (2004)). The term in the formula counts the number of spanning trees of that do not use the edge , and the term counts the spanning trees of that use the edge .

1. Retention of Redundant Graph Edges: In the above formula, is the given graph is a multi-graph, or if a contraction causes two vertexes to be connected to each other by multiple edges, then the redundant edges should not be removed, as that would lead to the wrong total. For instance, a bond graph connecting two edges by edges has different spanning trees, each consisting of one of these edges.

**Tutte Polynomial**

1. Sum over Internal/External Activity: The Tutte polynomial of a graph can be defined as a sum, over the spanning trees of the graph, of terms computed from *internal activity* and *external activity* of the tree. Its value at the arguments is the number of spanning trees, or, in a disconnected graph, the number of maximal spanning forests (Bollobas (1998)).
2. Computational Complexity using Contraction-Deletion Recurrence: The Tutte polynomial can be computed using a deletion-contraction recurrence, but its computational complexity is high: for many values of its arguments, computing it is exactly **#P**-complete, and it is also hard to approximate with a guaranteed approximation ratio. The point at which it can be evaluated using Kirchoff’s theorem, is one of the few exceptions (Jaeger, Vertigan, and Welsh (1990), Goldberg and Jerrum (2008)).

**Algorithms – Construction**

1. Spanning Tree using BFS/DFS: A single spanning tree of a graph can be found in linear time by either depth-first search or breadth-first search. Bothe of these algorithms explore then given graph, starting from an arbitrary vertex , by looping through the neighbors of the vertexes they discover and adding each unexplored neighbor to a data structure to be explored later. They differ in whether the data structure is a stack – in the case of depth-first search – or a queue – in the breadth-first search. In either case, one can form a spanning tree by connecting each vertex, other than the root vertex , to a vertex from which it was discovered. This tree is known as the depth-first search tree or the breadth-first search tree according to the graph exploration algorithm used to construct it (Kozen (1992)). Depth-first search trees are a special case of a class of spanning trees called the Tremaux trees, named after the 19th century discoverer of depth-first search (de Fraysseix and Rosenstiehl (1982)).
2. BFS/DFS in Parallel/Distributed Environments: Spanning trees are important in parallel and distributed computing, as a way of maintaining communications between a set of processors; see, for instance, the spanning tree protocol used by the OSI link-layer devices of the Shout protocol used for distributed computing. However, the breadth-first and the depth-first methods for constructing spanning trees on sequential computes are not well-suited for parallel and distributed computer (Reif (1985)). Instead, researchers have devised more specialized algorithms for finding spanning trees in these models of computation (Gallagher, Humblet, and Spira (1983), Gazit (1991), Bader and Cong (2005)).

**Algorithms - Optimization**

1. Spanning Trees under Optimal Condition: In certain fields of optimization theory, it is often useful to find a minimum spanning tree of a weighted graph. Other optimization problems in spanning trees have also been studied, including the maximum spanning tree, the maximum tree that spans vertexes, the spanning tree with the fewest edges per vertex, the spanning tree with the largest number of leaves, the spanning tree with the fewest leaves – closely related to the Hamiltonian path problem, the maximum diameter spanning tree, and the maximum dilation spanning tree (Eppstein (1999), Wu and Cao (2004)).
2. Optimal Spanning Trees in Euclidean Space: Optimal spanning tree problems have also been studied for a finite set of points in a geometric space such as the Euclidean space. For such an input, the spanning tree is again a set of trees that has as its vertexes the given points. The quality of the tree is measured in the same way as in a graph, using the Euclidean distance between pairs of points as the weight for each edge. Thus, for instance, a Euclidean minimum spanning tree is the same as the graph minimum spanning tree in a complete graph with Euclidean edge weights. However, it is not necessary to construct the graph in order to solve the optimization problem; the Euclidean minimum spanning tree problem, for instance, can be solved more efficiently in time by constructing Delaunay triangulation and then applying a linear planar graph minimum spanning tree algorithm to the resulting triangulation (Eppstein (1999)).

**Randomization**

1. Generation of Uniform Spanning Trees: A spanning tree chosen from among all the spanning trees with equal probability is called a uniform spanning tree. Wilson’s algorithm can be used to generate uniform spanning trees in polynomial time by a process of taking a random walk on the given graph and erasing the cycles created by this walk (Wilson (1996)).
2. Generating Random Minimal Spanning Tree: An alternative model for generating spanning trees randomly but not uniformly is the random minimal spanning tree. In this model, the edges of the graph are assigned random weights and then the minimum spanning tree of the weighted graph is constructed (McDiarmid, Johnson, and Stone (1997)).

**Enumeration**

Because a graph may have exponentially many spanning trees, it is not possible to list them all in polynomial time. However, algorithms are known for listing all spanning trees in polynomial time per tree (Gabow and Myers (1978)).

**In Infinite Graphs**

1. Infinite Graph – Axiom of Choice: Every finite connected graph has a spanning tree. However, for infinite connected graphs, the existence of spanning trees is equivalent to the axiom of choice. An infinite graph is connected if every pair of its vertexes forms the pair of end-points of a finite path. As with finite graphs, a tree is a connected graph with no finite cycles, and a spanning tree can be defined either as a maximal acyclic set of edges or as a tree that contains every vertex (Serre (2003)).
2. Equivalence to Zorn’s Lemma: The trees within a graph may be partially ordered by their subgraph relation, and infinite chain in this partial order has an upper bound, i.e., the union of the trees in the chain. Zorn’s lemma, one of many equivalent statements to the axiom of choice, requires that a partial order in which all chains are upper bounded have a maximal element; in the partial order on the trees of the graph, this maximal element must be a spanning tree. Therefore, if Zorn’s lemma is assumed, every infinite connected graph has a spanning tree (Serra (2003)).
3. Spanning Tree as a Choice Function: In the other direction, given a family of sets, it is possible to construct an infinite graph such that every spanning tree of the graph corresponds to a choice function of the family of sets. Therefore, if every infinite graph has a spanning tree, then the axiom of choice is true (Soukup (2008)).

**In Directed Multi-graphs**

The idea of a spanning tree can be generalized to directed multigraphs (Levine (2011)). Given a vertex on a directed multi-graph , an *oriented spanning tree*  rooted at is an acyclic subgraph of in which every vertex other than has an out-degree of . This definition is only satisfied when the *branches* of point towards .

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**Minimum Spanning Tree**

**Overview**

1. Definition of Minimum Spanning Tree: A *minimum spanning tree (MST)* or *minimum weight spanning tree* is the subset of the edges of a connected, edge-weighted, undirected graph that connects all vertexes together, without any cycles and with minimum possible total edge weight. That is, it is a spanning tree whose sum of edges is as small as possible (Wikipedia (2020)).
2. Minimum Spanning Tree vs. Forest: More generally, any edge-weighted undirected graph – not necessarily connected – has a *minimum spanning forest*, which is a union of minimum spanning trees for its connected components.
3. Specialization of the Generic Spanning Tree: A *spanning tree* for that graph would be a subset of those paths that have no cycles but still connects every vertex; there might be several spanning trees possible. A *minimum spanning tree* would be the one with the lowest total cost, representing the least expensive path.

**Multiplicity Properties**

If there are vertexes in the graph, then each spanning tree has edges. There may be several minimum spanning trees of the same weight; in particular, if all the edges of a given graph are the same, then every spanning tree of that graph is a minimum.

**Uniqueness Property**

1. Statement of the Uniqueness Property: If each edge has a distinct weight, then there will be only one unique, minimum spanning tree. This generalizes to spanning forests as well.
2. Proof of the Uniqueness Property:
   1. Assume the contrary, that there are two different MST’s – and .
   2. Since and differ despite containing the same nodes, there is at least one edge the belongs to one but not the other. Among such edges, let be the one with least weight; this choice is unique because the edge weights are all distinct. Without loss of generality, assume is in .
   3. Since is an MST, must contain a cycle with .
   4. As a tree, contains no cycles, therefore must have an edge that is not in .
   5. Since was chosen as the unique lowest weight edge among those belonging to exactly one of and , the weight of must be greater than the weight of .
   6. As and are part of the cycle , replacing with in therefore yields a spanning tree with smaller weight.
   7. This contradicts the assumption that is an MST.

More generally, of the edge weights are all not distinct, then only the multi-set of weights in minimum spanning trees is certain to be unique; it is the same for all minimum spanning trees.

**Minimum Cost Subgraph Property**

If the weights are *positive*, then a minimum spanning tree is in fact a minimum cost subgraph connecting all vertexes, since subgraphs containing cycles necessarily have more total weight.

**Cycle Property**

1. Statement of the Cycle Property: For any cycle in the graph, if the weight of an edge in is larger than the individual weights of all other edges of , then this edge cannot belong to an MST.
2. Proof of the Cycle Property: Assume the contrary, i.e., that belongs to an MST . Then deleting will break into two subtrees with two ends of in different subtrees. The remainder of connects the subtrees, hence there is an edge of in different subtrees, i.e., it reconnects subtrees into a tree with weight less than that of , because the weight is less than that of weight .

**Cut Property**

1. Statement of the Cut Property: For any cut of the graph, if the weight of an edge in the cut-set is strictly smaller than the weight of all other edges in the cut-set of , then this edge belongs to all MST’s of the graph.
2. Proof - Case of Single Minimum Edge: Assume that there is an MST that does not contain . Adding to will produce a cycle that crosses the cut once at and crosses back another edge . Deleting produces a spanning tree of strictly smaller weight than . This contradicts the assumption that was an MST.
3. Extension to Multiple Maximum Edges: By a similar argument. If more than one is of the same weight across the cut, then such edge is contained in some minimum spanning tree.

**Minimum-Cost Edge Property**

1. Statement of the Property: If the minimum cost edge of a graph is unique, then this edge is included in any MST.
2. Proof of the Statement: If was not included in the MST, removing any of the larger cost edges in the cycle formed after adding to the MST would yield a spanning tree of smaller weight.

**Contraction Property**

If is a tree of MST edges, then can be contracted into a single vertex while maintaining the invariant that the MST of the contracted graph plus gives the MST of the graph before contraction (Pettie and Ramachandran (2002a)).

**Algorithms**

1. Classical MST Algorithm #1 – Boruvka: The first algorithm for finding a minimum spanning tree was developed by Otakar Boruvka. In each stage, called the *Boruvka step*, it identifies a forest consisting of the minimum-weight edge incident to each vertex in the graph , then forms the graph

as the input to the next step. Here denotes the graph derived from by contracting edges in – by the cut property, these edges belong to the MST. Each Boruvka step takes linear time on . Since the number of vertexes is reduced by at least half in each step, Boruvka’s algorithm takes time (Pettie and Ramachandran (2002a)).

1. Classical MST Algorithm #2 - Prim: A second algorithm is Prim’s algorithm, which grows the MST one edge at a time. Initially, contains an arbitrary vertex. In each step, is augmented with the least-weight edge such that is in and is not in . By the cut property, all edges added to are in the MST. Its runtime is either or , depending on the structure used.
2. Classical MST Algorithm #3 - Kruskal: The third algorithm commonly in use is the Kruskal’s algorithm, which also takes time.
3. Classical MST Algorithm – Reverse-Delete: A fourth algorithm, not as commonly used, is the reverse-delete algorithm, which is the reverse of the Kruskal’s algorithm. Its runtime is
4. Greedy Algorithms with Polynomial Runtime: All these four are greedy algorithm. Since they run in polynomial time, the problem of finding such trees is in **FP**, and related decision problems such as finding whether an edge is in the MST or determining if the total minimum weight exceeds a certain value are in **P**.

**Faster Algorithms**

1. Hybrid Linear-Time Randomized Algorithm: In a comparison model, in which only allowed operations on edge-weights are pair-wise comparisons, Karger, Klein, and Tarjan (1995) found a linear time randomized algorithm based on a combination of the Boruvka’s algorithm and the reverse-delete algorithm (Pettie and Ramachandran (2002b)).
2. Non-Randomized Comparison Based Algorithm: The fastest randomized comparison-based algorithm with known complexity, by Chazelle (2000a, 2000b), is based on soft-heap, and approximate priority queue. It’s running time is where is the classical functional inverse of the Ackermann function. The function grows extremely slowly, so that for all practical purposes it may be considered a constant no greater than , thus Chazelle’s algorithm takes very close to linear time.

**Linear-Time Algorithms in Special Cases – Dense Graphs**

If the graph is dense, i.e.,

then a deterministic algorithm by Fredman and Tarjan (1987) finds the MAST in time . The algorithm executes in a number of phases. Each phase executes Prim’s algorithm many times, each for a limited number of steps. The runtime for each phase is . If the number of vertexes before a phase is , then the number of phases remaining after a phase is at most . Hence, at most phases are needed, which gives a linear runtime for dense graphs (Pettie and Ramachandran (2002a)). There are other algorithms that work in linear-time on dense graphs (Gabow, Galil, Spencer, and Tarjan (1986), Chazelle (2000b)).

**Linear Time Algorithm – Integer Weights**

If the edge weights are integers represented in binary, then deterministic algorithms are known that solve the problem in integer operations (Fredman and Willard (1994)). Whether the problem can be solved *deterministically* for a *general graph* in *linear time* by a comparison-based algorithm remains an open question.

**Decision Trees**

1. Idea behind the Decision Tree: Given graph where the nodes and the edges are fixed but the weights are unknown, it is possible to construct a binary decision tree (DT) for calculating the MST for any permutation of weights. Each internal node of a DT contains a comparison between two edges, i.e., “is the weight of the edge between and larger than that between and ?” The two children of the node correspond to the two possible answers “yes” and “no”. In each leaf of the DT, there is a list of edges from that correspond to an MST. The runtime complexity of the DT is the largest number of queries required to find the MST, which is just the depth of the DT. A DT for a graph is called *optimal* if it has the smallest depth of all correct DT’s for .
2. Steps for Determining Optimal Decision Trees: For every integer , it is possible to find the optimal decision trees for all graphs on vertexes by brute-force search. This search proceeds in two steps:
   1. Generate all potential DT’s
   2. Identify the correct DT’s
3. Generating all Potential DT’s:
   1. There are different graphs on vertexes.
   2. For each graph an MST can always be found using comparisons, e.g., by using Prim’s algorithm.
   3. Hence, the depth of an optimal DT is less than .
   4. Hence, the number of internal nodes in an optimal DT is less than
   5. Every internal node compares two edges. The number of edges is at most , so the different number of comparisons is at most .
   6. Hence, the number of potential DT’s is less than
4. Identifying the correct Decision Trees: To check if a DT is correct, it must be checked on all possible permutations of the edge weights.
   1. The number of such permutations is at most
   2. For each permutation, the MST problem is solved on a given graph using any existing algorithm, and the result is compared to the answer given by the DT
   3. The running time of any MST algorithm is at most , so the total time required to check all permutations is at most

Hence the total time required for finding an optimal DT for *all* graphs with vertexes is:

(Pettie and Ramachandran (2002a)).

**Optimal Algorithm**

1. Provably Optimal Deterministic Comparison based MST: Pettie and Ramachandran (2002a) have constructed a provably optimal deterministic comparison based minimum spanning tree algorithm. The following is a simplified description of the algorithm steps:
2. Optimal Decision Trees on Vertexes: Let

where is the number of vertexes. Find all optimal decision trees on vertexes. This can be done in using the Decision Trees above.

1. Graph Partition - Vertexes per Component: Partition the graph into components with at most vertexes per each component. This partition uses a *soft heap*, which *corrupts* a small number of edges of the graph.
2. MST using DT in each Component: Use the optimal decision trees to find an MST for the uncorrupted subgraph within each component.
3. Contraction of the Connected Components: Contract each component spanned by the MST’s to a single vertex, and apply any algorithm that works on dense graphs in time to the contraction of the uncorrupted subgraph.
4. Adding back the Corrupted Edges: Add back the corrupted edges to the resulting forest to form the subgraph guaranteed to contain the minimum spanning tree, and smaller by a smaller factor than the starting graph. Apply the optimal algorithm recursively to this graph.
5. Runtime of the Algorithm: The runtime of all steps in the algorithm is , *except for the step of using decision trees*. The runtime of this step is not known, but is known to be optimal – no algorithm can do better than the optimal decision tree. Thus, this algorithm has a peculiar property that it is *provably optimal* although its runtime complexity is *unknown*.

**Parallel and Distributed Algorithms**

1. Runtime in Parallel Environments: Research has also considered parallel algorithms for the MST problem. With a linear number of processors, it is possible to solve the problem in time (Chong, Han, Tak (2001), Pettie and Ramachandran (2002c)). Bader and Cong (2006) demonstrate an algorithm that can compute the MST’s 5 times faster on 8 processors than an optimized sequential algorithm.
2. Specialized Algorithms for Large Graphs: Other specialized algorithms have been designed for computing MST’s of a graph so large that it must be stored on disk at all times. These *external storage* algorithms, for example described by Dementiev, Sanders, Schultes, and Sibeyn (2004), can operate, by the author’s claims, as little as 2 to 5 times slower than a traditional in-memory algorithm. These rely on efficient external storage sorting algorithms and graph contraction techniques for reducing the graph’s size efficiently.
3. Distributed Approaches for Calculating the MST: The problem can also be approached in a distributed manner. If each node is considered a computer and no node knows anything except its own connected links, one can still calculate the distributed MST.

**MST on Complete Graphs**

1. Complete Graphs with i.i.d. Weights: Alan M. Frieze showed that given a complete graph on vertexes, with edge weights that are i.i.d. random variables with a distribution function satisfying then as approaches the expected weight of the MST approaches , where is Riemann Zeta function – more specifically, is the Apery’s constant. Frieze and Steele also proved convergence in probability. Svante Janson proved a CLT for the weight of the MST.
2. MST Sizes for Weights: For uniform random weights in , the exact expected size of the MAST has been computed for small complete graphs (Steele (2002)).

|  |  |  |
| --- | --- | --- |
| **Vertexes** | **Expected Size** | **Approximate Expected Size** |
| 2 |  |  |
| 3 |  |  |
| 4 |  |  |
| 5 |  |  |
| 6 |  |  |
| 7 |  |  |
| 8 |  |  |
| 9 |  |  |

**Applications**

1. Use in Network/Algorithm Construction: MST’s have direct applications in the design of networks, including computer networks, telecommunication networks, transportation networks, water supply networks and electrical grids – which they were first invented for, as indicated above (Graham and Hell (1985)). They are invoked as sub-routines in algorithms for other problems, including the Christofides algorithm for approximating the traveling salesman problem (Christofides (1976)), approximating the multi-terminal minimum cut problem – which is equivalent in the single terminal case to the maximum flow problem (Dahlhaus, Johnson, Papadimitriou, Seymour, and Yannakakis (1994)), and approximating the minimum-cost weighted perfect matching (Supowit, Plaistead, and Reingold (1980)).
2. Practical Use of MSTs:
   1. Taxonomy (Sneath (1957))
   2. Cluster Analysis: Clustering points in the plane (Asano, Bhattacharya, Kiel, and Yao (1988)), single-linkage clustering – a method of hierarchical clustering (Gower and Ross (1969)), and clustering gene expression data (Paivinen (2005)).
   3. Constructing trees for broadcasting in computer networks (Dalal and Metcalfe (1978))
   4. Image Registration (Ma, Hero, Gorman, and Michel (2000)), and Segmentation (Felzenszwalb and Huttenlocher (2004))
   5. Curvilinear feature extraction in computer vision (Suk and Song (1984))
   6. Hand-writing Recognition of Mathematical Expressions (Tapia and Rojas (2004))
   7. Circuit Design – Implementing Efficient Multiple Constant Multiplications, as used in Finite Impulse Response Filters (Ohlsson (2004))
   8. Regionalization of socio-geographic areas, the grouping of areas into homogenous, contiguous regions (Assuncao, Neves, Camara, and Da Costa Freitas (2006))
   9. Comparing eco-toxicology data (Devillers and Doro (1989))
   10. Topological Observability in Power Systems (Mori and Tsuzuki (1991))
   11. Measuring Homogeneity of Two-dimensional Materials (Filliben, Kafadar, and Shier (1983))
   12. Minimax Process Control (Kalaba (1963))
   13. Minimum spanning trees can also be used to describe financial markets (Mantegna (1999), Djauhari and Gan (2015)). A correlation matrix can be created by calculating a coefficient of correlation between any two stocks. This matrix can be represented topologically as a complex network and an MST can be constructed to visualize relationships.

**Related Problems**

1. Subset Vertexes Steiner Tree: The problem of finding a Steiner tree of a subset of vertexes, that is, the minimum tree that spans a given subset, is known to be **NP**-complete (Garey and Johnson (1979)).
2. -Minimum Spanning Tree: A related problem is the minimum spanning tree (-MST), which is the tree that spans some subset of vertexes in a graph with minimum weight.
3. Smallest Spanning Trees: A set of *smallest* *spanning trees* is a subset of spanning trees such that no spanning tree outside the subset has a smaller weight (Gabow (1997), Eppstein (1992), Frederickson (1997)). Note that this problem is unrelated to minimum spanning tree.
4. Euclidean Minimum Spanning Tree: The Euclidean minimum spanning tree is a spanning tree of a graph with edge weights corresponding to the Euclidean distance between vertexes which are points in the plane – or space.
5. Rectilinear Minimum Spanning Tree: The rectilinear minimum spanning tree is a spanning tree of a graph with edge weights corresponding to the rectilinear distance between vertexes which are points in the plane – or space.
6. Distributed Minimum Spanning Tree: In the distributed model where each node is considered a computer and no node knows anything except its own connected links, one can consider distributed minimum spanning tree. The mathematical definition of the problem is the same, but there are different approaches for a solution.
7. Capacitated Minimum Spanning Tree: The capacitated minimum spanning tree is a tree that a marked node – origin, or root – and each of the subtrees attached to the node contains no more than nodes. is called the tree capacity. Solving the CMST optimally is **NP**-hard (Jothi and Raghavachari (2005)), but good heuristics such as Esau-Williams and Sharma produce solutions close to optimal in polynomial time.
8. Degree Constrained Minimum Spanning Tree: The degree constrained minimum spanning tress is a spanning tree in which each of the vertexes is connected to no more than other vertexes for some given number . The case is a special case of traveling salesman problem, so the degree-constrained minimum spanning tree is **NP**-hard in general.
9. Directed Graph Minimum Spanning Tree: For directed graphs, the minimum spanning tree problem is called the Arboresence problem and can be solved in quadratic time using the Chu-Liu/Edmonds algorithm.
10. Maximum Spanning Tree: A *maximum spanning tree* is a spanning tree with weight greater than or equal to the weight of every other spanning tree. Such a tree can be found with algorithms such as Prim’s or Kruskal’s after multiplying the edge weights by and solving the MST problem on the new graph. A path in the minimum spanning tree is the widest path in the graph between its two end-points; among all the possible paths, it maximizes the weight of the minimum-weight edge (Hu (1961)). Maximum spanning trees find applications in parsing algorithms for natural languages (McDonald, Pereira, Ribarov, and Hajic (2005)) and in training algorithms for conditional random fields.
11. Dynamic Minimum Spanning Tree: The *dynamic MST* problem concerns the update of a previously computed MST after an edge weight change in the original graph of the insertion/deletion of a vertex (Spira and Pan (1975), Chin and Houck (1978), Holm, de Lichtenberg, and Thorup (2001)).
12. Minimum Labeling Spanning Tree: The minimum labeling spanning tree problem is to find a spanning tree with the least type of labels if each edge in a graph is associated with a label from a finite label set instead of a weight (Chang and Leu (1997)).
13. Minimum Bottleneck Spanning Trees: A bottleneck is the highest weight edge in a spanning tree. A spanning tree is a *minimum bottleneck spanning tree* – or *MBST* – if the graph does not contain a spanning tree with a smaller bottleneck edge weight. An MST is necessarily an MBST – provable by the cut property – but an MBST is not necessarily an MST.

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**Prim’s Algorithm**

**Overview**

1. Purpose of the Prim’s Algorithm: Prim’s algorithm – also known as Jarnik’s algorithm – is a greedy algorithm that finds the minimum spanning tree for a weighted, undirected graph. This means that it finds the subset of the edges that form a tree that includes every vertex, where the total weight of all the edges in the tree is minimized. The algorithm operates by building this tree one vertex at a time, from an arbitrary starting vertex, at each step adding the cheapest possible connection from the tree to another vertex (Wikipedia (2019)).
2. Developers of the Algorithm: The algorithm was developed by the Czech mathematician Jarnik (1930) and later re-discovered and re-published by Prim (1957) and Dijkstra (1959). Therefore, it is also sometimes called the *Jarnik’s algorithm* (Sedgewick and Wayne (2011)), *Prim-Dijkstra algorithm* (Cheriton and Tarjan (1976)), *Prim-Jarnik algorithm* (Rosen (2011)), or the *DJP algorithm* (Pettie and Ramachandran (2002)).
3. Comparison with Kruskal’s and Boruvska’s Algorithms: Other well-known algorithms for this problem include Kruskal’s algorithm and Boruvska’s algorithm (Tarjan (1983)). These algorithms find a minimum spanning forest in a possibly disconnected graph; in contrast, the most basic form of the Prim’s algorithm only finds minimum spanning trees in connected graphs. However, by running Prim’s algorithm separately for each connected component of the graph, it can also be used to find the minimum spanning forest (Kepner and Gilbert (2011)). In terms of their asymptotic time complexity, these three algorithms are equally fast for sparse graphs, but slower than other more sophisticated algorithms (Cheriton and Tarjan (1976), Pettie and Ramachandran (2002)). However, for graphs that are sufficiently dense, Prim’s algorithm can be made to run in linear time, meeting or improving the time bounds for other algorithms (Tarjan (1983)).

**Description**

1. Overview of the Algorithm Steps: The algorithm may be informally described as performing the following steps:
   1. Initialize a tree with a single vertex, chosen arbitrarily from the graph.
   2. Grow the tree by one edge. Of the edges that connect the tree to vertices not yet in the tree, find the minimum weight edge, and transfer it to the tree.
   3. Repeat the previous step until all the vertices are in the tree.

In more detail, it may be implemented following the pseudocode below.

1. Initialization of Edges and Costs: Associate each vertex of the graph with a number - the cheapest cost of connection to - and an edge - the edge providing the cheapest connection. To initialize these values, set all values of to - or to any number larger than the maximum edge weight – and set each to a special flag indicating that there is no edge connecting to earlier vertices.
2. Initializing the Forest and the Vertices: Initialize an empty forest and a set of vertices that have not yet been included in – initially all vertices.
3. Iteration over the Queue Elements: Repeat the following steps until the is empty:
   1. Find and remove a vertex from the having the minimum possible value of
   2. Add to and, if is not the special flag value, also add to
   3. Loop over the edges connecting to other vertices . For each such edge, if still belongs to and has a smaller weight than , perform the following steps:
      1. Set to the cost of edge
      2. Set to point to edge
4. Retrieve the Forest containing the MST’s: Return
5. Starting Vertex for the Algorithm: As described above, the starting vertex for the algorithm will be chosen arbitrarily, because the first iteration of the main loop will have a set of vertices in that all the same weight, and the algorithm will automatically start a new tree in when it completes the spanning tree of each connected component of the input graph. The algorithm may be modified to start with any particular vertex by setting to be a number smaller than other values of – for instance, zero – and it may be modified to find only a single spanning tree rather than an entire spanning forest – matching more closest the informal description – by stopping whenever it encounters another vertex flagged as having no associated edge.
6. Choices for implementing the Queue: Different variations of the algorithm differ from each other in how the object is implemented: as a simple linked-list, as an array of vertexes, or as a more complicated priority queue data structure. The choices lead to differences in time complexity of the algorithm. In general, a priority queue will be much quicker at finding the vertex with minimum cost, but will entail more expensive updates when the value of changes.

**Time Complexity**

1. Determinants of the Time Complexity: The time complexity for the Prim’s algorithm depends on the data structures used for the graphs and for ordering the edges by weight, which can be done using a priority queue. The table below shows the typical choices.
2. Table Time Complexity by Algorithm:

|  |  |
| --- | --- |
| **Minimum Edge Weight Data Structure** | **Total Time Complexity** |
| Adjacency Matrix, Searching |  |
| Binary Heap and Adjacency List |  |
| Fibonacci Heap and Adjacency List |  |

1. Implementation using Adjacency Matrix/List: A simple implementation of Prim’s, using an adjacency matrix or an adjacency list graph representation and linearly using an array of weights to find the minimum weight edge to add, requires running time. However, this running time can be greatly improved further by using heaps to implement finding minimum weight edges in the algorithm’s inner loop.
2. Heap Based Edge Weight Ordering: A first improved version uses a heap to store all edges of the input graph, ordered by their weight. This leads to an worst-case running time. But storing vertexes instead of edges can improve it still further. The heap should order their vertexes by their smallest edge weight that connects them to any vertex in a partially constructed minimum spanning tree (MST) – or if no such edge exists. Every time a vertex is chosen and added to the MST, a decrease-key operation is performed on all vertexes , setting the key to the minimum of its previous value and the edge cost of .
3. Impact of Denseness and Queue Implementation: Using a simple binary heap data structure, Prim’s algorithm can be shown to run in time where is the number of edges and is the number of vertexes. Using a more sophisticated Fibonacci heap, this can be brought down to which is asymptotically faster when the graph is dense enough that is , and linear time when is at least . For graphs of even greater density, having at least edges for some

Prim’s algorithm can be made to run in linear time even more simply, by using a -ary heap in place of a Fibonacci heap (Johnson (1975), Tarjan (1983)).

**Proof of Correctness**

1. Basic Thrust of the Algorithm: Let be a connected, weighted graph. At every iteration of Prim’s algorithm, an edge must be found that connects a vertex in the subgraph to a vertex outside the subgraph. Since is connected, there will always be a path to every vertex. The output of Prim’s algorithm is a tree, because the edge and the vertex added to are connected.
2. An Alternate Minimum Spanning Tree: Let be a minimum spanning tree of the graph . If

then is a minimum spanning tree. Otherwise, let be the first edge added during the construction of tree that is not in , and let be the set of vertexes connected by edges added before edge . Then one endpoint of edge is in set and the other is not.

1. Differences between the Current and the Alternate MSTs: Since tree is a spanning graph of , there is a path in tree joining the two endpoints. As one travels along the path, one encounters an edge joining as vertex in set to one that is not in . Now, at the iteration where edge was added to tree , edge could have also been added, and it would have been added instead of edge if its weight was less than . Since it was not added, it may be concluded that
2. Reconstructing Current from Alternate MST: Let tree be a graph obtained by removing edge and adding edge to the tree . It is easy to show that tree is connected, has the same number of edges as tree , and the total weight of its edges is not larger than that of tree , therefore it is also a minimum spanning tree of graph , and it contains and all the edges added to before it during the construction of set .
3. Metrics Comparison between the MSTs: On repeating the steps above, eventually a minimum spanning tree of graph that is identical to tree is obtained. This shows that is a minimum spanning tree. The minimum spanning allows for the first subset of the first subregion to be expanded into a smaller subset , which is assumed to be minimum.

**Parallel Algorithm**

1. Parallelizable Component of the Prim’s Algorithm: The main loop pf the Prim’s algorithm is inherently sequential and thus not parallelizable. However, the inner loop, which determines the next edge of the minimum weight that does not form a cycle, can be parallelized by dividing the vertexes and edges between the available processors (Grama, Gupta, Karypis, and Kumar (2003)). The pseudocode below demonstrates this.
2. Partition the Vertexes among the Processors: Assign each processor a set of consecutive vertexes of length .
3. Dividing the Edges among the Processors: Create , , , and as in the sequential algorithm above and divide and as well as the graph between all the processors such that each processor holds the incoming edges to its set of vertexes. Let , denote the parts of and stored on processor .
4. Local Minimum Vertexes and their Eventual Union: Repeat the following steps until is empty:
   1. On every processor, find the vertex having the minimum value in - the local solution.
   2. Min-reduce the local solution to find the vertex having the minimum possible value of – the global solution.
   3. Broadcast the selected node to every processor.
   4. Add to , and if is not special value flag, add to .
   5. On every processor, update and as in the sequential algorithm.
5. Return the Forest containing the MSTs: Return .
6. Performance of the Parallelized Version: This algorithm can generally be implemented on a distributed machine (Grama, Gupta, Karypis, and Kumar (2003)) as well as on shared memory machines (Quinn and Deo (1984)). It has also been implemented in graphical processing units (GPUs) (Wang, Huang, and Guo (2011)). The running time is , assuming that the *reduce* and the *broadcast* operations can be performed in (Grama, Gupta, Karypis, and Kumar (2003)). A variant of the Prim’s algorithm for shared memory machines, in which Prim’s sequential algorithm is being run in parallel, starting from different vertexes, has also been explored (Setia, Nedunchezhian, and Balachandran (2015)). It should, however, be noted that more sophisticated algorithms exist to solve the distributed minimum spanning tree problem in a more efficient manner.

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**Kruskal’s Algorithm**

**Introduction**

1. Principal Idea behind Kruskal’s Algorithm: *Kruskal’s algorithm* (Kruskal (1956), Wikipedia (2020)) is a minimum spanning tree algorithm which finds an edge of the least possible weight that connects any two trees in the forest (Cormen, Leiserson, Rivest, and Stein (2009)).It is a greedy algorithm in graph theory as it finds a minimum spanning tree for a connected, weighted graph adding increasing cost arc at each step. This means that it finds the subset of edges that forms a tree that includes every vertex, where the total weight of all the edges in the tree is minimized. If the graph is not connected, then it finds a *minimum spanning forest* – a minimum spanning tree for each component.
2. Alternate Algorithms for Extracting MSFs: Other algorithms for this problem include Prim’s algorithm, reverse-delete algorithm, and Boruvka’s algorithm.

**The Algorithm**

1. Forest with Vertexes Per Tree: Create a forest - a set of trees – where each vertex in the graph is a separate tree.
2. Set of all Graph Edges: Create a set containing all the edges in the graph.
3. Edge-Based Processing and Tree Update: While is not empty and is not yet spanning:
   1. Remove and edge with minimum weight from
   2. If the removed edge connects two different trees, then add it to the forest , combining the two trees into a single tree.
4. Minimum Spanning Tree and Forest: At the termination of the algorithm, the forest forms a set of minimum spanning trees of the graph. If the graph is connected, the forest has a single component, and forms a minimum spanning tree.

**Complexity**

1. Asymptotic Bounds Using /: Kruskal’s algorithm can be shown to run in or equivalently, in , where is the number of edges in the graph and is the number of vertexes, all using simple data structures. These running times are equivalent because:
   1. is at most  and

is

* 1. Each isolated vertex is a separate component of the minimum spanning forest. If one ignores isolated vertexes, one obtains

so is .

1. Rationale behind the Bound Estimate: This bound may be achieved as follows. First, sort the edges by weight using a comparison sort in time; this allows the step that removes an edge with minimum weight from to operate in constant time. Next, a disjoint-set data structure is used to keep track of which vertexes are in which components. This needs operations; since in each iteration where a vertex is connected to a spanning tree, two *find* operations and possibly one union for each edge are needed. Even a simple disjoint-set data structure such as disjoint set forests with union by rank can perform operations in time. Thus, the total time is
2. Sophisticated Disjoint Sets and Sorters: Provided that the edges are already sorted or can be sorted in linear time – for example, with counting sort or radix sort, the algorithm can use a more disjoint set data structure to run in , where is an extremely slowly growing inverse of the single-valued Ackermann function.

**Proof of Correctness**

The proof consists of two parts. First, it is proved that the algorithm produces a spanning tree. Second, it is proved that the constructed tree is of minimal weight.

**Spanning Tree**

Let be a connected, weighted graph, and be a subgraph produced by the algorithm. cannot have a cycle, being within one subtree and not between two different trees. cannot be disconnected, since the first encountered edge that joins the two components of would have been added by the algorithm. Thus is a spanning tree of .

**Minimality**

1. Proposition: Existence of an MST: It may be shown, using induction, that the following proposition by induction is true; if is the set of edges at any stage in the algorithm, then there is some minimum spanning tree that contains .
2. Induction Proof - Validity at Start: Clearly is tree at the beginning when is empty; any spanning tree will do, and there exists one, because a connected weighted graph always has a minimum spanning tree.
3. Inductive Proof - Intermediate Stage Validity: Now assume that is true for some non-final edge state and let be a minimum spanning tree that contains .
   1. If the next chosen edge is also in , then is true for .
   2. Otherwise, if is not in , then has a cycle . This cycle contains edges that do not belong to , since does not form a cycle when added to but does in . Let be an edge which is in but not in . Note that also belongs to , and by has not been considered by the algorithm. must therefore haver a weight at least a large as . Then is a tree, and it has the same or less weight as . So is a minimum spanning tree containing and again holds.
4. Completing the Inductive Proof: Therefore, by the principle of induction, holds when has become a spanning tree, which is only possible if is a minimum spanning tree itself.

**Parallel Algorithm**

1. Strategies for Parallelizing the Algorithm: Kruskal’s algorithm is inherently sequential and hard to parallelize. It is, however, possible to perform the initial sorting of the edges in parallel, or alternatively, to use a parallel implementation of the binary heap to extract the minimum-weight edge in every iteration (Quinn and Deo (1984)). As parallel sorting is possible in time on processors (Grama, Gupta, Karypis, and Kumar (2003)), the runtime of the Kruskal’s algorithm can be reduced to , where is again the inverse of the single-valued Ackermann function.
2. The Filter-Kruskal Parallel Version: The variant of Kruskal’s algorithm, named Filter-Kruskal, has been described by Osipov, Sanders, and Singler (2009) and is better suited for parallelization. The basic idea behind Filter-Kruskal is to partition the edges in a way similar to quicksort and to filter out the edges that connect the vertexes of the same tree to reduce the cost of sorting.
3. Advantages of the Filter-Kruskal Scheme: Filter-Kruskal lends itself better for parallelization as sorting, filtering, and partitioning can be performed easily by distributing the edges between the processors (Osipov, Sanders, and Singler (2009)).
4. Other Approaches to Kruskal Parallelization: Finally, other variants of a parallel implementation of Kruskal’s algorithm have been explored. Examples include a scheme to that uses helper threads to remove edges that are definitely not part of the MST in the background (Katsigiannis, Anastopoulos, Konstantinos, and Koziris (2012)), and a variant that runs the sequential algorithm in subgraphs, and then merges those subgraphs until only one, the final MST, remains (Loncar, Skrbic, and Balaz (2014)).

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**Boruvka’s Algorithm**

**Overview**

1. Definition of Boruvka’s Algorithm: Boruvka’s algorithm is a greedy algorithm for finding a minimum spanning tree in a graph for which all edge weights are distinct, or a minimum spanning forest in case of a graph that is not connected (Wikipedia (2019)).
2. Principal Steps behind the Algorithm: The algorithm begins by finding the minimum-weight edge incident to each vertex of the graph, and adding all of the edges to the forest. Then, it repeats a similar process of finding the minimum-weight edges from each tree constructed so far to a different tree, and adding all of these edges to the forest. Each repetition of this process reduces the number of trees, within each connected component of the graph, to at most half of the former value, so after logarithmically many repetitions the process finishes. When it does, the set of edges it has added forms the minimum spanning forest.

**Special Cases**

If the edges do not have distinct weights, a consistent tie-breaking rule, i.e., breaking ties by the object identifiers of the edge, can be used. An optimization is to remove from each edge that is found to connect two vertexes in the same component as each other.

**Complexity**

Boruvka’s algorithm can be shown to take iterations of the outer loop until it terminates, and therefore to run in time . In planar graphs, and more generally in families of graphs closed under graph minor operations, it can be made to run in linear time, by removing all but the cheapest edge between each pair of components after each stage of the algorithm (Eppstein (1999), Mares (2004)).

**Other Algorithms**

1. Prim’s and Kruskal’s MST Algorithms: Other algorithms for this problem include Prim’s algorithm and Kruskal’s algorithm. Fast parallel algorithms can be obtained by combining Prim’s algorithm with Boruvka’s (Bader and Cong (2006)).
2. Fast Randomized and Deterministic Algorithms: A faster randomized MST algorithm based in part on Boruvka’s algorithm dur to Karger, Klein, and Tarjan (1995) runs in time. The best known minimum spanning tree algorithm by Chazelle (2000) is also based in part on Boruvka’s and runs in time, where is the inverse of the Ackermann’s function. These randomized and deterministic algorithms combine steps of the Boruvka’s algorithm, reducing the number of components that need to be connected, with steps of a different type that reduce the number of edges between pairs of components.

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**Reverse-Delete Algorithm**

**Overview**

1. Purpose of the Reverse-Delete Algorithm: The reverse-delete algorithm is an algorithm in graph theory used to obtain a minimum spanning tree from a given connected, edge-weighted graph. It first appeared in Kruskal (1956), but it should not be confused with the Kruskal algorithm, which appears in the same publication. If the graph is disconnected, the algorithm will find a minimum spanning tree for each disconnected part of the graph. The set of these minimum spanning trees is called a minimum spanning forest, which contains every vertex in the graph Wikipedia (2019)).
2. Greedy Nature of the Algorithm: The algorithm is a greedy algorithm. choosing the best choice given any situation. It is the reverse of Kruskal’s algorithm, which is another greedy algorithm to find a minimum spanning tree. Kruskal’s algorithm starts with an empty graph and adds edges while the reverse-delete algorithm starts from an empty graph and deletes edges from it.
3. Steps in Reverse-Delete Algorithm:
   1. Start with a graph , which contains a list of edges .
   2. Go through in decreasing order of edge weights.
   3. For each edge, check if deleting the edges will further disconnect the graph.
   4. Perform any deletion that does not lead to additional disconnection.

**Running Time**

The algorithm can be shown to run in using the big- notation, where is then number of edges and is the number of vertexes. This bound is achieved as follows:

1. Sorting the edges by weight using comparison sort takes time, which can be simplified to using the fact that the largest can be is .
2. There are iterations in the loop.
3. Deleting an edge, checking the continuity in the resulting graph, and, if it is disconnected, re-inserting the edge, can be done in time per operation (Thorup (2000)).

**Proof of Correctness: Approach**

The proof consists of two parts. First, it is proved that the edges that remain after the algorithm is applied form a spanning tree. Second, it is proved that the spanning tree is of minimal weight.

**Proof of Correctness: Part One**

The remaining subgraph produced by the algorithm is not disconnected since the algorithm checks for that. The result subgraph cannot contain a cycle, since if it does, a move along the edges would encounter the maximum edge in the cycle and that would be deleted. Thus, must be a spanning tree of the main graph .

**Proof of Correctness: Part Two**

1. Inductive Proof for the Algorithm: This part shows that the following proposition is true by induction; if is the set of edges that remain at the end of the edge-removal loop, then there is some minimum spanning tree with edges that are a subset of .
2. Starting Point for the Induction: Clearly holds before the start of the edge-removal loop. Since a weighted, connected graph always has a minimum spanning tree, and since contains all the edges of the graph, the minimum spanning tree must be a subset of .
3. Validity for an Intermediate Edge Set: Assume is true for some non-final edge set and let be a minimum spanning tree that is contained in . It needs to be shown that, after deleting the edge in the algorithm, there exists some - possible different – spanning tree that is a subset of .
4. Edge not a Member of : If the next deleted edge does not belong to , then

is a subset of , and continues to hold.

1. Edge a Member of : Otherwise belongs to ; first, note that the algorithm only removes edges that do not cause a disconnected ness in . Thus, does not cause disconnectedness. However, since is a member of , deleting causes a disconnectedness in . Assume that separates into subgraphs and . Since the whole graph is connected after deleting , there must exist another path between and , there must exist a cycle in before removing . There must be another edge in this cycle – call it – that is not in but is in , since if all the cycle edges were in , it would not be a tree anymore. The next step is to show that

is a minimum spanning tree that is a subset of .

1. Proof that is Spanning: First, it is shown that is a *spanning tree*. It is clear that deleting an edge in the tree and adding another one does not cause a cycle, but instead another tree with the same vertexes. Since was a spanning tree, must also be a *spanning tree*, as adding does not cause any cycles when is removed.
2. Proof that is an MST: Second, it is shown that is a *minimum* spanning tree. In the treatment below, is the weight function. There are three cases for the comparison between the weights of and .
   1. The case

is impossible, since this causes the weight of to be less than that of , as it contradicts the notion that is a minimum spanning tree.

* 1. Likewise, it is impossible to have

since going through the edges in decreasing order of the edge weights would result in being seen first. Since there is a cycle , removing would not cause any disconnectedness in , so the algorithm would have removed it from earlier. This would imply that does not exist in , which is a contradiction, since it has been proved earlier that exists.

* 1. Therefore,

so is also a *minimum* spanning tree, so holds again.

1. Final Step of the Inductive Proof: As a result, holds when the edge removal loop is completed, i.e., all the edges have been seen, proving that at the end becomes a *spanning tree*. Since must have a *minimum* spanning tree as its subset, must be a *minimum spanning tree* itself.

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**A Minimum Spanning Tree Algorithm with Inverse Ackermann Type Complexity**

**Abstract**

Chazelle (2000b) presents a deterministic algorithm for computing a minimum spanning tree of a connected graph. Its running time is where is the classical functional inverse of the Ackermann’s function and - respectively, - is the number of vertexes – respectively, edges. The algorithm is comparison-based; it uses references, not arrays, and it makes no numeric assumptions on edge costs.

**Introduction**

1. History of the MST Problem: The history of the minimum spanning tree (MST) problem is long and rich, going as far back as Boruvka’s work in 1926 (Boruvka (1926), Graham and Hell (1985), Nesetril (1997)). In fact, MST is perhaps the oldest open problem in computer science and combinatorial optimization (Nesetril (1997)).
2. Standard Solutions in Time: Textbook algorithms run in time, where and denote, respectively, the number of vertexes and edges in the graph. Improvements to were given independently by Yao (1975) and Cheriton and Tarjan (1976).
3. Algorithm with Time Complexity : Later, Fredman and Tarjan (1987) lowered the complexity to where is the number of log iterations necessary to map to a number less than . In the worst case

and the running time is .

1. Algorithm with Time Complexity : Soon after, the complexity was further reduced to by Gabow, Galil, Spencer, and Tarjan (1986).
2. Randomized Algorithm with Linear Expected Runtime: Recently, Karger, Klein, and Tarjan (1995) have discovered a randomized algorithm with linear expected complexity.
3. Integer Cost Linear Time Algorithm: If the edge costs are integers, and the model allows bucketing and bit manipulation, it is possible to solve the problem in linear time deterministically, as was shown by Fredman and Willard (1994).
4. Linear Time Comparison Based Algorithm: To achieve a similar result in a comparison-based model has long been a high priority objective in the field of algorithms. The reason for that is, first, the illustrious history of the MST problem; second, the fact that it to the heart of matroid optimization.
5. Deterministic Time MST Algorithm: This chapter does not resolve the MST problem, but it takes a significant step towards to a solution and charts out a new line of attack. The main result is a deterministic algorithm for computing MST of a connected graph in time where is the functional inverse of Ackermann’s function defined in Tarjan (1975). The algorithm is comparison-based it uses references, not arrays, and it makes no numeric assumptions on the edge costs.
6. Non greedy Approach to Matroid Optimization: In addition to providing a new complexity bound, the larger contribution of Chazelle (2000b) is to introduce a non-greedy approach to matroid optimization, which will hopefully prove useful beyond minimum spanning trees. The key idea is to compute sub-optimal independent sets in a *non-greedy* fashion, and them progressively improve upon them until an optimal basis is reached.
7. Gradual MST Build-out using Soft-Heap: Specifically, an approximate priority queue, called a *soft heap* (Chazelle (2000a)), is used to construct a good, but not necessarily minimum, spanning tree. The quality of the tree is progressively refined until an MST is finally produced.
8. Chazelle (2000b) MST Run-time Lemma: The MST of a connected graph with vertexes and edges can be computed in .
9. Origin of the Inverse Ackermann Bounds: While it is doubtful that bound it optimal, it is definitely natural. Given a spanning tree , to verify that it is a minimum can be done in linear time (Komlos (1985), Dixon, Rauch, and Tarjan (1992), King (1997)); the problem is to check that any edge outside is the most expensive along the cycle it forms with . With real costs, this can be viewed as a problem of computing over the semi-group along the paths of a tree. Interestingly, this problem requires time over an arbitrary sub-group (Tarjan (1978), Chazelle and Rosenberg (1992)). The lower bound suggests that in order to improve upon the algorithm, specific properties of will have to be exploited. This is done statically in Komlos (1985), Dixon, Rauch, and Tarjan (1992), King (1997). Chazelle (2000b) speculates that an answer might come from a dynamic equivalent.
10. Organization of the Chapter: The chapter is organized as follows. This section precedes a brief overview of the algorithm, a discussion of the concept of edge corruption, and a review of soft heaps. The main structural variants of the algorithm are then introduced and its components are discussed in detail. The next section proves its correctness, and the complexity is analyzed later.

**The Algorithm at a Glance**

1. Input – A Connected, Undirected Graph: The input is a connected, undirected graph with no self-loops, where each edge is assigned a cost . These costs are assumed to be distinct elements from a totally ordered universe – a non-restrictive assumption, s ties can be broken arbitrarily. As is well known, the MST of such a graph is unique.
2. Criterion for the Graph Contractibility: A subgraph of is *contractible* if its intersection with is connected. What makes this notion useful is that can be assembled directly from and , where is the graph derived directly from by contracting into a single vertex.
3. Identification of Contractible Subgraph: Previous algorithms identify the contractible subgraphs on the fly as the explored portion of the MST grows. The first idea is to reverse this process, i.e., to certify contractibility of *before* computing its MST.
4. Advantages of Pre-computing Subgraph Contractibility: The advantage should be obvious. Computing MST is bound to be easier if it is known that is contractible, for then one need to look only at edges with *both* end-points in . Otherwise, the edges in one end-point in must also be visited. This makes genuine divide-and-conquer possible.
5. Soft Heaps to compute Contractibility: The challenge is to discover a contractible subgraph without computing its MST at the same time. Since current techniques are not useful, Chazelle (2000b) turns to soft heaps.
6. Vertex Disjoint Contractible Subgraph Decomposition: To compute , is first decomposed into vertex disjoint contractible subgraphs of suitable size. Next each subgraph is contracted into a single vertex to form a minor of (a minor is a subgraph derived from a sequence of edge contractions and their implied vertex deletions), which are similarly decomposed into vertex disjoint contractible subgraphs, etc.
7. Forming the Contractible Subgraphs Hierarchy: This process is iterated until becomes a single vertex. This forms a hierarchy of contractible subgraphs, which can be modeled by a perfectly balanced tree ; its leaves are vertexes of ; an internal node with children is associated with a graph whose vertexes are contractions of the graphs .
8. Contractible Nodes at Different Levels: Each level of represents a certain minor of , and each  is a contractible subgraph of the minor associated with the level of its children. In this associated, the leaf level corresponds to , while the root corresponds to the whole graph contracted into a single vertex.
9. Recursive Computation of the Subgraph MST: Once is available, the MST of each is computed recursively. Because the ’s are contractible, gluing together the trees produces the .
10. Tree Height and Level Vertex Count: There is considerable freedom in choosing the height of and the number of vertexes of each – which, it should be noted, is also the number of children of .
11. Time Required for Constructing : The tree is computed in time.
12. Tree Height/Level Vertex Trade-off: If is chosen large then ’s can be kept small; the recursive computation within each is very fast, but building is slow. Conversely, a small height speeds up the construction of but, by making the ’s bigger, it makes recursion more expensive. This is where Ackermann’s function comes into play, by providing the best possible trade-off.
13. Choice for Level Vertex Count: Let denote the height of in , which is defined as the maximum of edges from to a leaf below. A judicious choice is

if

and

if

where

is minimum such that

with

for a large enough constant , and

for any

for any

for any

1. Expansion Node Level Vertex Count: It is easily proven by induction that the *expansion* of relative to , i.e., the subgraph of whose vertexes end up in , has precisely vertexes. This follows from the identity
2. Level Vertex Count of : If it is assumed for simplicity that is actually equal to , the previous identity is true for all , including the root of . It follows immediately that coincides with the height of .
3. MST Runtime Inductive Proof #1: This section now proves by induction on that if the number of vertexes of satisfies

then can be computed in time, where is a large enough constant. For the sake of this overview, the basis case

is omitted.

1. MST Runtime Inductive Proof #2: To apply the induction hypothesis on the computation cost of , note that the number of nodes in satisfies

so it can be seen by visual inspection that, in the formula above, must be replaced by and by . This gives a cost of where is the number of edges in .

1. MST Runtime Inductive Proof #3: Summing up over all internal nodes

allows bounding the computational costs of all ’s by

which is

1. MST Runtime Inductive Proof #4: Adding to this time claimed earlier for computing yields, for large enough

which proves the claim. As shown later, the choice of and implies that

so the running time of the MST algorithm is .

1. Edge Cases Impact on Runtime: This informal discussion leads to the heart of the matter: how to build in time. A number of peripheral difficulties have been swept under the rug, which in the end results in an algorithm significantly more sophisticated than the one just outlined. Indeed, quiet a few things can go wrong along the way, non as serious as *edge corruption*, an unavoidable by product of soft heaps, which is discussed next.

**Edge Corruption**

1. Edge Corruption due to Soft Heap: In the course of computing , certain edges of become *corrupted*, meaning that their costs are raised. To make matters worse, the cost of a corrupted edge can be raised more than once. The reason for all this has to do with soft heap, the approximate priority queue used for identifying contractible subgraphs – more on this later.
2. Corrupted Edges that are Problematic: Some corrupted edges are trouble, while other are not. To understand this phenomenon, one of the most intriguing aspects of the analysis, the scheduling of the overall constructed must be discussed.
3. Weighted, Post Order DFS Run: It would be tempting to build bottom-up level by level, but that would be a mistake. Indeed, it is imperative to maintain a connected structure. So, instead, is computed in post-order: children first, parent last.
4. Active Path of the Visited Nodes: Let be the current visited node in , and let be the *active path*, i.e., the path from the root . The subgraphs are currently being assembled, and as soon as is ready, it is contracted into one vertex, which is then added to .
5. Eliminating the Single Child Parents: A minor technical note: if is the leftmost child of , that is, the first child visited chronologically, then does not yet have any vertex, and so it makes sense to omit from the path altogether. The benefit of such short-cuts is that by avoiding one-child parents, each of is sure to have at least on vertex, which itself is a vertex of or a contraction of a connected subgraph.
6. Tree Construction Induced Edge Type Change: As long as an edge of has exactly one vertex in , it is said to be of a *border* type. Of course, the type of an edge changes over time: successively, unvisited, border, along the active path contracted.
7. Cases when Corruption is Problematic: Corruption can only strike edges when they are of the border type, since it is then that they are in soft heaps. At first, corruption might seem fatal; if all the edges become corrupted, doesn’t it become an MST problem with entirely wrong costs? But in fact, corruption causes harm only in one specific situation: an edge is said to have become *bad* if it is a corrupted border edge at the time its incident is contracted into one vertex. Once bad always bad, but like any corrupted edge its cost can still rise.
8. Consequences of Zerto Bad Edges: Remarkably, it can be shown that if no edges ever turn bad, the algorithm would behave as though no corruption ever occurred, regardless of how much actually took place. The goal, this, is to fight badness rather than corruption.
9. Limiting the Bad Edges Count: Chazelle (2000b) shows that the number of bad edges may be limited to within . The number of edges corrupted, but never bad, is irrelevant.
10. Producing the MST from : Once is built, all the edge costs are restored to their original values, and all the bad edges are removed. A recursion is carried out within what is left of the ’s to produce a spanning forest . Finally, the bad edges are thrown back in, and a recursion is carried out again to produce the minimum spanning tree. There are subtleties in these various recursions, which is explained later. This overview is now closed with a quick sketch of the soft heap.

**The Soft Heap**

1. Edge Selection: A simple priority queue, called a *soft heap*, is the main vehicle for selecting good candidate edges. The data structures stores items from a totally ordered universe, and supports the following operations.

6

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**Breadth-first Search**

**Overview**

1. Algorithm for Traversing a Graph: *Breadth-first search (BFS)* is an algorithm for traversing or searching a tree or a graph data structure. It starts at the tree root – or some arbitrary vertex of a graph, referred to as the search key – and explores all neighboring nodes at the present depth prior to moving onto the vertexes at the next depth level (Wikipedia (2020)).
2. Comparison to Depth-first Search: It uses the opposite strategy as depth-first search, which instead explores the vertexes as far as possible before being forced to backtrack and expand other nodes (Cormen, Leiserson, Rivest, and Stein (2009)).
3. Characteristics of the Algorithm:

|  |  |
| --- | --- |
| **Class** | Search Algorithm |
| **Data Structure** | Graph |
| **Worst-case Performance** |  |
| **Worst-case Space Complexity** |  |

**Objective**

1. Input: A *graph* and a *starting vertex root* of the graph
2. Output: The goal state. The *parent* link traces the shortest path back to the *root*.

**Implementation**

1. Similarity to Non-recursive DFS: This non-recursive implementation is similar to the non-recursive implementation of depth-first search, but differs from it in two ways:
   1. It uses a queue – First In First Out – instead of a stack, and
   2. It checks whether a vertex has been discovered before enqueueing the vertex rather than delaying this check until the vertex is dequeued from the queue.

The queue contains the frontier along which the algorithm is currently searching.

1. Labeling Mechanism for Discovered Vertexes: Vertexes can be labeled as having been discovered by storing them in a set, or by an attribute in each vertex, depending on the implementation.
2. Parent Attribute of each Vertex: The *parent* attribute for each vertex is useful for accessing the vertexes in the shortest path, for example, by backtracking from the destination vertex up to the starting vertex once the BFS has been run, and the predecessor vertexes have been set.
3. Constructing the Breadth-first Tree: Breadth-first search produces a so-called *breadth-first tree*.

**Time and Space Complexity Analysis**

1. Time-complexity incurred by BFS: The time complexity can be expressed as , since every vertex and every edge will be explored in the worst-case. is the number of vertexes and is the number of edges in the graph. Note that may vary between and , depending upon how sparse the input is.
2. Space Complexity of BFS: When the number of vertexes in the graph is known ahead of time, and additional data structures have been used to determine which data structures have been already added to the queue, the space complexity can be expressed as where is the cardinality of the set of vertexes. This is in addition to the space required for the graph itself, which may vary depending on the graph representation used by an implementation of the algorithm.
3. Space Time Complexity for Large Graphs: When working with graphs that are too large to store explicitly – or infinite – it is more practical to describe the complexity of the breadth-first search in different terms; to find the number of vertexes from the starting vertex – measured in terms of the number of edge traversals – BFS takes time and memory, where is the *branching factor* of the graph, the average out-degree (Russell and Norvig (1995)).

**Completeness Analysis**

1. Completeness in Infinite Graphs: In the analysis of the algorithm, the input to the BFS is assumed to be a finite graph, represented explicitly using an adjacency list or a similar representation. However, in application of graph traversal methods in artificial intelligence, the input may be an implicit representation of an infinite graph. In this context, a search method is described as being complete f it is guaranteed to find a goal state if one exists.
2. Completeness in BFS vs. DFS: Breadth-first search is complete, but depth-first search is not. When applied to infinite graphs represented implicitly, breadth-first search will eventually find the goal state, but depth first search may get lost in parts of the graph that have no goal state and never return (Coppin (2004)).

**BFS Ordering**

1. Enumeration of BFS Ordered Vertexes: An enumeration of the vertexes of a graph is said to be a BFS ordering if it is the possible output of the application of BFS to the graph.
2. Symbology for BFS Ordering Statement: Let

be a graph with vertexes. Let be the neighbors of . Let

be a list of distinct elements of . For

let be the least such that is a neighbor of , if such an exists, and otherwise.

1. Formal Statement of BFS Enumeration: Let

be an enumeration of the vertexes of . The enumeration is said to be a BFS ordering – with source – if, for all

is the vertex

such that is minimal. Equivalently, is a BFS ordering if, for all

with

there exists a neighbor of such that

**Applications**

Breadth-first search can be used to solve many problems in graph theory, for example:

1. Copying garbage collection, Cheney’s algorithm
2. Finding the shortest path between nodes and , with path length measured by the number of edges – an advantage over DFS (Aziz and Prakash (2010))
3. Reverse Cuthill-McKee mesh numbering
4. Ford-Fulkerson method for computing maximum flow in a flow network
5. Serialization/de-serialization of a binary tree vs. serialization in sorted order, allows the tree to be re-constructed in an efficient manner
6. Construction of the *failure function* of the Aho-Corasick pattern matcher
7. Testing bipartiteness of a graph

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**Depth-first Search**

**Overview**

1. Description of Depth-first Search: *Depth-first Search (DFS)* is an algorithm for searching tree or graph data structures. The algorithm starts at the root vertex – selecting some arbitrary vertex as a root vertex in the case of a graph – and explores as far as possible in each branch before backtracking (Wikipedia (2020)).
2. Tremaux Trees for Solving Mazes: A version of depth-first search was investigated by Charles Tremaux as a strategy for solving mazes (Sedgewick (2002), Even (2011)).

**Properties**

1. Characteristics of Depth-first Search:

|  |  |
| --- | --- |
| **Class** | Search Algorithm |
| **Data Structure** | Graph |
| **Worst-case Performance** | for explicit graphs traversed without repetition, for implicit graphs with branching factor searched to a depth |
| **Worst-case Space Complexity** | if the entire graph is traversed without repetition  for implicit graphs without elimination of duplicate values |

1. Time/Space Analysis of DFS: The time and the space analysis of DFS differs according to its application area. In theoretical computer science, DFS is typically used to traverse and entire graph, and takes time (Cormen, Leiserson, Rivest, and Stein (2009)); linear in the size of the graph. In these applications, it also uses space in the worst case to store the stack of vertexes in the current search path as well as the set of already visited vertexes. Thus, in this setting, the time and the space bound are the same as that for breadth-first search and the choice of which of these two algorithms to use depends less on their complexity and more on the different properties of the vertex orderings the two algorithms produce.
2. Case of Large/Infinite Graphs: For applications of DFS in relation to specific domains, such as searching for solutions in artificial intelligence or web crawling, the graph to be traversed is often either too large to be visited in its entirety, or infinite; DFS may suffer from non-termination. In such cases, the search is performed only to a limited depth; due to limited resources such as memory or disk space, one typically does not use data structures to keep track of the set of all previously visited vertexes.
3. Limited Depth-Search Complexity Analysis: When search is performed to a limited depth, the time is still linear in terms of the number of expanded vertexes and edges – although this number is not the same as the size of the entire graph because some vertexes may be searched more than once and the others not at all – but the space complexity for this version of DFS is only proportional to depth limit, and as a result, is much smaller than the space needed for searching to the same depth using breadth-first search. For such applications, DFS also lends itself much better to heuristic methods for choosing a likely-looking branch.
4. Iterative Deepening Depth-first Search: When an appropriate depth limit is not known a priori, iterative deepening depth-first search applies a DFS repeatedly with a sequence of increasing limits. In the artificial intelligence model of analysis, with a branching factor greater than one, iterative deepening increases the running time only by a constant factor over the case in which the correct depth is known due to the geometric growth in the number of vertexes per level.

**DFS Traversal**

1. Output Search Tree from DFS: DFS may also be used to collect a sample of graph vertexes. However, incomplete DFS, similar to incomplete BFS, is biased towards vertexes of high degree.
2. Tremaux Tree and Iterative Deepening: The edges traversed from a DFS search form a Tremaux tree, a structure with important applications in graph theory. Performing the search without remembering previously remembered vertexes results in a cycle. Iterative deepening is one technique to avoid infinite loop and to reach all nodes.

**Edges from a DFS Output**

A convenient description of a DFS of a graph is in terms of the spanning tree of vertexes reached during the search. Based on this spanning tree, the edges from the original graph can be divided into three classes; *forward edges*, which point from the vertex of a tree to one of its descendants, *back edges*, which point from a vertex to one of the ancestors, and *cross edges*, which do neither. Sometimes *tree edges*, which belong to the spanning tree itself, are classified separately from forward edges. If the original graph is undirected, then all of its edges are tree edges or back edges.

**Ordering of the DFS Output**

1. Enumeration of the DFS Vertexes: An enumeration of the vertexes of a graph is said to be a DFS ordering if it is the possible output of the application of DFS to the graph.
2. Symbology for DFS Ordering Statement: Let

be a graph with vertexes. Let

be a list of distinct elements of . For

let be the greatest such that is a neighbor of , if such an exists, and otherwise.

1. Formal Statement of DFS Enumeration: Let

be an enumeration of the vertexes of . The enumeration is said to be a DFS ordering – with source – if, for all

is the vertex

such that is maximal. Let be the neighbors of . Equivalently, is a BFS ordering if, for all

with

there exists a neighbor of such that

**Vertex Orderings**

1. DFS Run Linear Vertex Ordering: It is possible to use depth-first search to linearly order the vertexes of a graph or tree. There are four possible ways of doing this.
2. Pre-Ordering: A *pre-ordering* is a list of vertexes in the order in which they were first visited by the DFS algorithm. This is a compact and a natural way of describing the progress of the search. A pre-ordering of an expression tree is the expression in Polish notation.
3. Post-Ordering: A *post-ordering* is a list of vertexes in the order that they were *last* visited by the algorithm. A post-ordering of an expression tree is the expression in reverse Polish notation.
4. Reverse Pre-ordering: A *reverse pre-ordering* is the reverse of a pre-ordering, i.e., a list of vertexes in the opposite order of their first visit. Reverse pre-ordering is not the same as post-ordering.
5. Reverse Post-ordering: A *reverse post-ordering* is the reverse of a post-ordering, i.e., a list of vertexes in the opposite order of their last visit. Reverse post-ordering is not the same as pre-ordering.
6. DFS Ordering for Binary Trees: For binary trees, there is additionally *in-ordering* and *reverse in-ordering*.
7. Topological Sorting of a DAG: Reverse post-ordering produces a topological sorting of any directed acyclic graph. The ordering is also useful in control-flow analysis as it often represents a natural linearization of the control flows.

**Implementation**

1. Input and Outputs of DFS:
   1. Input => A graph and a vertex of
   2. Output => All vertexes reachable from are labeled as discovered
2. Recursive and Non-recursive Implementations: The order in which the vertexes are discovered in the recursive DFS is called the lexicographic order (Goodrich and Tamassia (2001), Cormen, Leiserson, Rivest, and Stein (2009)). An example of non-recursive implementation of DFS with worst-case space complexity of is shown in Kleinberg and Tardos (2006).
3. Order of the Neighbors Processed: The recursive and the non-recursive variations of the DFS visit the neighbors of each vertex in the opposite order from each other: the first neighbor of visited by the recursive variation is the first one in the list of adjacent edges, while in the non-recursive variation, the first visited neighbor is the last one in the list of adjacent edges.
4. Comparison between Non-recursive DFS and BFS: The non-recursive implementation is similar to BFS, but it differs from it in two ways:
   1. It uses a stack instead of a queue.
   2. It delays checking whether a vertex has been discovered until the vertex is popped from the stack rather than making this check before adding the vertex.

**Applications**

Applications the use DFS as a building block include:

1. Finding connected components.
2. Topological sorting.
3. Finding components connected by 2 edges or 2 vertexes.
4. Finding components connected by 3 edges or 3 vertexes.
5. Finding the bridges of a graph.
6. Generating the words in order to plot the limit set of a group.
7. Finding strongly connected components.
8. Planarity Testing (Hopcroft and Tarjan (1974), de Fraysseix, de Mendez, and Rosenstiehl (2006)).
9. Solving puzzles with only one solution, such as mazes. DFS can be adapted to find all solutions to a maze by including only vertexes in the current path in the visited set.
10. Maze generation using randomized DFS.
11. Finding bi-connectivity in graphs.

**Complexity**

1. Parallelizability of Recursive Lexicographic DFS: Given a graph , let

be the ordering computed by the standard recursive DFS algorithm. Reif (1985) considered the complexity of computing this lexicographic depth-first search ordering from the graph, given a source. A decision version of the problem, i.e., testing whether some vertex occurs before some vertex in this order, is **P**-complete, meaning that it is a *nightmare for parallel processing* (Mehlhorn and Sanders (2008)).

1. DFS Parallelization using Randomization Algorithms: A depth-first search ordering – not necessarily the lexicographic one – can be computed by a randomized parallel algorithm in the complexity class RNC (Aggarwal and Anderson (1988)). Until recently, it has remained unknown whether a DFS traversal could be constructed by a deterministic parallel algorithm, in the complexity class NC (Karger and Motwani (1997)).

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**Dijkstra’s Algorithm**

**Introduction**

1. Focus of the Dijkstra’s Algorithm: *Dijkstra’s algorithm* (or *Dijkstra’s Shortest Path First Algorithm*, *SPF Algorithm*) (Wikipedia (2020)) is an algorithm for finding the shortest paths between nodes in a graph, which may represent, for example, road networks (Dijkstra (1959)).
2. Variants of the Dijkstra Algorithm: The algorithm exists in many variants. Dijkstra’s original algorithm found the shortest path between two given nodes (Dijkstra (1959)), but a more common variant fixes a single node as the *source* node and finds the shortest path from the source to all other nodes in the graph, producing a shortest path tree.
3. Applications of the Algorithm: For a given source node in the graph, the algorithm finds the shortest path between that node and every other (Mehlhorn and Sanders (2008)). It can also be used for finding the shortest path to a single destination node by stopping the algorithm once the shortest path to the destination has been determined. For example, if the nodes of the graph represent the cities and the edge path costs represent driving distances between pairs of cities connected by a direct road, Dijkstra’s algorithm can be used to find the shortest route from one city to all other. A widely used application of the shortest path algorithm is network routing protocols, notably IS-IS (Intermediate System to Intermediate System) and OSPF (Open Shortest Path First). It is also employed as a sub-routine in other algorithms such as Johnson’s.
4. Generalization of the Dijkstra’s Algorithm: The Dijkstra algorithm uses labels that are positive or real numbers, which are totally ordered. It is be generalized to use any labels that are partially ordered, provided that the subsequent labels – produced when traversing an edge – are monotonically non-decreasing. This generalization is called the generic Dijkstra shortest-path algorithm (Szczesniak, Jajszczyk, and Wozna-Szczesniak (2019)).
5. Performance Customization for Specialized Solutions: Dijkstra algorithm uses a data structure for storing and querying partial solutions sorted by distance from the start. The original algorithm uses a queue and runs in time – where is the number of nodes. The idea of this algorithm is also given in Leyzorek, Gray, Johnson, Ladew, Meaker, Petry, and Seitz (1957). Fredman and Tarjan (1987) propose using a Fibonacci heap min-priority queue to optimize the running time complexity to where is the number of edges. This is asymptotically the fastest-known single-source shortest path algorithm for arbitrary directed graphs with unbounded non-negative weights. However, specialized cases – such as bounded/integer weights, directed acyclic graphs, etc. – can indeed be improved further as detailed in the section on Specialized Variants.
6. Characteristics of the Algorithm:

|  |  |
| --- | --- |
| **Class** | Search Algorithm |
| **Data Structure** | Graph |
| **Worst-case Performance** |  |

1. Special Variant – Uniform Cost Search: In some fields, artificial intelligence in particular, Dijkstra’s algorithm or a variant of it is known as *uniform cost search* and formulated as an instance of the more general idea of best-first search.

**Algorithm**

1. Idea behind the Dijkstra Algorithm: Let the starting node be called the *initial node*. Let the *distance of node*  be the distance from the initial node to . Dijkstra’s algorithm will assign some initial distance values and try to improve them step-by-step.
2. Maintain the Set of Unvisited Nodes: Mark all nodes unvisited. Create a set of all unvisited nodes called the *unvisited set*.
3. Assignment of Beginning Node Distances: Assign to every node a tentative distance value; set it to zero for the initial node and to infinity for all other nodes. Set the initial node as current.
4. Comparison Based Node Distance Update: For the current node, consider all of its unvisited neighbors and calculate their *tentative* distances through the current node. Compare the newly created *tentative* distance and assign the smaller value.
5. Criteria for Marking as *Unvisited*: When all of the unvisited neighbors of the current node have been visited, mark the current node as visited and remove it from the *unvisited set*. A visited node will never be checked again.
6. Criterion for Algorithm Termination: If the destination node has been marked visit – when planning a route between two specific nodes – or if the smallest tentative distance among the nodes in the *unvisited set* is infinity – when planning a complete traversal; this occurs when there is no connection between the initial node and the remaining unvisited nodes – then stop. The algorithm has finished.
7. Criteria for the Algorithm Iteration: Otherwise, select the unvisited node that is marked with smallest tentative distance, set it as the current node, and go back to the step *Comparison based Distance Update*.
8. Termination before Setting *Destination Visited*: When planning route, it is actually not necessary to wait until the destination node is *visited* as above; the algorithm can stop once the destination node has the smallest tentative distance among all *unvisited* nodes – and thus could be selected as the next *current*.

**Characteristics**

The algorithm makes no attempt of direct exploration towards the destination as one might expect. Rather, the sole consideration in determining the next *current* intersection is its distance from the starting point. This algorithm therefore expands outward from the starting point, interactively considering every node that is closest in terms of the shortest path distance until it reaches the destination. When understood this way, it is clear how the algorithm necessarily finds the shortest path. However, this may also reveal one the algorithm’s weaknesses; its relative slowness in some topologies.

**Generalization of the Problem**

1. Source to Destination Complete Path Set: A more general problem would be to find all the shortest paths between *source* and *target* – there may be several ones of the same length. Then, instead of storing only a single node in each entry of , all the vertexes that satisfy the relaxation condition would be stored.
2. Storing the Set of Parents: For example, if an intermediate node and connect to and both of them lie on different shortest paths through – because the edge cost is the same in both cases – both and would be added to . When the algorithm completes, data structure will actually describe a graph that is a subset of the original graph with some edges removed.
3. DFS Based Path Finding Algorithm: Its key property will be that is the algorithm is run with some starting node, then every path from that node to every other node in the new graph will be the shortest path between these nodes in the original graph, and all paths of that length in the original graph will be present in the new graph. Then to actually find all the shortest paths between two given nodes, a path finding algorithm like depth first search will be used on the new graph.

**Using a Priority Queue**

1. Minimum Priority Queue Data Structure: A queue is an abstract data type that provides three basis operations: , , and . As mentioned earlier, using such a data structure can lead to faster computing times than using a basic queue. Notably, the Fibonacci heap (Fredman and Tarjan (1987)) or Brodal queue offer optimal implementations for these three operations.
2. Gradually Filling up the Queue: Instead of filling up the priority queue with all nodes in the initialization phase, it is also possible to initialize it with only those containing the ; then, inside the shortest path examination block, the node must be inserted if not already in the queue, instead of performing a operation (Mehlhorn and Sanders (2008)).
3. Data Structures with Faster Runtimes: Other data structures can be used to achieve even faster runtimes in practice (Chen, Chowdhury, Ramachandran, Roche, and Tong (2007)).

**Proof of Correctness**

1. Induction on the Visited Vertexes: Proof of Dijkstra’s algorithm is constructed by induction on the number of visited nodes.
2. Invariant Hypothesis for Visited Vertexes: For each visited node , is considered the shortest distance from the to ; and for each unvisited node , is assumed to be the shortest distance when traveling via visited nodes only, from to . This assumption is only considered if a path exists, otherwise the distance is set to infinity. Note that is not considered to be the actual shortest distance for unvisited nodes.
3. Triviality of the Inductive Base Case: The base case is when there is just one visited node, namely the initial node , in which case the hypothesis is trivial.
4. Assuming Validity for Arbitrary : Assume that the hypothesis is valid for visited nodes. In this case, one chooses an edge where has the least distance and the edge is such that

is considered to be the shortest distance from to because, if there were a shorter path, and was the first unvisited node in the alternate path, then by the original hypothesis,

which creates a contradiction. Similarly, if there were a shorter path to without using unvisited nodes, and if the last but one node on that path were , then

which is also a contradiction.

1. Final Step of the Induction: After processing it will still be true that for each unvisited node , will be the shortest distance from to using visited nodes only, because if there were a shorter path doesn’t go by if would have been found out previously, and if there were a shorted path using it would have been updated when processing .

**Running Time**

1. Edges/Vertex Based Running Time: Bounds of the running time of a Dijkstra algorithm on a graph with edges and vertexes can be expressed as a function of the number of edges denoted , and the number of vertexes denoted , using the big- notation. The complexity bound depends mainly on the data structure used to represent the set . In the following, upper bounds can be simplified because is for any graph, but that simplification disregards the fact that in some problems, other upper bounds on may hold.
2. List Based Running Time Estimate: For any data structure for the vertex set , the running time is where and are the complexities of and operations in , respectively. The simplest version of Dijkstra’s algorithm stores the vertex list as an ordinary linked list or array, and is simply a linear search through all the vertexes in . In this case, the running time is
3. Adjacency List Based Graph Representation: If the graph is stored as an adjacency list, the running time for a dense graph – where

is For sparse graphs, that is graphs with far fewer than edges, Dijkstra’s algorithm can be more efficiently implemented by storing the graphs in the form of adjacency lists using a self-balancing binary search tree, binary heap, pairing heap, or Fibonacci heap as a priority queue to implement extracting minimum efficiently.

1. Times for Different Queue Types: To perform steps in a binary heap efficiently, it is necessary to use an auxiliary data structure that maps each vertex to its position in the heap and to keep this structure up to date as the priority queue changes. With a self-balancing binary search tree or binary heap, the algorithm requires time in the worst case, where represents the binary logarithm ; for connected graphs this can be simplified to . The Fibonacci heap improves this to .
2. Binary Heap Average Case Times: When using binary heaps, the average case time complexity is lower than the worst case; assuming that edge costs are drawn independently from a common probability distribution, the expected number of operations is bounded by , giving a total running time of (Mehlhorn and Sanders (2005)).

**Practical Optimizations and Infinite Graphs**

1. Lazy Initialization of the Priority Queue: In common presentations of the Dijkstra’s algorithm, initially all nodes are entered into the priority queue. This is, however, not necessary; the algorithm can start with a priority queue that contains only one item, and insert new items as they are discovered – instead of doing a , check whether the key is in the queue, and if it is, decrease the key, otherwise insert it (Mehlhorn and Sanders (2008)).This variant has the same worst-case bounds as the common variant, but otherwise maintains a smaller priority queue in practice, speeding up the queue operations (Felner (2011)).
2. Size Benefits of Lazy Initialization: Moreover, not inserting all nodes in the graph makes it possible to extend the algorithm to find the shortest path from a single source to the closest of a set of target nodes on infinite graphs or those too large to represent in memory. The resulting algorithm is called *uniform cost search* in artificial intelligence literature (Nau (1983), Russell and Norvig (2009), Felner (2011)).
3. Alternative Runtime Complexity Estimate: The complexity for the above search can be expressed in an alternate way for very large graphs; when is the length of the shortest path from the start node to any node satisfying the *goal* predicate, each edge has a cost at least , and the number of neighbors per node is bounded by , then the algorithm’s worst case time and space complexity is both (Russell and Norvig (2009)).
4. Further Optimizations for Specific Situations: Further optimization of the Dijkstra’s algorithm for the single-target case includes bi-directional variants, goal directed variants such as the algorithm, graph pruning algorithms to determine which nodes are likely to form the middle segment of the shortest paths (reach-based routing), and hierarchical descriptions of the input graph that reduce routing to connecting and to their respective *transit nodes* followed by the shortest computation between these transit node using a *highway* (Wagner and Willhalm (2007)). Combinations of such techniques may be needed for optimal practical performance on specific problems (Bauer, Delling, Sanders, Schieferdecker, Schultes, and Wagner (2010)).

**Specialized Variants**

1. Bounded, Small Integer Arc Weights: When arc weights are small integers bounded by a parameter , a monotone priority queue can be used to speed up the Dijkstra’s algorithm. The first algorithm of this type was *Dials’ algorithm*, which used a bucket queue to obtain a running time that depends on the diameter of a graph with integer edge weights (Dial (1969)). The use of van Emde Boas tree as a priority queue brings the complexity to (Ahuja, Mehlhorn, Orlin, and Tarjan (1990)). Another interesting variant based on the combination of a new radix heap and the well-known Fibonacci heap runs in time (Ahuja, Mehlhorn, Orlin, and Tarjan (1990)). Finally, the best algorithms for this special case are as follows. The algorithm given by Thorup (2000) runs in time, and the algorithm given by Raman (1997) runs in time.
2. Optimization for Directed Acyclic Graph: Also, for directed acyclic graphs, it is possible to shortest paths from a given starting vertex in linear time, by processing the vertexes in a topological order, and calculating the path length of each vertex to be then minimum length obtained by any of its incoming edges (Cormen, Leiserson, Rivest, and Stein (2009)).
3. Undirected Connected Graphs with Integer Weights: In the special case of integer weights and undirected connected graphs, Dijkstra’s algorithm can be completely countered with a linear complexity algorithm, given by Thorup (1999).

**Related Problems and Algorithms**

1. Ranked List of Suboptimal Solutions: The functionality of Dijkstra’s original algorithm can be extended with a variety of modifications. For example, sometimes it is desirable to present solutions that are less than mathematically optimal. To obtain a ranked-list of less-than-optimal solutions, the optimal solution is first calculated. A single edge containing the optimal solution is removed from the graph, and an optimal solution to this new graph is calculated. The secondary solutions are then ranked and presented after the first optimal solution.
2. Usage in Link State Routing Protocols: Dijkstra’s algorithm is usually the working principle behind link-state routing protocols, with OSPF and IS-IS being the most common ones.
3. Comparison with Bellman-Ford Algorithm: Unlike Dijkstra’s algorithm, Bellman-Ford algorithm can be used on graphs with negative edge weights, as long as the graph contains no negative cycle reachable from the source vertex . The presence of such cycles means that there is no shortest path, since the total weight becomes lower each time the cycle is traversed. It is possible to adapt Dijkstra’s algorithm to handle negative weight edges by combining it with the Bellman-Ford algorithm to remove negative edges and detect negative cycles, such an algorithm is called Johnson’s algorithm.
4. Relation to the Algorithm: The algorithm is a generalization of the Dijkstra’s algorithm that cuts down on the size of the subgraph that must be explored, if additional information is available that provides a lower bound on the distance to the target. This approach can be viewed from the perspective of linear programming; there is a natural linear program for computing shortest paths, and solutions to its dual linear programs are feasible if and only if they form a consistent heuristic. This feasible dual/consistent heuristic defines a non-negative reduced cost, and is essentially running Dijkstra with those reduced costs. If the dual satisfies the weaker condition of admissibility, then is instead more akin to the Bellman-Ford program.
5. Relation to Prim’s Algorithm: The process that underlies the Dijkstra’s algorithm is similar to the greedy process used in Prim’s algorithm. Prim’s purpose is to find the minimum spanning tree that connects all nodes in a graph; Dijkstra is concerned only with two nodes. Prim does not evaluate the total weight of the path from the starting node, only the individual edges.
6. Relation to Breadth First Search: Breadth-first-search can be viewed as a special case of the Dijkstra algorithm on unweighted graphs, where the priority queue degenerates into a FIFO queue.
7. Relation to Fast-Marching Method: The fast-marching method can be viewed as a continuous version of the Dijkstra’s algorithm which computes geodesic distances in a triangular mesh.

**Dynamics Programming Perspective**

1. SPF Dynamic Programming Functional Equations: From a dynamic programming point of view, Dijkstra’s algorithm is a successive approximation scheme that solves the dynamic programming functional equation for the shortest path problem by the *Reaching* method (Denardo (2003), Sniedovich (2006, 2010)).
2. SPF under the Principle of Optimality: Dijkstra’s explanation of the logic behind the algorithm is as follows (Dijkstra (1959)): *Find the path of minimal total length between two givens nodes P and Q; This uses the fact that, if R is a node on the minimal path from P to Q, knowledge of this implies the knowledge of the minimal path from P to R.* The above explanation is a paraphrase of Bellman’s *Principle of Optimality* in the context of the shortest path problem.

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**Bellman-Ford Algorithm**

**Overview**

1. Focus of Bellman-Ford Algorithm: The Bellman-Ford algorithm is an algorithm that computes the shortest path from a single source vertex to all of the other vertexes in a weighted digraph (Bang-Jensen and Gutin (2008). Wikipedia (2020)). It is slower than Dijkstra’s algorithm for the same problem but is more versatile, as it is capable of handling graphs in which some of the edge weights are negative numbers.
2. Algorithm’s Handling of Negative Cycles: Negative edge weights are found in various applications of graphs, hence the usefulness of this algorithm (Sedgewick and Wayne (2011)). If a graph contains a *negative cycle*, i.e., a cycle whose edges sum to a negative value, that is reachable from any source, then there is no *cheapest* path; any path that has a point on a negative cycle can be made cheaper by one more walk around the negative cycle. In such a case, the Bellman-Ford algorithm can detect and report the negative cycle (Bang-Jensen and Gutin (2008), Kleinberg and Tardos (2022)).
3. Characteristics:

|  |  |
| --- | --- |
| **Class** | Single-source shortest-path problem for weighted directed graphs |
| **Data Structure** | Graph |
| **Worst-case Performance** |  |
| **Best-case Performance** |  |
| **Worst-case Space Complexity** |  |

**The Algorithm**

1. Similarities with the Dijkstra Algorithm: Like Dijkstra’s algorithm, Bellman-Ford proceeds by relaxation, in which approximations to the correct distance are replaced by better ones until they eventually reach the solution. In both algorithms, the approximate distance to each vertex is always an over-estimate of the true distance, and is replaced by the minimum of its old value and the length of the newly found path.
2. Differences with the Dijkstra’s Algorithm: However, Dijkstra’s algorithm uses a priority queue to select greedily the closes vertex that has not yet been processed, and performs this relaxation on all of its outgoing edges; by contrast, the Bellman-Ford algorithm simply relaxes *all* the edges, and does this times, where is the number of vertexes in the graph.
3. Gradual Approach towards the Solution: In each of these repetitions, the number of vertexes with correctly calculated distances grows, from which it follows that eventually all vertexes will have their correct distances. This method allows the Bellman-Ford algorithm to be applied to a wider class of inputs than Dijkstra.
4. Algorithm’s Worst-case Runtime: Bellman-Ford runs in time where and are the number of vertexes and edges, respectively.
5. Initializing the Distances from the Source: The algorithm first initializes the distance to the source to zero and all other nodes to infinity. Then for all edges, if the distance to the destination can be shortened by taking the edge, the distance is updated to the new lower value.
6. Shortest Path in Edges: At each iteration that the edges are scanned, the algorithm finds all shortest paths of length of at most edges, as well as some paths longer than edges.
7. Longest Possible Path without a Cycle: Since the longest possible path without a cycle can be edges, the edges must be scanned times to ensure that the shortest path has been found for all nodes.
8. Check for Negative-weight Cycles: A final scan of all the edges is performed, and if any distance is updated, then a path of length edges has been found which can only occur if at least one negative cycle exists in the graph.

**Proof of Correctness**

1. Intermediate Vertex Distance Lemma: The correctness of the lemma can be shown by induction. The lemma contains two statements. After iterations of the main loop:
   1. If is not infinity, it is equal to the length of some path from to , and:
   2. If there is a path from to with at most edges, then is at most the length of the shortest path from to with at most edges.
2. Verifying the Base Inductive Case: For the base case of induction, consider

and the moment before the main loop is executed for the first time. Then, for the source vertex,

which is correct. For other vertexes

which is also correct because there is no path from to with edges.

1. First Part of the Induction: For the inductive case, the first part is proved first. Applying the inductive assumption when a vertex’s distance is updated by

it is clear that is the length of some path from to . Then is the length of the path from to that follows the path from to and then goes to .

1. Second Part of the Induction: For the second part, consider a shortest path – there may be more than one – from source to with at most edges. Let be the last vertex before on this path. Then, the part of the path from to is a shortest path from to with at most edges, and one could then append to this path with at most edges that is strictly shorter than – a contradiction. By inductive assumption, after iterations is at most the length of this path from to . Therefore, is at most the length of . In the iteration, gets compared with and is set equal to it if is smaller. Therefore, after iterations, is at most the length of , the length of the shortest path from to that uses at most edges.
2. Verifying the Negative Weight Cycle: If there are no negative-weight cycles, then every shortest path visits each vertex at most once, so that, finally, no further improvements can be made. Conversely, suppose no improvement can be made. Then, for any cycle with vertexes

Summing around the cycle, the and terms cancel, leaving

i.e., ever cycle has a non-negative weight.

**Finding Negative Weights**

When the algorithm is used to find the shortest paths, the existence of negative cycles is a problem, preventing the algorithm from finding a correct answer. However, since it terminates upon finding a negative cycle, the Bellman-Ford algorithm can be used in applications in which this is the target to be sought – for example, in cycle-canceling techniques in network flow analysis (Bang-Jensen and Gutin (2008)).

**Applications in Routing**

1. Distributed Version of Bellman-Ford: A distributed version of the Bellman-Ford algorithm is used in distance-vector routing protocols, for example, the Routing Information Protocol (RIP). The algorithm is distributed because it involves a number of nodes – routers – within an Autonomous System, a collection of IP networks typically owned by an ISP.
2. Distance Vector Routing Protocol Steps: It consists of the following steps:
   1. Each node calculates the distance between itself and all other nodes within the AS and stores this information in a table.
   2. Each node sends its table to all neighboring nodes.
   3. When a node receives distance table from its neighbors, it calculates the shortest routes to all other nodes and updates its own tables to reflect any changes.
3. Drawbacks of the Bellman-Ford Scheme: The main disadvantages of the Bellman-Ford algorithm in this setting are as follow:
   1. It does not scale well.
   2. Changes in network topology are not reflected quickly since updates are spread node-by-node.
   3. Count to infinity occurs if link or node failures render a node unreachable from some set of other nodes, these nodes may spend forever gradually increasing their estimates of the distance to it, and in the meanwhile, there may be routing loops.

**Improvements**

1. Early Termination of the Main Iterator: The Bellman-Ford algorithm may be improved in practice – although not in the worst-case – by the observation that, if the iteration of the main loop of the algorithm terminates without making any changes, the algorithm can be immediately terminated, as subsequent iterations will not make any more changes. With this early termination condition, the main loop may in some cases uses fewer than iterations, even though the worst of the algorithm remains unchanged.
2. Reducing the Number of Relaxations: Yen (1970) describes two more improvements for a Bellman-Ford algorithm for a graph without negative-weight cycles; again, while making the algorithm faster in practice, they do not change its worst-case bound. The first improvement reduces the number of relation steps that need to be performed within each iteration of the algorithm.
3. Vertexes that have finished Updating: If a vertex has a distance value that has not changed since the last time the edges out of were relaxed, then there is no need to relax the edges out of a second time. In this way, as number of vertexes without the correct distance values grows, the number whose outgoing edges that need to be relaxed in each iteration shrinks, leading to a constant-factor savings in time for dense graphs.
4. Vertex Ordering and Edge Partitioning: The second improvement first assigns an arbitrary linear order on all vertexes and then partitions the set of edges into two subsets. The first subset contains all edges such that The second, , contains edges such that
5. Position Based Vertex Visitation Order: Each vertex is visited in the order , relaxing each outgoing edge from that vertex in . Each vertex is then visited in the order , relaxing each outgoing edge from that vertex in .
6. Reduction in the Worst-case Iteration Count: Each iteration of the main loop of the algorithm, after the first one, adds at least two edges to the set of edges whose relaxed distances match the correct shortest path distances; one from and the other from . This modification reduces the number of iterations of the main loop of the algorithm from to (Cormen, Leiserson, Rivest, and Stein (2009), Sedgewick and Wayne (2011)).
7. Random Permutation of the Vertex Ordering: Another improvement, by Bannister and Eppstein (2012), replaces the arbitrary linear order of the vertexes used in Yen (1970) second improvement by a random permutation. This change makes the worst case of Yen’s improvement – in which the edges of a shortest strictly alternate between the two subsets and – very unlikely to happen. With a randomly permuted vertex ordering, the expected number of iterations needed in the main loop is at most (Sedgewick and Wayne (2011)).

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**Johnson’s Algorithm**

**Overview**

1. Johnson’s Algorithm – Purpose and Methodology: Johnson’s algorithm is a way to find the shortest paths between all pairs of vertexes in an edge-weighted, directed graph. It allows some of the edge weights to be negative, but no negative weight cycles may exist. It works by using a Bellman-Ford algorithm to compute a transformation of the input graph that removes all negative weights, allowing Dijkstra’s algorithm to be used on the transformed graph (Johnson (1977), Black (2004), Cormen, Leiserson, Rivest, and Stein (2009), Wikipedia (2019)).
2. Disjoint Paths of Minimum Length: A similar re-weighting technique is also used in Suurballe’s algorithm for finding two disjoint paths of minimum total length between the same two vertexes in a graph with non-negative edges (Suurballe (1974)).
3. Characteristics:

|  |  |
| --- | --- |
| **Class** | All pairs shortest path problem for weighted graphs |
| **Data Structure** | Graph |
| **Worst-case Performance** |  |

**Algorithm Description**

1. New Node with Zero Edge Weights: Johnson’s algorithm consists of four steps (Black (2004), Cormen, Leiserson, Rivest, and Stein (2009)). In the first step, a new node is added to the graph, connected by zero-weight edge to the other nodes.
2. Bellman Ford with the new Node as the Source: The Bellman-Ford algorithm is used in the second step, starting from the new vertex , to find for each vertex the minimum height of a path from to . If this step detects a negative cycle, the algorithm is terminated.
3. Re-weighting of the Original Graph: In the next step, the edges of the original graph are re-weighted using the values computed by the Bellman-Ford algorithm; an edge from to , having length , is given the new length .
4. Removal of the Inserted Node: Finally, is removed, and Dijkstra’s algorithm is used to find the shortest paths from each node to every other vertex in the re-weighted graph.

**Correctness**

1. Uniform Weight Adjustment across Pairs: In the re-weighted graph, all paths between a pair and of nodes have then same quantity added to them. To see this, let be an path. Its weight in the re-weighted graph is given by . Every is cancelled by in the bracketed expression, and, therefore, the following remains for : . The bracketed expression is the weight of in the original weighting.
2. Zero Re-weighting of Paths: Since the re-weighting adds the same amount to every path, a path is the shortest path in the original weighting if and only if it is a shortest path after re-weighting. The weight if the edges that belong to a shortest path from to any node is zero, and therefore the lengths of the shortest paths from to every node becomes zero in the re-weighted graph; however, they still remain shortest paths.
3. Consequence - No Negative Edge Weights: Therefore, there can be no negative edges; if edge had a negative weight after the re-weighting, then the zero-length path from to together with this edge would form a negative-length path from to , contradicting the fact that all vertexes have zero distance from .
4. Dijkstra’s Algorithm Optimal Path Guarantee: The non-existence of negative edges ensures the optimality of the paths found by the Dijkstra’s algorithm. The distances in the original path may be calculated using the distances calculated by the Dijkstra’s algorithm in the re-weighted graph by reversing the re-weighting transformation (Cormen, Leiserson, Rivest, and Stein (2009)).

**Analysis**

The time complexity of this algorithm, using Fibonacci heaps’ implementation of the Dijkstra’s algorithm, is ; the algorithm uses for the Bellman-Ford stage, and for each of the instantiations of the Dijkstra’s algorithm. Thus, when the graph is sparse, the total time can be faster than the Floyd-Warshall algorithm, which solves the problem in (Cormen, Leiserson, Rivest, and Stein (2009)).

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**Search Algorithm**

**Overview**

1. Focus on and its Limitations: is a graph traversal and path search algorithm, which is often used on account of its completeness, optimality, and optimal efficiency (Russell and Norvig (2018), Wikipedia (2020)). One major practical drawback is its space complexity as it stores all generated nodes in memory. Thus, in practical travel-routing systems, it is generally out-performed by algorithms that can pre-process the graph to attain better performance (Delling, Sanders, Schultes, and Wagner (2009)), as well as memory bounded approaches; however, is still the best solution in many cases (Zeng and Church (2009)).
2. Heuristics Based Generalization of Dijkstra: First published by Hart, Nilsson, and Raphael (1968), algorithm can be seen as an extension of Dijkstra’s algorithm. achieves better performance by using heuristics to guide its search.

**Introduction**

1. Origin of the Algorithm: was originally created as part of the Shakey project, which had the aim of building a mobile robot that could plan its own actions. The original proposal was to use the Graph Traverser Algorithm (Doran and Michie (1966)) for path planning (Nilsson (2009)).
2. Initial Cut of the Heuristics: Graph Traverser is guided by a heuristic function , the estimated distance from the node to the goal node; it entirely ignores , the distance from the start node to . It was suggested later by Bertram Raphael to use the sum (Nilsson (2009)).
3. Admissibility and Consistency of Heuristics: Peter Hart invented the concepts now called admissibility and consistency of heuristic functions. was originally designed for finding least cost paths when the cost of a path is the sum of its edge costs, but it has been shown that can be used for finding optimal paths for any problem satisfying the conditions of a cost algebra (Edelkamp. Jabbar, and Lluch-Lafuente (2005)).
4. Origin of the Algorithm’s Consistency: Hart, Nilsson, and Raphael (1968) constructed a theorem that states that no -like algorithm could expand fewer nodes than if the heuristic function is consistent and ’s tie-breaking rule is suitably chosen. Here -like means that the algorithm searches by extending paths originating at the start node one edge at a time, just as does. This excludes, for example, algorithms that search backwards from goal or in both directions simultaneously. In addition, algorithms covered by this theorem must be admissible and *not more informed* than .
5. Validation of the Algorithm’s Consistency: A *correction* was published later (Hart, Nilsson, and Raphael (1972)) claiming that consistency was not required, but this was shown to be false in Dechter and Pearl’s definitive study of ’s optimality – called optimal efficiency – which gave an example of with a heuristic that was admissible but not consistent, expanding arbitrarily more nodes than an alternative -like algorithm (Dechter and Pearl (1985)).

**Description**

1. Least-cost Best-first Search: is an informed search algorithm, or a best-first search, meaning that it is formulated in terms of weighted graphs; starting from a specific starting node of a graph, it aims to find that path to a given goal node having the smallest cost – least distance traveled, shortest time, etc. It does this by maintaining a tree of paths at the starting node and expanding those paths one edge at a time until the termination criterion is satisfied.
2. Selecting the Path to Extend: At each iteration of its main loop, needs to determine which of its paths to extend. It does so based on the cost of the path and an estimate of the cost required to extend the path all the way to the goal.
3. Components of the Cost Heuristic: Specifically, selects the path that minimizes

where is the next node on the path, is the cost of the path from the start node to , and is a heuristic function that estimates the cost of the cheapest path from to goal. terminates when the path it uses to extend is the path from start to goal or if there are no paths eligible to be extended.

1. Admissible Nature of the Heuristic: The heuristic function is problem-specific. If the heuristic function is admissible, meaning that is over-estimates the actual cost to get to the goal, is guaranteed to return a least-cost path from start to goal.
2. Priority Queue Based Edge Choice: Typical implementations of use a priority queue to perform the repeated selection of minimum estimated cost nodes to expand. This priority queue is known as an *open set* or *fringe*.
3. Node with the Lowest Heuristic: At each step of the algorithm, the node with the lowest value is removed from the queue, the and the values of its neighbors are updated accordingly, and these neighbors are added to the queue.
4. Node-to-Target Cost Heuristic: The algorithm continues until a node has a lower value than any node in the queue, or until the queue is empty. Goal nodes may be passed over multiple times if there remain other nodes with lower values, as they may lead to a shorter path to the goal. The value of the goal is then the cost of the shortest path, since at the goal is zero in an admissible heuristic.
5. Vertexes on the Shortest Path: The algorithm described so far gives only the length of the shortest path. To find the actual sequence of steps, the algorithm can be easily revised so that each node on the path keeps track of its predecessor. After the algorithm is run, the ending node will point to its predecessor, and so on, until a node’s predecessor is the start node.
6. Euclidean Distance as an Admissible Heuristic: As an example, when searching for a shortest route on a map, might represent the straight-line distances to the goal, since that is physically the smallest possible distance between any two points.
7. Criterion that makes the Heuristic Consistent: If the heuristic satisfies the additional condition

for every edge of the graph – where denotes the length of the edge – then is called monotone, or consistent. With a consistent heuristic, is guaranteed to find an optimal path without processing any node more than once, and is equivalent to running Dijkstra’s algorithm with the reduced cost

1. Implementation Caveats: If a node is reached by one path, removed from the priority queue, and subsequently reached by another path, it will be added to the priority queue again. This is essential to guarantee that the path returned is optimal if the heuristic function is admissible but not consistent. If the heuristic is consistent, when a node is removed from the priority queue, the path to it is guaranteed to be optimal, so the comparison with the updated will always fail if the node is reached again.

**Implementation Details**

1. Handling Ties on Heuristic Scores: There are as number of optimization or implementation details that can significantly affect the performance of an implementation. The first detail to note is that the way the priority queue handles ties can have a significant effect on performance is some situations. If the ties are broken so that the queue behaves in a LIFO manner, will behave like depth-first search among equal cost paths, avoiding exploring more than one equally optimal solution.
2. Retention of the Predecessor Node: When a path is required at the end of a search, it is common to keep with each node a reference to the node’s parent. At the end of the search, these nodes can be used to recover the optimal path.
3. Case of Identical Processor Nodes: If these references are being kept, then it can be important that the same node doesn’t appear in the priority queue more than once, each entry corresponding to a different path to the node, and each with a different cost.
4. Cost Based Tie Breaking: A standard approach here is to check if a node to be added already appears in the priority queue. If it does, then the priority and the parent pointers are changed to correspond to the lower cost path.
5. Searching Element in a Priority Queue: A standard binary heap based priority queue does not directly support the operation of searching for one of its elements, but it can be augmented with a hash-table that maps elements to their position in the heap, allowing this decrease priority operation to be performed in logarithmic time. Alternatively, a Fibonacci heap can perform the same decrease-priority operations in constant amortized time.

**Special Cases**

1. Dijkstra’s Algorithm – Zero Forward Heuristic: Dijkstra’s algorithm, as another example of uniform cost search algorithm, can be viewed as a special case of where

for all (de Smith, Goodchild, and Longley (2007), Hetland (2010)).

1. DFS Implementation using a Global Counter: General depth-first search can be implemented using by considering that there is a global counter initialized to a very large value. is assigned to all of the newly discovered neighbors of a node every time a node is processed. After each single assignment, the counter is decreased by . Thus, the earlier a node is discovered, the higher is its value.
2. Efficiency of the Zero Forward Heuristic: Both Dijkstra’s algorithm and depth-first can be implemented more efficiently without including an value at each node.

**Properties – Termination and Completeness**

1. Completeness in Finite Graphs: On finite graphs with non-negative edge weights, is guaranteed to terminate and is *complete*, i.e., it will always find a solution – a path from start to goal – if one exists.
2. Conditional Termination in Infinite Graphs: On infinite graphs with a finite branching factor and edge costs that are bounded away from zero, i.e.,

for some fixed , is guaranteed to terminate if and only there exists a solution.

**Properties – Admissibility**

1. Search Algorithm Admissibility vs. Heuristic Admissibility: A search algorithm is said to be *admissible* if it is guaranteed to return to an optimal solution. If the heuristic function used by is admissible, then itself is admissible. An intuitive *proof* of this is as follows.
2. Optimistic Nature of the Heuristic: When terminates its search, it has found a path from start to goal whose actual cost is lower than the estimated cost of any path from start to goal through any open node, i.e., the node’s value. When the heuristic is admissible, these estimates are optimistic – under the caveats below – so can safely ignore those nodes because they cannot possibly lead to a cheaper solution than the one it already has. In other words, will never overlook the possibility of a lower cost path from start to goal so it will continue to search until no such possibilities exist.
3. Caveat behind the Optimal Heuristic: The actual proof is a bit more involved, because the values at the open nodes are not guaranteed to be optimistic even if the heuristic is admissible. This is because the values at the open nodes are not guaranteed to be optimal, so the sum is not guaranteed to be optimistic.

**Properties - Optimal Efficiency**

1. Definition of Optimal Efficiency: Algorithm is optimally efficient with respect to a set of alternative algorithms on a set of problems if for every problem in and every algorithm in the set of nodes expanded by by solving is a subset of – possibly equal to – the set of nodes expanded by in solving .
2. Impact of Heuristic Admissibility/Consistency: The definitive examination of the optimal efficiency of was done by Dechter and Pearl (1985). They considered a variety of definitions of and in combination with ’s heuristic being merely admissible or being both admissible and consistent.
3. Consistent Heuristic and Admissible Algorithm: The most interesting and positive result they proved is that , with its consistent heuristic, is optimally efficient with respect to all -like search algorithms on all *non-pathological* search problems. Roughly speaking, Dechter and Pearl’s notion of non-pathological problems is what is now referred to as *tie-breaking*.
4. Heuristic Admissible but not Consistent: This result does not hold it ’s heuristic is admissible but not consistent. In that case, Dechter and Pearl show that there exist -like algorithms that can expand arbitrarily fewer nodes than on some non-pathological problems.
5. Optimally Efficient Node Set Expansion: Optimal efficiency is about the *set* of nodes expanded, not the *number* of node expansions – the number of iterations of ’s main loop. When the heuristic being used is admissible but not consistent, it is possible for a node to be expanded by many times, an exponential number of times in the worst-case (Martelli (1977)). In such circumstances, Dijkstra’s algorithm would outperform by a large margin.

**Bounded Relaxation**

1. Relaxing the Optimal Admissibility Criterion: While the admissibility criterion guarantees an optimal solution path, it also means that must examine all equally meritorious paths to find the optimal path. To compute approximate shortest paths, it is possible to speed up the search at the expense of optimality by relaxing the admissibility criterion.
2. Allowance for -admissible Relaxations: Often one wants to bound this relaxation, so there is a guarantee that the solution path is no worse than times the optimal path solution. This new guarantee is referred to an -admissible. There are a number of -admissible algorithms.
3. Weighted /Static Weighting: If is an admissible heuristic function, in the weighted version of search one uses

as a heuristic function (Pohl (1970)), and perform search as usual, which eventually happens faster than using , since fewer nodes are expanded. The path then found by the search algorithm can have a cost of at most times that of the least cost path in the graph (Pearl (1984)).

1. Dynamic Weighting: Dynamic weighting (Pohl (1973)) uses the cost function

where

and is the depth of the search, and is the anticipated length of the search.

1. Sampled Dynamic Weighting: This uses sampling of the nodes to better estimate and de-bias the heuristic (Koll and Kaindl (1992)).
2. : uses two heuristic functions (Pearl and Kim (1982)). The first is the FOCAL list, which is used to select the candidate nodes, and the second is used to select the most promising node from the FOCAL list.
3. : selects nodes with the function where and are constants (Ghallab and Allard (1983)). If no nodes can be selected, the algorithm will backtrack with the function where and are constants.
4. : attempts to promote depth-first exploitation by preferring recently expanded nodes (Reese (1999)). uses the cost function

where

where and are constants with

and is the most recently expanded node.

**Complexity**

1. Worst-case: Unbounded Search Space: The time complexity of depends on the heuristic. In the worst-case of a unbounded search space, the number of nodes expanded is exponential in the depth of the solution – the shortest path - , where is the branching factor, the average number of successors per state (Russell and Norvig (2018)). This assumes that a goal exists at all, and is reachable from the start state; if it is not, and the search space is infinite, the algorithm will not terminate.
2. Heuristics Induced Effective Branching Factor: The heuristic function has a major impact on the practical performance of the search, since a good heuristic allows to prune away many of the nodes that an uninformed search would expand. Its quality can be expressed in terms of the effective branching factor , which can be determined empirically for a problem instance by measuring the number of the nodes expanded, and the depth of the solution, and then solving (Russell and Norvig (2018))

Good heuristics are those with low effective branching factor, the optimal being

1. Criteria for Polynomial Time Search: The time complexity is a polynomial when the search space is a tree, there is a single goal state, and the heuristic function meets the following condition:

where is the optimal heuristic, the exact cost to get from to the goal. In other words, the error of will not grow faster than the logarithm of the perfect heuristic that returns the true distance from to the goal (Pearl (1984), Russell and Norvig (2018)).

1. Drawback – Space Complexity: The space complexity of is the same as all other graph search algorithms, as it keeps all the generated nodes in memory (Russell and Norvig (2018)). In practice, this turns out to be the biggest drawback of the search, leading to the development of memory-bound heuristic searches, such as Iterative Deepening , memory-bounded , and .

**Applications**

is often used for path-finding in applications such as video games, but was originally designed as a general graph traversal algorithm (Hart, Nilsson, and Raphael (1968)). It finds application in diverse problem, including the problem of parsing using stochastic grammars in NLP (Klein and Manning (2003)). Other cases include informational search with online learning (Kagan and Ben-Gal (2014)).

**Relation to Other Algorithms**

Some common variants of Dijkstra’s algorithm can be viewed as a special case of where the heuristic

for all nodes (de Smith, Goodchild, and Longley (2007), Hetland (2010)); in turn, both Dijkstra and are special cases of dynamic programming (Ferguson, Likhachev, and Stentz (2005)). itself is a special case of generalization of branch-and-bound (Nau, Kumar, and Kanal (1984)).

**Variants**

1. Anytime (Hansen and Zhou (2007) or Anytime Repairing () (Likhachev, Gordon, and Thrun (2003))
2. Block
3. Field
4. Fringe
5. Fringe Saving ()
6. Generalized Adaptive ()
7. Incremental Heuristic Search
8. Informational Search (Kagan and Ben-Gal (2014))
9. Iterative Deepening ()
10. Jump-point Search
11. Lifelong Planning ()
12. Multiplier-accelerated () (Li and Zimmerle (2019))
13. New Bidirectional () (Pijls and Post (2010))
14. Simplified Memory Bounded ()
15. Real-time (Korf (1990))
16. Time-bounded () (Bjornsson, Bulitko, and Sturtevant (2009))

can also be adapted to a bi-directional search algorithm. Special care needs to be taken for the stopping criterion.

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**Floyd-Warshall Algorithm**

**Overview**

1. Alternate Names for the Algorithm: Floyd-Warshall algorithm (also called Floyd’s algorithm, Roy-Warshall algorithm, Roy-Floyd algorithm, or WFI algorithm) is an algorithm for finding shortest paths in a weighted graph with positive or negative edge weights, but with no negative cycles (Rosen (2003), Cormen, Leiserson, Rivest, and Stein (2009), Wikipedia (2020)).
2. All Pairs Shortest Path Trail: A single execution of the algorithm will find the lengths – summed weights – of shortest paths between all pairs of vertexes. Although it does not return details of the paths themselves, it is possible to reconstruct the paths with simple modifications to the algorithm.
3. Re-purposed Versions of the Algorithm: Versions of the algorithm can also be used for finding the transitive closure of a relation, or – in connection with the Schulze voting system – widest paths between all pairs of vertexes in a weighted graph.
4. Characteristics:

|  |  |
| --- | --- |
| **Class** | All Pairs Shortest Path Problem (for Weighted Graphs) |
| **Data Structure** | Graph |
| **Worst-case Performance** |  |
| **Best-case Performance** |  |
| **Average Performance** |  |
| **Worst-case Space Complexity** |  |

**History and Naming**

Floyd-Warshall algorithm is an example of dynamic programming, and was published in its currently recognized form by Floyd (1962). However, it is essentially the same as algorithms previously published by Roy (1959), and also by Warshall (1962) for finding a transitive closure of a graph, and is closely related to Kleene’s algorithm for converting a deterministic finite automaton into a regular expression (Kleene (1956)). The modern formulation of the algorithm as three nested for-loops was first described by Ingerman (1962).

**Algorithm**

1. Pair-wise All Paths Comparison: The Floyd-Warshall algorithm compares all possible paths through the graph between each pair of vertexes. It is possible to do this with comparisons in a graph, even though there may be up to edges in the graph, and every combination of edges is tested. It does so by incrementally improving an estimate on the shortest path between two vertexes, until the estimate is optimal.
2. Pair Path using Intermediate Vertex: Consider a graph with vertexes numbered through . Further, consider a function that returns the shortest path from to using vertexes only from the set as intermediate points along the way. Now, given this function, the goal is to find the shortest path from each to each using *any* vertex in .
3. Shortest Path through a Vertex: For each of these pairs of vertexes, the could be either:
   1. a path that does not go through , i.e., only uses vertexes in the set , or:
   2. a path that goes through , from to , and then from to , both only using intermediate vertexes in .
4. Mechanism for Constructing a Path: Obviously, the best path from to that only uses vertexes through is defined by , and it is clear that if there were a better path from through to , then the length of this path would be the concatenation of the shortest path from to – only using intermediate vertexes in , and the shortest path from to – again, only using intermediate vertexes in .
5. Setting up the Recursion Scheme: If is the weight of the edge between vertexes and , one can define in terms of the following recursive formula; the base case is

and the recursive case is

1. Progressive Scan through Intermediate Vertexes: The formula above is the heart of the Floyd-Warshall algorithm. The algorithm works by first computing for all pairs for

then

and so on. This process continues until

at which stage the shortest paths for all pairs will have been found using any intermediate vertexes.

**Behavior with Negative Cycles**

1. Algorithm Failure Under Negative Cycles: A negative cycle is a cycle whose edges sum to a negative value. There is no shortest path between any pair of vertexes which form part of a negative cycle, because path lengths from to can be arbitrarily small, i.e., negative. For numerically meaningful output, the Floyd-Warshall algorithm assumes that there are no negative cycles. Nevertheless, if there are negative cycles, the Floyd-Warshall algorithm can be used to detect them.
2. Scheme for Detecting Negative Cycles:
   1. The Floyd-Warshall algorithm iteratively revises the path lengths between all pairs of vertexes including where
   2. Initially, the length of the path is is zero
   3. A path can only improve upon this if it has length less than zero, i.e., denotes a negative cycle.
   4. Thus, after the algorithm, will be negative if there exists a negative length path from back to
3. Examining the Floyd-Warshall Path Matrix: Hence, to detect the negative cycles using the Floyd-Warshall algorithm, one can inspect the diagonal of the path matrix, and the presence of a negative number indicates that the graph contains at least one negative cycle. To avoid numerical problems, one should check for negative numbers on the diagonal of the path matrix within the inner *for-loop* of the algorithm (Hougardy (2010)). Obviously, in an undirected graph, a negative edge creates a negative cycle, i.e., a close walk, involving its incident edges.

**Path Reconstruction**

The Floyd-Warshall algorithm typically only provides the lengths of the paths between all pairs of vertexes. With simple modifications, it is possible to create a method to reconstruct the actual path between any two vertex endpoints. While one may be inclined to store the actual path from each vertex to each other vertex, this is not necessary, and in fact, is very costly in terms of memory. Instead, the shortest path tree can be calculated for each node in time using memory to store each tree which allows efficient re-construction of a path between any two connected vertexes.

**Analysis**

Let

be the number of vertexes. To find all of for all and from those of requires operations. Since one begins with

and computes the sequence of matrices , the total number of operations used is

The complexity of the algorithm is therefore .

**Applications and Generalizations**

1. Shortest Paths in Directed Graphs: Floyd’s algorithm.
2. Transitive Closure of Directed Graphs: This is the Warshall algorithm. In the original formulation, the graph is unweighted and represented by a Boolean adjacency matrix. Then the addition operation is replaced by logical conjunction (AND) and the minimum operation by logical disjunction (OR).
3. Regular Language for Finite Automaton: Finding a regular expression denoting the regular language accepted by a finite automaton – this is Kleene’s algorithm, a closely related generalization of the Floyd-Warshall algorithm (Gross and Yellen (2003)).
4. Inversion of Real Matrices: This is the Gauss-Jordan algorithm (Penaloza (2005)).
5. Optimal Routing: In this application, one is interested in finding the path with the maximum flow between two vertexes. This means that, instead of taking the minima in the algorithm above, one instead takes the maxima. The edge weights represent fixed constraints on the flow. Path weights represent bottlenecks; so, the addition operation above is replaced by a minimum operation.
6. Fast Computation of Path Finder Networks.
7. Widest Paths/Maximum Bandwidth Paths.
8. Difference Bound Matrices: Computing canonical form of difference bound matrices (DBM’s)
9. Computing the Similarity between Graphs.

**Comparisons with other Shortest Path Algorithms**

1. Sparse vs. Dense Graph Problems: The Floyd-Warshall algorithm is a good choice for computing paths between all pairs of vertexes in dense graphs, in which most or all pairs of vertexes are connected by edges. For sparse graphs, with non-negative weights, the better choice is to use Dijkstra’s algorithm for each possible starting vertex, since the running time for repeated Dijkstra (using Fibonacci heaps) is better than the running time of the Floyd-Warshall algorithm when is significantly smaller than . For sparse graphs with negative edges, but no negative cycles, Johnson’s algorithm can be used, with the same asymptotic running time as the repeated Dijkstra approach.
2. Custom Algorithms for Special Situations: There are also known algorithms using fast-matrix multiplication to speed up all-pairs shortest path computation on dense graphs, but these typically make extra assumptions on the edge weights, such as requiring them to be small integers (Zwick (2002), Chan (2010)). In addition, because of the high constant factors in their running time, they would only provide a speed-up over the Floyd-Warshall algorithm for very large graphs.

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**Selection Algorithm**

**Overview**

1. Order Statistic Selection Algorithm: A selection algorithm is an algorithm for finding the smallest number in a list or an array; such a number is called the  *order statistic*. This includes the cases of finding the minimum, the maximum, and the median elements (Wikipedia (2019)).
2. Linear/Sublinear Worst-case Time: There are time, i.e., worst-case linear time, selection algorithms, and sublinear performance is possible for structured data; in the extreme, for an array of sorted data.
3. Super-problems Employing Selection Algorithms: Selection is a sub-problem of more complex problems like the nearest neighbor and the shortest path problems.
4. Selection as Generalization of Sorting: Many selection algorithms are derived by generalizing a sorting algorithm, and conversely some sorting algorithms can be derived as repeated applications of selection.
5. Minimum/Maximum Finding Selection Algorithms: The simplest case of a selection algorithm is finding a minimum – or maximum – element by iterating through the list, keeping track of the running minimum/maximum – the minimum/maximum so far – and can be seen as being related to the selection sort.
6. Selection Algorithms for Median Finding: Conversely, the hardest case of a selection algorithm is finding the median. In fact, a specialized median selection algorithm can be used to build a general selection algorithm, as in median of medians.
7. Quickselect - Average/Worst-case Performance: The best-known selection algorithm is quickselect, which is related to quicksort; like quicksort, it has asymptotically optimal average performance, but poor worst-case performance, though it can be modified to give optimal worst-case performance as well.

**Selection by Sorting**

1. Selection Algorithm using Full Sorting: By sorting the list or array and the selecting the desired element, selection can be reduced to sorting. This method is inefficient for selecting a single element, but is efficient when many selections need to be made from an array, in which case only one initial, expensive sort is needed, followed by many cheap selection operations - for an array, though selection is in a linked list, even if sorted, due to lack of random access. In general, sorting requires time, where is the length of the list, although a lower bound is possible with non-comparative sorting algorithms like radix sort and counting sort.
2. Selection from Partially Sorted List: Rather than sorting the whole list or array, one can use instead partial sorting to select the largest or smallest elements. The smallest – resp. the largest – element is then the largest – resp., smallest – element of the partially sorted list; this then takes to access in an array and to access in a list.

**Unordered Partial Sorting**

1. Unordered Partially Sorted Element List: If partial sorting is relaxed so that the smallest elements are returned, but not in order, the factor of can be eliminated. An additional maximum selection taking time is required, but since

this still yields an asymptotic complexity of . In fact, partition-based selection algorithms yield both the smallest element itself and the smallest elements, with the other elements not in order. This can be done in time – average complexity of quickselect, and the worst-case complexity of refined partition-based algorithms.

1. Selection Induced Unordered Partial List: Conversely, given a selection algorithm, one can easily get an unordered partial sort, i.e., smallest elements, not in order – in time by iterating through the list and recording all the elements less than the element. If this results in fewer than elements, any remaining elements equal the element. Care must be taken, due to the possibility of equality of the elements; one must not include all elements less than *or equal to* the element, as elements greater than the element may also be equal to it.
2. Selection vs. Unordered Partial Sorting: Thus, unordered partial sorting – lowest elements, but not ordered – and selection of the element are very similar problems. Not only do they have the same asymptotic complexity but a solution to either one can be converted into a solution to the other by a straightforward algorithm, e.g., finding a maximum of elements, of filtering elements of a list below the cutoff of the value of the element.

**Partial Selection Sort**

1. Minimum/Maximum Partial Selection Sort: A simple example of selecting by partial sorting is to use a partial selection sort. The obvious linear time algorithm to find the minimum – resp. maximum – iterating over the list and keeping track of the minimum – resp. maximum – element so far can be seen as a partial selection sort that selects the smallest – resp. largest – element. However, many other partial sorts also reduce this algorithm for the case , such as partial heap sort.
2. Partial Sorting Solution - Trivial Implementation: More generally, a partial selection sort yields a simple selection algorithm which takes time. This is asymptotically inefficient, but can be sufficiently if is small, and is easy to implement. Specifically, one simply finds the extremum value and moves it to the beginning, repeating on the remaining lists until elements have been accumulated, and then return the element.

**Partition-Based Selection**

1. Comparison between Quickselect and Quicksort: Linear performance can be achieved by a partition-based selection algorithm, most basically quickselect. Quickselect is a variant of quicksort – in both one chooses a pivot and partitions the data by it, but while quicksort recurses on both sides of the partition, quickselect only recurses on one side, namely the side on which the desired element is.
2. Time Complexity of Quickselect Algorithm: As with quicksort, this has optimal performance, in this case linear, but poor worst-case performance, in this case quadratic. This occurs, for instance, when taking the first element as the pivot and searching for the maximum element, if the data is already sorted. In practice, this can be avoided by choosing a random element as the pivot, which yields almost certain linear performance. Alternatively, a more careful deterministic pivot strategy can be used, such as median of medians.
3. Optimization by using the Hybrid Introselect Algorithm: These are combined in the hybrid introselect algorithm, analogous to introsort, which starts with quickselect, but falls back to median of medians if the progress is slow, resulting in both fast average performance and average worst-case performance of .
4. Space Complexity of the Algorithm: The partition-based algorithms are generally done in place, which thus results in partially sorting the data. They can be done out of place, not changing the original data, at the cost of additional space.

**Median Selection as Pivot Strategy**

1. Using Median as the Pivot: A median-selection algorithm can be used to yield a general solution or sorting algorithm, by applying it as the pivot strategy in quickselect or quicksort; if the median-selection algorithm is asymptotically optimal, i.e., linear time, the resulting selection or sorting algorithm is as well. In fact, exact median is not necessary – an approximate median is sufficient. In the median of medians selection algorithm, the pivot strategy computes an approximate median and uses this as the pivot, recursing on a smaller set to compute this pivot. In practice, the overhead of the pivot computation is significant, so these algorithms are generally not used, but this technique is of theoretical interest in related selection and sorting algorithms.
2. Optimization achieved using Median Pivot: Specifically, given a median-selection algorithm, one can use it as a pivot strategy in quickselect, thereby obtaining a selection algorithm. If the median-selection algorithm is optimal, meaning , then the resulting general selection algorithm is also optimal, again meaning linear. This is because quicksort is a divide-and-conquer algorithm, and using a median at each pivot means that at each step the search set decreases by half in size, so the overall complexity is a generic series times the time complexity of a single step, in fact

times, summing the whole series.

1. Median Pivot Based Sorting Algorithm: Similarly, given a median-selection algorithm or general selection algorithm applied to find the median, one can use it as a pivot strategy in quicksort, obtaining a sorting algorithm. If the selection algorithm is optimal, meaning , then the resulting sorting algorithm is optimal, meaning . The median is the best pivot for sorting, as it evenly divides the data, and thus guarantees optimal sorting, assuming the selection algorithm is optimal. A sorting analog to median-of-medians exists, using the pivot strategy, i.e., approximate median, in quicksort, and similarly yields an optimal quicksort.

**Incremental Sorting by Selection**

1. Sorting by Repeated Selection: Converse to selection by sorting, one can incrementally sort by repeated selection. Abstractly, selection only yields a single element – the element. However, practical selection algorithms frequently involve partial sorting, or can be modified to do so.
2. Benefits Gained by Partial Sorting: Selecting by partial sorting naturally sorts the array, sorting the elements up to , and selecting by partitioning also sorts some elements; the pivots are sorted to their correct positions, with the element being the final pivot, and the elements between the pivots have values between the pivot values.
3. Partition Based on Selection vs. Sorting: The difference between partition-based selection and partition-based sorting, as in quickselect versus quicksort, is that in selection one recurses on only one side of each pivot, sorting only on pivots – on average pivots are used – rather than recursing on both sides of the pivot.
4. Partial Selection Amortizes Sorting Costs: This can be used to speed up subsequent selections on the same data; in the extreme, a fully sorted array allows for selection. Further, compared with doing a full sort, incrementally sorting by repeated selection amortizes the cost over multiple selections.
5. Leveraging Previously Sorted Data Ranges: For partially sorted data – up to – so long the partially sorted data and the index up to which the data is sorted are recorded, subsequent selections of less than can simply select the element, as it is already sorted, while selections of greater than only need to sort elements above the position.
6. Benefits of Storing Pivot Lists: For partitioned data, if the list of pivots is stored – for example, in a sorted list of indexes – then subsequent selections only need to select the index between the two pivots – the nearest pivots below and above. The biggest gain is from the top-level pivots, which eliminate costly large partitions; a single pivot near the middle of the data cuts the time for future selections in half. The pivot list will grow over subsequent selections, as the data becomes more sorted, and can even be passed to a partition-based sort as the basis of a full sort.

**Using Data Structures to Select in Sublinear Time**

1. Organized Data Sublinear Access Times: Given an unorganized list of data, linear time is needed to find the minimum element, because every element has to be examined. If the list is organized, for example, by keeping it sorted at all times, then selecting the largest element is trivial, but then insertion requires linear time, as do other operations such as combining two lists.
2. Tree Structures and Frequency Tables: The strategy to find an order statistic in sublinear time is to store the data in an organized fashion using suitable data structures that facilitate the selection. Two such data structures are tree-based structures and frequency tables.
3. Heap Structure Operations Time Requirements: When only the minimum or the maximum is needed, a good approach is to use a heap, which is able to find the minimum or the maximum element in constant time, while all other operations, including insertion, are or better.
4. Self-Balancing Binary Search Tree: More generally, a self-balancing binary search tree can easily be augmented to make it possible to both insert an element and find the largest element in time; this is called an *order statistic tree*. Each node simply stores a count of how many descendants it has, and uses this to determine which path to follow. The information can be updated efficiently since adding a node only affects the counts of its largest element in ancestors, and the tree rotation only affects the count of nodes involved in the rotation.
5. Data Range-aware Hashtable: Another simple strategy is based on some of the same concepts as the hashtable. When the range of values is known beforehand, one can divide the range into sub-intervals and assign these to buckets. When an element is inserted, it is added to the bucket corresponding to the interval it falls in.
6. Locating the Order Statistic: To find the minimum or the maximum element, one scans from the beginning or the end looking for the first non-empty bucket and find the minimum of the maximum element in the bucket. In general, to find the element, one maintains a count of the number of elements in each bucket, then scans the buckets from left to right adding up the counts until the bucket containing the desired element is found, then uses the expected linear-time algorithm to find the correct element in that bucket.
7. Maintenance Overhead with Hashtables: If one chooses of roughly size , and the input is close to being uniformly distributed, this scheme can perform selections in expected time. Unfortunately, this strategy is also sensitive to clustering of elements in a narrow interval, which may result in buckets with large numbers of elements; clustering can be eliminated through a good hash function, but finding the element with the has value is not very useful. Additionally, like hash-tables, this structure requires table re-sizings to maintain efficiency as elements are added and becomes much larger than .
8. Frequency Tables for Descriptive Statistics: A useful case of this is finding an order statistic in a finite range of data. Using the above table with bucket interval of and maintaining counts in each of the buckets is much superior to other methods. Such hashtables are like frequency tables used to classify data in descriptive statistics.

**Lower Bounds**

1. Lower Bound on the Comparisons: Knuth (1997) discusses a number of lower bounds for the number of comparisons required to locate the smallest entries of an unorganized list of items, using only comparisons. There is a trivial lower bound of for the maximum or the minimum entry.
2. Comparisons Lower Bound - Explicit Expression: The story becomes more complex for other indexes. Defining as the minimum number of comparisons required to find the smallest values, Knuth (1997) references S. S. Kislitsyn to show an upper bound on this value:

for

the bound is achievable for

but better, more complex bounds are known for larger .

**Space Complexity**

The required space complexity of selection is additional storage, in addition to storing the array in which the selection is being performed. Such space complexity can be achieved while preserving optimal time complexity.

**Online Selection Algorithm**

1. Extremum of a Stream: Online selection may refer narrowly to computing the smallest element of a stream, inn which case the partial sorting algorithms – with space for the smallest elements so far – can be used, but partition-based algorithms cannot be.
2. Probabilistic Selection of Extremum: Alternatively, selection itself may be required to be online, that is, an element can only be selected from a sequential input at the instant of observation, and each selection – or refusal – is irrevocable. The problem is to select, under these constraints, a specific element of the input sequence – for example, the largest or the smallest value – with the largest probability. This problem can be tackled by the Odds algorithm, which yields an optimal selection under an independence condition; it is also optimal itself as an algorithm with the number of computations being linear in the length of the output.
3. Secretary Problem - Probability Maximizing Selection: The simplest example is the secretary problem of choosing the maximum with high probability, in which case the optimal strategy on random data is to track the running maximum on the first elements and reject them, and then select the first element that is higher than this maximum.

**Related Problems**

One may generalize the selection problem to apply to ranges within a list, yielding the problem of range queries. The question of range median queries – computing the medians of multiple ranges – has also been analyzed.

**References**

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**Quickselect**

**Overview**

1. Order Statistic Selection Algorithm: *Quickselect* is a selection algorithm to find the smallest element in an unordered list. It is related to the quicksort sorting algorithm; like quicksort, it was developed by Hoare (1961), and thus is also known as *Hoare’s selection algorithm* (Wikipedia (2019)). Like quicksort, it is efficient in practice and has good average-case performance, but has poor worst-case performance. Quickselect and its variants are the selection algorithms most often used in efficient real-world implementations.
2. Relation to the Quicksort Algorithm: Quickselect uses the same overall approach as quicksort, choosing one element as the pivot and partitioning the data into two based on the pivot, accordingly as less than or greater than the pivot. However, instead of recursing in both sides, as in quicksort, quickselect only recurses on one side – the side with the element it is searching for. This reduces the average complexity from to , with a worst-case of .
3. In-place Partially Soring Algorithm: As with quicksort, quickselect is generally implemented as an in-place algorithm, and beyond selecting the element, it also partially sorts the data.
4. Quickselect Characteristics:

|  |  |
| --- | --- |
| **Class** | Selection Algorithm |
| **Data Structure** | Array |
| **Worst-case Performance** |  |
| **Best-case Performance** |  |
| **Average Performance** |  |

**Algorithm**

1. Linear-time Pivot Based Partitioning: Typical implementations of quicksort contain a partition procedure that can, in linear time, group a list – ranging from indexes left to right – into two parts; those less than a certain element, and those greater than or equal to that element. A variation of the partition scheme, known as the Lomuto partitioning scheme, is simpler but slightly less efficient than Hoare’s original partition scheme.
2. One-sided Single Recursive Call: In quicksort, both branches are recursively sorted, leading to the best case time. However, when doing selection, the partition in which the desired element lies in is already known, since the pivot is in its final sorted position, with all those preceding it in an unsorted order and all those following it in an unsorted order. Therefore, a single recursive call locates the desired element in the correct position, and this can be built upon for quickselect.
3. Origin of Linear Time Performance: Note the resemblance to quicksort: just as the minimum-based selection algorithm is a partial selection sort, quickselect is also a partial quicksort, generating and partitioning only of its partitions. This simple procedure has expected linear performance, and, like quicksort, has quiet good average performance in practice. It is also an in-place algorithm, requiring only a constant memory overhead if tail call optimization is available, or if the tail recursion can be eliminated with a loop.

**Time Complexity**

1. Sensitivity to the Pivot Choice: Like quicksort, quickselect has good average performance, but is sensitive to the pivot that is chosen. If good pivots are chosen, meaning ones that consistently decrease the search set by a given fraction, the search set decreases in size exponentially, and by induction – or summing the geometric series – the performance can be seen to be linear, as each step is linear and the overall time is a constant times this – depending on how quickly the search set reduces.
2. Consistent Choice of Bad Pivots: However, if bad pivots are consistently chosen, such as decreasing by only a single element each time, the worst-case performance is quadratic - . This occurs for example in searching for the maximum element of a set, using the first element as a pivot, and having sorted data.

**Variants**

1. Median-of-3 Pivot Strategy: The easiest solution is to choose a random pivot, which yields almost certain linear time. Deterministically, one can choose a median-of-3 pivot strategy – as in quicksort – which yields linear performance on partially sorted data, as is common in the real world. However, contrived sequences can still cause worst-case complexity; David Musser describes a *median-of-3 killer* sequence that allows an attack against that strategy, which was one motivation for his introselect algorithm.
2. Introselect - Robust Fallback Augmented Quickselect: One can ensure linear performance even in the worst-case by using a more sophisticated pivot strategy; this is done in the median-of-medians algorithm. However, the overhead of computing the pivot is high, and this is generally not used in practice. One can combine basic quickselect with median-of-medians as fallback to get both fast average case performance and linear worst-case performance; this is done introselect.
3. Improvement in the Time Complexity: Finer computations of average time complexity yield a worst-case of

for random pivots in the case of median; other are faster (Eppstein (2007)). The constant can be improved to by a more complicated pivot strategy, yielding the Floyd-Rivest algorithm, which has an average complexity of for median, with other being faster.

**References**

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**Median of Medians**

**Overview**

1. Median-of-Medians Algorithm: The *median-of-medians* is an approximate median selectin algorithm, frequently used to supply a good pivot for an exact selection algorithm, mainly the quickselect, that selects the largest element of an initially unsorted array (Wikipedia (2020)).
2. Benefit of this Pivot Selector: Median of medians finds an approximate median in linear-time only, which is a limited but additional overhead for quickselect. When this approximate median is used as an improved pivot, the worst-case complexity of quickselect reduces significantly from quadratic to *linear*, which is also the asymptotically optimal worst-case complexity of any selection algorithm.
3. Approximate Median Selection Algorithm: In other words, median-of-medians is an approximate median-selection algorithm that helps building an asymptotically optimal, exact selection algorithm, especially in the sense of worst-case complexity, by producing good pivot elements.
4. Practical Deployment of the Algorithm: Median of medians can also be used as a pivot strategy in quicksort, yielding an optimal algorithm, with a worst-case complexity of . Although this approach optimizes the asymptotic worst-case quite well, it is typically outperformed in practice by instead choosing random pivots for its average complexity for solution and average complexity for sorting, without any overhead of computing the pivot.
5. Guaranteed Linear Worst-case Performance: Similarly, median-of-medians is used in the hybrid *introselect* algorithm as a fallback for pivot selection until the largest is found. This again ensures a worst-case linear performance, in addition to average-case linear performance; introselect starts with quickselect, with random pivot as default, to obtain good performance, and then falls back to modified quickselect with the pivot obtained from median-of-medians with pivot obtained from median of medians if the progress is too slow. Even though asymptotically similar, such hybrid algorithm will have a lower complexity than a straightforward introselect by up to a constant factor – both in the average-case as well as the worst-case – at any finite length.
6. Blum-Floyd-Pratt-Rivest-Tarjan: The algorithm was published in Blum, Floyd, Pratt, Rivest, and Tarjan (1973), and thus is called **BFPRT** after the last names of the authors. In the original paper, the algorithm was referred to as **PICK**, referring to quickselect as **FIND**.
7. Algorithm Characteristics:

|  |  |
| --- | --- |
| **Class** | Selection Algorithm |
| **Data Structure** | Array |
| **Worst-case Performance** |  |
| **Best-case Performance** |  |
| **Worst-case Space Complexity** | auxiliary |

**Outline**

1. Time Complexity of Naïve Quickselect: Quickselect is linear time on average, but it can require quadratic time with poor pivot choices. This is because quickselect is a divide-and-conquer algorithm, with each step taking time that is linear in the size of the remaining search set. If the search set decreases exponentially quickly in size, i.e., by a fixed proportion, this yields a geometric series times the factor of a single step, and thus overall linear time. However, if the search set decreases slowly in size, such as linearly – by a fixed number of elements, in the worst-case only reducing one element each time, then a linear sum of linear steps yields quadratic overall time – formally, triangular numbers grow exponentially. For example, the worst-case occurs when pivoting on the smallest element at each step, such as applying quickselect to the maximum element of an already sorted data and taking the first element as the pivot each time.
2. Optimization using Good Pivoting Strategy: If one instead chooses consistently *good* pivots, this is avoided and one always gets linear performance even in the worst case. A *good* pivot is one for which one can establish that a constant proportion of elements fall above and below it, as then the search set decreases by at least a constant proportion each step, hence exponentially quickly, and the overall time remains linear. The median is a good pivot – the best for sorting, and the best overall for selection – decreasing the search set by half at each step. Thus, if one can compute the median in linear time, this only adds linear time to each step, and thus the overall complexity of the algorithm remains linear.
3. Median of Medians Performance Improvement: The median-of-medians algorithm computes an approximate median, namely a point that is guaranteed to be between the 30th and the 70th percentiles, i.e., in the middle 4 deciles. Thus, the search set decreases by at least 30%. The problem is reduced to 70% of the original size, which is a fixed proportion smaller. Applying the same algorithm on the now smaller set recursively until only one or two elements remain results in a cost of

**Algorithm**

1. General Template of the Selection Algorithm: As stated earlier, median-of-medians is used as a pivot selection strategy in the quickselect algorithm. Typical implementations carefully handle the left and the right indexes, as well as the ; it is better to use the same index for the left, the right, and to avoid handle index conversion.
2. Median-of-Median Partition Function: Typical implementations also contain a partition routine that can, in linear time, group the list of indexes ranging from left to right into three parts – those less than a certain element, those equal to it, and those greater than the element, in a three-way problem. The grouping into three parts ensures that the media-of-medians maintains a linear execution time in the case of many or all coincident elements.
3. Median-of-medians Pivot Selector: The Pivot function is the actual median-of-medians algorithm. It divides its input – a list of length – into groups of at most elements, computes the median of each of these groups (see below), then recursively computes the true median of the medians found in the previous step (Cormen, Leiserson, Rivest, and Stein (2009)). Pivot function calls the select function above; this is an instance of mutual recursion.
4. Median-of-medians - Subset Median Calculator: The median selector of a group of at most elements is often built into its own function; an easy way to implement this is insertion sort (Cormen, Leiserson, Rivest, and Stein (2009)). It can also be implemented as a decision tree.

**Properties of the Pivot**

Of the groups, half the number of groups, i.e.,

have their median less than the pivot, the median-of-medians. Another half the number of groups, again

have their median greater than the pivot. In each of the groups less than the pivot, there are two elements smaller than their respective medians, which are smaller than the pivot. Thus, each of the groups have at least elements that are smaller than the pivot. Similarly, in each of the groups with median greater than the pivot, there are two elements that are greater than their respective medians, which are greater than the pivot. Thus, each of the groups have at least elements that are greater than the pivot. Hence, the pivot is less than elements and greater than another elements. Therefore, the chosen median splits the elements somewhere between and , which assumes worst-case linear behavior of the algorithm.

**Proof of Running Time**

1. Expression for the Time Taken: Let be the time it takes to run a median-of-medians quickselect algorithm on any array of size . From the analysis above, this time is
2. Components of the Time Taken:
   1. The part is for finding the *true* median of the medians, by running an independent quickselect on them, since finding a mean is just a special case of selecting a -largest element.
   2. The term is for the partitioning work to create the two sides, one of which quickselect will recurse on. Each element is visited a constant number of times in order to form them into groups and take each median in time.
   3. The part is for the actual quickselect recursion fort the worst case, in which the element is in the bigger partition that may be of size maximally.
3. Proof of Linear Time Consumption: From the above, using induction one can easily show that

**Analysis**

1. Origin of the Linear Runtime: The key step is reducing the problem to selecting two links whose total length is shorter than the original list, plus a linear factor for the reduction step. This allows a simple induction to show that the overall running time is linear.
2. Choice of Five-Element Groups: The specific choice of the group of five elements is explained as follows. First, computing the median of an odd list is faster and simpler; while one could use an even list, this would require taking the average of the two middle elements, which is slower than simply selecting the exact middle element. Second, five is the smallest odd number such that the median-of-medians works. With groups of only three elements, the resulting list of medians to search in is of length , and this reduces the list to recurse into length . Thus, this still leaves elements to search in, not reducing the problem sufficiently. The individual lists are shorter, however, and one can bound the resulting complexity to by the Akra-Bazzi method, but it does not prove linearity.
3. Increasing the Size of Groups: Conversely, one may instead group by , , or more elements (), and this does work. This reduces the size of the list of medians to , and the size of list to recurse asymptotes at , as the quadrants approximate at , since the size of the overlapping lines decreases proportionally. This reduces the scaling factor from asymptotically down to , but accordingly raises the term for the partitioning work. Finding the median of a larger group takes longer, but it is a constant factor that depends only on , and thus does not change the overall performance as grows. In fact, considering the number of comparisons in the worst-case, the constant factor is .
4. Fixed Number of Lists in the Array: If one instead groups the other way, say dividing the element list into lists, computing the median of each, and then computing of these – grouping by a constant fraction, not a constant number - one does not as clearly reduce the problem, since it requires computing 5 medians, each in a list of elements, and then recursing on a list of length at most . As with grouping by , the overall length is not shorter – in fact, longer – and one can thus only prove super-linear bounds. Grouping into a square of lists of length is similarly complicated.

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**Floyd-Rivest Algorithm**

**Overview**

1. Focus of the Floyd-Rivest Algorithm: The *Floyd-Rivest algorithm* is a selection algorithm that has an optimal expected number of comparisons within lower-order terms (Wikipedia (2019)). It is functionally equivalent to quickselect, but runs faster in practice than average (Floyd and Rivest (1975a, 1975b)). It has an expected running time of and an expected number of comparisons of .
2. Algorithm Characteristics:

|  |  |
| --- | --- |
| **Class** | Selection Algorithm |
| **Data Structure** | Array |
| **Average Performance** |  |

**Algorithm**

1. Structure of the Floyd-Rivest Algorithm: The Floyd-Rivest algorithm is a divide-and-conquer algorithm, sharing many similarities with quickselect. It uses sampling to help partition the list into three sets. It then recursively selects the smallest element from the appropriate set.
2. Drawing a Small Random Sample: Select a small random sample from the list .
3. Selection of the Partition Pivots: From recursively select two elements and such that

These two elements will be the *pivots* for the partition and are expected to contain the smallest element of the entire list between them – in a sorted list.

1. Partition into Three Subsets: Using and partition into three subsets; , , and . will contain elements with values less than , will contain elements with values between and , and will contain the elements with values greater than .
2. Assign Elements into Appropriate Subsets: Partition the remaining elements in , that is, the elements in , by comparing them to or and placing them into the appropriate set. If is smaller than half the number of elements in rounded up, the remaining elements should be compared to first and then only to if they are smaller than . Otherwise, the remaining elements should be compared to first and only to if they are greater than .
3. Recursively Extracting the Order Statistic: Based on the value of , apply the algorithm recursively to the appropriate set to select the smallest element in .

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**Introselect**

**Overview**

1. Idea behind the Introselect Algorithm: *Introselect* – short for *introspective selection* – is a selection algorithm that is a hybrid of quickselect and median of medians which has fast average performance and optimal worst-case performance (Wikipedia (2020)).
2. Relation to the Introsort Algorithm: Introselect is related to the introsort sorting algorithm: these are analogous refinements to basic quicksort and quickselect algorithm, in that they both start with the quick algorithm, which has good optimal performance and low overhead, but fall back to an optimal worst-case algorithm – with higher overhead – if the quick algorithm does not progress rapidly enough.
3. Optimal Average and Worst Cases: Both algorithms were designed by Musser (1997) with purpose of providing generic algorithms for the C++ Standard Library that have both fast performance and optimal worst-case performance, thus allowing the performance requirements to be highlighted.
4. Algorithm Characteristics:

|  |  |
| --- | --- |
| **Class** | Selection Algorithm |
| **Data Structure** | Array |
| **Worst-case Performance** |  |
| **Best-case Performance** |  |

**Algorithm**

1. Methodology of the Introsort Algorithm: Introsort achieves practical performance comparable to quicksort while preserving worst-case behavior by creating a hybrid of quicksort and heapsort. Introsort starts with quicksort, so it achieves performance similar to quicksort if quicksort works, and falls back to heapsort – which has optimal worst-case performance – if the quicksort does not progress quickly enough.
2. Methodology of the Introselect Algorithm: Introselect works by optimistically starting out with quickselect and switching to a linear time worst-case selection algorithm – the Blum-Floyd-Pratt-Rivest-Tarjan median-of-medians algorithm – if it recurses too many times without making sufficient progress. The switching strategy is the main technical content of this algorithm. Simply limiting the recursion to constant depth is not good enough, since this would make the algorithm switch on all sufficiently large lists. Musser (1997) discusses a couple of simple approaches.
3. Tracking Sized of the Processed Sub-partitions: Keep track of the list of sizes of the sub-partitions processed so far. If at any point recursive calls have been made without halving the list size, for some positive small , switch to the worst-case linear algorithm.
4. Tracking Cumulative Sizes of the Generated Partitions: Sum the sizes of all the partitions generated so far. If this exceeds the list size times some small positive constant switch to the worst-case algorithm. The sum is easy to track on a single scalar variable.
5. Guaranteed Limit on Recursion Depth: Both approaches limit the recursion depth to

and the total running time to .

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**Order Statistic Tree**

**Overview**

1. Order Statistic Tree Operations Supported: An *order-statistic tree* is a variant of a binary search tree – or, more generally, a B-tree – that supports two additional operations beyond insertion, lookup, and deletion:
   1. => Finds the smallest element stored in the tree
   2. => Finds the rank of element in the tree, i.e., its index in the sorted list of elements of the tree
2. Time Complexity of the Extra Operations: Both operations can be performed in worst-case time when a self-balancing tree is used as the base data structure.

**Augmented Search Tree Implementation**

1. Augmenting the Regular Search Tree: To turn a regular search tree into an order-statistic tree, the nodes of the tree need to store one additional value, which is the size of the sub-tree rooted at that node, i.e., the number of nodes below it.
2. Invariants Mandated during Tree Modifications: All operations that modify the tree must adjust this information to the preserve the invariant

where

by definition.

1. Implementation of Select and Rank: Implementation of and is fairly trivial, as is illustrated in Cormen, Leiserson, Rivest, and Stein (2009) and Wikipedia (2019).
2. Additional Augmentations for Specific Trees: Order-statistic trees can be further amended with book-keeping information to maintain balance, i.e., the tree height can be added to get an order statistic AVL tree, or a color bit to get a red-black order statistic tree. Alternatively, the size field can be used in conjunction with w weight-balancing scheme at no additional storage cost (Roura (2001)).

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**Maximum Sub-array Problem**

**Overview**

1. Maximum Sum Subarray Problem: The *maximum sum subarray problem* is the task of finding a contiguous subarray with the largest sum within a given one-dimensional array of numbers. Formally, the task is to find indexes and with

such that the sum is as large as possible (Wikipedia (2020)). Some formulations of the problem also allow the empty subarrays to be considered; by convention, the sum of all values of the empty subarray is zero. Each member in the input array can be positive, negative, or zero (Bentley (1989)).

1. Maximum Sum Subarray Problem Characteristics: Some properties of the problem are:
   1. If the array contains all negative numbers, then the problem is trivial; the maximum subarray is the entire array.
   2. If the array contains all non-positive numbers, then a solution is any subarray of size containing the maximal value of the array, or the empty subarray, if it is permitted.
   3. Several different subarrays may have the same maximum sum.
2. Approaches to Solving the Problem: As discussed in Bentley (1989), this problem can be solved using several different algorithmic techniques, including brute-force, divide-and-conquer, dynamic programming, and reduction to shortest paths.

**Background**

1. Digitized Images Simplified MLE Model: The maximum subarray problem was proposed by Ulf Grenander in 1977 as a simplified model for the maximum likelihood estimation of patterns in digitized images (Bentley (1984)).
2. Rectangular Subarray with Maximum Sum: Grenander was looking to find a rectangular subarray with maximum sum in a 2D array of real numbers. A brute-force approach to the 2D problem runs in time; because this was prohibitively slow, Grenander proposed the 1D problem to gain insight into the structure.
3. Solution for the 1D Problem: Grenander derived an algorithm that solves the problem in time, improving the brute-force running time of . He did this by using a pre-computed table of cumulative sums

to compute the subarray sum

in constant time.

1. Improvements by Shamos and Kadane: Michael Shamos devised an divide-and-conquer algorithm for it. Jay Kadane designed a algorithm (Gries (1982), Bentley (1984, 1989)), which is as fast as possible, since every algorithm must at least scan the array once, which already takes time.
2. Solutions of Gries/Bird: Gries (1982) obtained the same -time algorithm by applying Dijkstra’s *standard strategy*; Bird (1989) derived it purely by algebraic manipulation of the brute-force algorithm using the Bird-Meertens formalism.
3. 2D Distance-Matrix Multiplication Approaches: Grenander’s 2D generalization can be solved in time either by using Kadane’s algorithm as a sub-routine, or through a divide-and-conquer approach. Slightly faster algorithms based on distance-matrix multiplication have been proposed by Tamaki and Tokuyama (1998) and Takaoka (2002).
4. Optimality of the above Solutions: There is some evidence that no significantly faster algorithm exists; an algorithm that solves the 2D maximum subarray problem in time, for any

would imply a similarly fast algorithm for the all-pairs shortest paths problem (Backurs, Dikkala, and Tzamos (2016)).

**Applications**

1. Usage in Genomic Sequence Analysis: Genomic sequence analysis employs maximum subarray algorithms to identify important biological segments of protein sequences. These problems include conserved segments, GC-rich regions, tandem-repeats, low- complexity filters, DNA binding domains, and regions of high charge.
2. Brightest Areas in Bitmap Images: In computer vision, maximum subarray algorithms are used on bitmap images to detect the brightest area in an image.

**Kadane’s Algorithm**

1. Basic Thrust of the Algorithm: Kadane’s algorithm scans the given array from left to right. At the step, it computes the subarray with the largest sum ending at ; the sum is maintained in the variable . Moreover, it computes the subarray with the largest sum anywhere in , maintained in the variable , and easily obtained as the maximum of all values of so far.
2. Running Update of the Variable: As a loop invariant, in the step, the old value of holds the maximum over all

of the sum – note that the sum is when

corresponding to the empty subarray . Therefore, is the maximum over all

of the sum . To extend the latter maximum to cover also the case

it is sufficient also to consider the empty subarray . This is done by assigning as the new value of , which after that holds the maximum over all

of the sum .

1. Disallowing the Empty Subarray Inputs: The above version of the algorithm will return if the input contains no positive elements – including when the input is empty. For a variant of the problem that allows empty subarrays, should be initialized to instead (Bentley (1989)). Further, should be updated as In the case where the input contains no positive element, the returned value is that of the largest element, i.e., the least negative value, or if the input array is empty.
2. Starting/Ending Maximum Subarray Indexes: The algorithm can be modified to keep track of the starting and the ending subarray indexes of the maximum subarray as well.
3. Trivial Instance of Dynamic Programming: Because of the way the algorithm uses optimal structures, i.e., the maximum subarray ending at each position is calculated in a simple way from a related but smaller and overlapping problem – the maximum subarray ending at the previous position – this algorithm can be viewed as a simple/trivial example of dynamic programming.
4. Runtime Complexity of the Algorithm: The runtime complexity of Kadane’s algorithm is (Gries (1982), Bentley (1989)).

**Generalizations**

1. Higher Dimension Maximum Subarray Sums: Similar problems may be posed for higher dimensional arrays, but their solutions are more complicated, see, e.g., Takaoka (2002).
2. Largest Subarray Sums in 1D: Brodal and Jorgensen (2007) show how to find the largest subarray sums in a 1D array, in the optimal time bound .
3. Maximum Sum Disjoint Subarrays: The maximum sum disjoint subarrays can also be computed in optimal time bound (Bengtsson and Chen (2007)).

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**Subset Sum Problem**

**Overview**

1. Statement of the Subset Sum Problem: The *subset sum problem* is an important decision problem in complexity theory and crystallography. There are equivalent formulations of the problem. One of them is: given a set – or multi-set – of integers, is there a non-empty subset whose sum is zero? The problem is **NP**-complete, meaning that while it is easy to confirm whether a proposed solution is valid, it may be inherently prohibitive to determine in the first place whether any solution exists (Wikipedia (2020)).
2. Relationship to Knapsack and Partition Problems: The problem can be equivalently formulated as follows: Given the integers or natural numbers does any subset of them sum precisely to (Kleinberg and Tardos (2022))? Subset sum can be thought of as a special case of the knapsack problem (Martello and Toth (1990)). One interesting special case of the subset sum is the partition problem, in which is half the sum of all the elements in the set, i.e.,

**Complexity**

1. Parameters Determining the Problem Complexity: The complexity of the subset sum problem can be viewed as depending on two parameters - , the number of decision variables, and , the precision of the problem, stated as the number of binary digit values that it takes to state the problem.
2. Exponential Complexity on the Smaller Parameter: The complexity of the best-known algorithms is exponential in smaller of the two parameters and . Thus, the problem is most difficult if and are of the same order. It only becomes easy if either or becomes very small.
3. Solutions for Small : If – the number of variables – is small, then an exhaustive search for the solution is practical. If – the number of digit values – is a small fixed number, then there are dynamic programming algorithms that can solve it exactly. Efficient algorithms for both small and small cases are given below.

**Exponential Time Algorithm**

1. Naïve Exponential in Approach: There are several ways to solve the subset sum problem in time exponential in . The most naïve algorithm would be to cycle through all subsets of numbers, and, for every one of them, heck if the subset sums to the correct target. The running time is of the order , since there are subsets, and, to check each subset, one needs to sum at most elements.
2. Sum Lists of Split Subsets: A better exponential time algorithm is known which works in time . The algorithm splits arbitrarily the elements into two sets of each. For each of the two sets, it stores a list of the sums of all possible subsets of its elements.
3. Sorted List of Subset Sums: Each of these two lists is then sorted. Using a standard comparison sorting algorithm for this step would take time .
4. Sorting/Merging an Extra Element: However, given a sorted list of sums for elements, the list can be expanded into two sorted lists with the introduction of a element, and these two sorted lists can be merged in time . Thus, each list can be generated in sorted form in time .
5. Sum across Two Sorted Lists: Given the two sorted lists, the algorithm can check if the element of the first array and an element of the second array sum up to in time . To do that, the algorithm passes through the first array in decreasing order – starting at the largest element – and the second array in increasing order – starting at the smallest element. Whenever the sum of the first element in the current array and the current element in the second array is more than , the algorithm moves to the next element in the first array. If it is less than , the algorithm moves to the next element in the second array. If two elements that sum to are found, it stops (Horowitz and Sahni (1974)).

**Pseudo-polynomial Time Dynamic Programming Solution**

1. Setup of Dynamic Programming Framework: The problem can be solved in pseudo-polynomial time using dynamic programming. Suppose the sequence is sorted in the increasing order, and one wishes to determine if there is a non-empty subset that sums to .
2. Dynamic Programming Boolean Decision Function: Define the boolean valued function to be the value – *true* or *false* – of: “there is a non-empty subset of which sums to ”. Thus, the solution to the problem “Given a set of interest, is there a non-empty subset whose sum is zero?” is .

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