

Shahar Perets ~ DS Shit Cheat Sheet

(1.0) ADTs

List. List(), Retrieve(L, i), Insert(L, b, i), Delete(L, i), Length(L) *optional*: Search(L, b), Concat(L_1, L_2), Plant(L_1, i, L_2), Split(L, i) *special cases*: Retrieve/Insert/Delete-First/Last.

Dictionary. Dictionary(), Insert(D, X), Delete(D, x), Search(D, k), Min($D()$), Max($D()$), Successor(D, x), Predecessor(D, x) (for rank trees): Select(D, k) [the k^{th} smallest element], Rank(D, k) [the position in sorted order].

Stack. (LIFO) Push(L, b) [=ins.-last], Top(L) [=ret.-last], Pop(L) [=del.-last]. (all $\mathcal{O}(1)$ using arrays)

Queue. (FIFO) Enqueue(L, b) [=ins.-last], Head(L) [=ret.-first], Dequeue(L) [=del.-first]. (all $\mathcal{O}(1)$ using circular arrays)

Deque. Queue + Stack

Priority Queue. Insert(x, Q), Min(Q), Delete-Min(Q), (optional:) Decrease-Key(x, Q, Δ), Delete(x, Q)

Vector. Vector(m), Get(V, i), Set(V, i , val). (All $\mathcal{O}(1)$ using *legals* and *positions* arrays that reference each other) d

```
function isGarbage(i) is
    if 0 ≤ positions[i] <= legals.size and
       legals[positions[i]] = i then
        return false
    end
    return true
end
Graph. Edge( $i, j$ ), Add-Edge( $i, j$ ), Remove-Edge( $i, j$ ), InDeg( $i$ ), OutDeg( $i$ ) etc.
```

(2.0) Graphs

Definition 1 (Topological sorting algo.). Input: directed graph / Output: numbering $(n_i)_{i=1}^N$ of the graph nodes where $\forall (i, j) \in E: n_i < n_j$.

Theorem 1. Topological Sorting exists iff the graph doesn't contain cycles

```
while there are sources do
    find source v;
    n_i ← k;
    k ← k + 1;
    remove v from the graph
end
if k = n numbering completed, otherwise isn't possible.
```

building “source queue” takes $\mathcal{O}(n)$, dequeuing source $\mathcal{O}(1)$, and enqueueing new sources to sources-queue $\mathcal{O}(d_{\text{out}}(i))$. Total $\mathcal{O}(n + m)$ for topological ordering.

Definition 2. A *source* is a node that has no incoming edges.

Remark 1. any DAG has at least one source

(3.0) Complexity

Definition 3. Suppose there's a data structure with k types of operations $(T_i)_{i=1}^k$, then for sequence of operations $(op)_{i=1}^n$, then:

$$\text{time}(op_1 \dots op_n) \leq \sum_{i=0}^n \text{bound}(\text{type}(op_i))$$

Where (W.C. bound) $\text{worst}(T_i)$ is the maximal time for a single operation typed T_i , and (amortized bound) $\text{amort}(T_i)$ is a series of bounds for cost of every valid sequence $(op_i)_{i=1}^n$.

Amortization methods. aggregation (regular average), accounting (bank method), and potential function (defined to be the balance of the bank) that satisfies $\text{amort}(op_i) = \text{time}(op_i) + \Phi_i - \Phi_{i-1}$.

Potential for doubling by $1 + \alpha$. $\Phi := \begin{cases} \frac{1+\alpha}{\alpha}n - \frac{M}{\alpha} & n > \frac{M}{\alpha+1} \\ 0 & \text{else} \end{cases}$ yields to un amortized bound of $\mathcal{O}\left(\frac{1+\alpha}{\alpha} + 1\right)$

$$\sum_{i=0}^n x^i = \frac{x^{n+1}-1}{x-1} = \Theta(x^n) (x \neq 1)$$

$\sum_{i=1}^n \frac{1}{i} = H_n = \Theta(\log n)$ $\log n! = \Theta(n \log n)$
Theorem 2. $\alpha + \beta = 1 \wedge T(n) \leq cn + T(\alpha) + T(\beta n) \implies T(n) = \mathcal{O}(n)$.

(3.1) Asymptotic Notations

$f = \mathcal{O}(g) \iff \exists n_0, c > 0 \forall n \geq n_0: f(n) \leq cg(n)$
 $f = \Omega(g) \iff \exists n_0, c > 0 \forall n \geq n_0: f(n) \geq cg(n)$
 $f = \Theta(g) \iff f = \Omega(g) \wedge f = \mathcal{O}(g)$
 $f = o(g) \iff \forall c \exists n_0 \forall n \geq n_0: f(n) \leq cg(n)$
 $f = \omega(g) \iff \forall c \exists n_0 \forall n \geq n_0: f(n) \geq cg(n)$
 $f = \Omega(g) \iff g = \mathcal{O}(f)$

$$f_1 = \mathcal{O}(g_1) \wedge f_2 = \mathcal{O}(g_2) \implies f_1(n) + f_2(n) = \mathcal{O}(\max(g_1(n), g_2(n)))$$

$$f = \mathcal{O}(g) \iff \limsup_{n \rightarrow \infty} \frac{f(n)}{g(n)} < \infty$$

$$f = \Omega(g) \iff \limsup_{n \rightarrow \infty} \frac{f(n)}{g(n)} > 0$$

$$f = o(g) \iff \lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0$$

$$f = \omega(g) \iff \lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \infty$$

(3.2) Master Theorem

let $f: \mathbb{R} \rightarrow \mathbb{R}$ be an function, and let $a \leq 1, b > 1$ be constants, assuming $T: \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}$, $T(n) = a \cdot T\left(\frac{n}{b}\right) + f(n)$, then:

- $\exists \epsilon > 0. f(n) = \mathcal{O}(n^{\log_b a - \epsilon}) \implies T(n) = \Theta(n^{\log_b a})$
- $f(n) = \Theta(n^{\log_b a}) \implies T(n) = \Theta(n^{\log_b a} \cdot \log n)$
- $\exists \epsilon > 0. f(n) = \Omega(n^{\log_b a + \epsilon}) \wedge \exists c > 1, n_0 \geq 0. \forall n \geq n_0. a \cdot f\left(\frac{n}{b}\right) \leq c \cdot f(n) \implies T(n) = \Theta(f(n))$

Note that $\frac{n}{b}$ could be $\left\lfloor \frac{n}{b} \right\rfloor$ nor $\left\lceil \frac{n}{b} \right\rceil$

(4.0) Dictionaries

(4.1) General Trees

Definition 4. a in *full* tree all internal nodes have exactly i children.

Definition 5. a *BST* satisfies: $\forall x \forall y$ if y is in the left subtree of x , then $y.\text{key} < x.\text{key}$, and vise-versa.

Definition 6. *height* of a node = maximal length of down-ward path between that node and a leaf.

Definition 7. *depth* of a node is the length of the path up the tree to the root.

Theorem 3. *minimal height of a tree is $\lfloor \log n \rfloor$*

Definition 8. a *BST* is balanced if $h = \mathcal{O}(\log n)$

Theorm 4. for a given set of n distinct keys, there are $\frac{1}{n+1} \binom{2n}{n}$ (catalan number) *BSTs*.

Theorm 5. the expected search complexity in a random *BST* is $\leq (1 + 4) \log n$.

Lemma 1. the heights of a binary tree containing ℓ leaves $\geq \log \ell$.

Tree walks. pre: head \rightarrow SLR, in: LSR, post: LRS

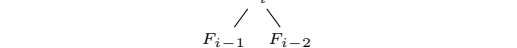
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(4.2) AVL trees

Definition 9. an AVL tree is a *BST* where $\forall v \in V: |\text{BF}(v)| \leq 1$

Theorm 6. and AVL tree is balanced. Further more: $n \leq \log_{\phi} n \approx 1.44 \log n$.

Definition 10. Fibonacci tree F_i is:



Theorm 7. an AVL tree with minimum edges is a fibonacci tree, sized $f_n = \frac{\phi^n - \bar{\phi}^n}{\sqrt{5}}$, $\bar{\phi} = \frac{1 + \sqrt{5}}{2}$.

Definition 11. a *rank tree*, is a tree that maintains the size of each subtree, hence supports the rank & select operations in $\mathcal{O}(\log n)$.

Theorm 8. if the information that a given attribute f defined for each node, can be computed merely from its direct children (local attribute), then we can maintain f in an AVL tree.

Lemma 2. the sum of the keys lesser than v , and the sum of the keys in the subtrees, can be implemented both without harming time complexity.

Lemma 3. Between $(s, t) = \text{Tree-Rank}(t) - \text{Tree-Rank}(s) + 1$

Remark 2. The theorem above is sufficient condition but not necessary.

Definition 12. a *Finger Tree* is a tree that has a pointer to a specific node.

Theorm 9. in a finger tree *Select*(T, k) can be implemented in $\mathcal{O}(\log k)$.

Theorm 10. Given a sorted array, we can create an AVL tree in $\mathcal{O}(n)$ on which $h = \lfloor \log n \rfloor$

Join(T_1, T_2): where $T_1 < x < T_2$ is done $\mathcal{O}(h_{T_1} + h_{T_2} + 1)$ (see image). Split(T, x): splits T into $T_1 < x < T_2$ in $\mathcal{O}(\log n)$ using joins.

(4.3) B-trees

Definition 13. a *B-tree* ($d, 2d$) satisfies:

- each non-leaf expect for the root has $d \leq r \leq 2d$ children (hence $d - 1$ to $2d - 1$ keys);
- all leaves are at the same depth;
- the root has between 2 and $2d$ children (hence 1 to $2d - 1$ keys).

Definition 14. a B^+ -tree is a B-tree with keys only on leafs.

Definition 15. a B^* -tree is a B-tree with nodes $\frac{2}{3}$ full (instead of $\frac{d}{2d} = \frac{1}{2}$ full).

Theorm 11. at depth h there are at least $2d^{h-1}$ nodes.

Theorm 12. a *B-tree* ($d, 2d$) with n edges and h height fulfills $n \geq d^h$, $h \leq \log_d n$

Theorm 13. search in a *b-tree* requires $\mathcal{O}(\log_d n)$ I/Os, and $\mathcal{O}(\log_2 d \cdot \log_d n) = \mathcal{O}(\log n)$ operations in total.

Lemma 4. In a B-tree #leaves = #internal nodes + 1

Theorm 14. Ins./Del. rebalancing cost is W.C. $\mathcal{O}(\log n)$, and using button-up amort. (ins.+del.) $\mathcal{O}(1)$, using top-down $\Omega(\log_d n)$

Insertions

Button-Up. Find and insert in the appropriate leaf. If the current node is overflowing: split. If the parent is overflowing: split (etc., recursively). Requires a total of $\mathcal{O}(d \log_d n)$ operations.

Top-Down. if a node is full, we will split it on the way down while searching.

Button-Up non-leaf deletion. replace the item by its predecessor and delete the predecessor (must be a leaf).

Deletions

Button-Up leaf deletion. if the current node is underflowing, borrow and terminate and if not possible fuse and recursively check if the parent if underflowing.

Top-Down leaf deletion. while searching, checking if the items along the way contains d keys, otherwise borrow or fuse.

Top-Down non-leaf deletion. replace the node with its predecessor, while making sure that nodes along the way contains at least d keys.

(5.0) Priority Queue

(5.1) Binary Heap

Definition 16. a *binary minimum binary heap* is an almost perfect BST (only possibly misses nodes at the last level), and satisfies the heap order: the keys at the children of v are greater than they key in v .

Lemma 5. the height of binary heap is $\lfloor \log n \rfloor$

Theorm 15. in a d -ary heap representation as an array (in brackets for binary):

$$\text{Left}(i) = dk - (d - 2) \quad (2i) \quad \text{Right}(i) = dk + 1 \quad (2i + 1)$$

$$\text{Parent}(i) = \left\lfloor \frac{k + (d - 2)}{d} \right\rfloor \quad \left(\left\lfloor \frac{i}{2} \right\rfloor \right)$$

Heapify-Down(i): if **Parent**(i) is bigger, then replace i with **Parent**(i), and recursively continue on **Parent**(i).

Heapify-Up(i): exchange with the smallest child until fixed.

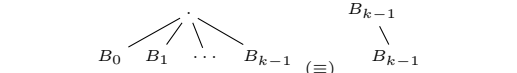
Insert: insert on the last place in the array, then heapify up. **Delete:** delete the required place in the array (the root) the replace it with the last one, then heapify down until fixed (in d -ary $\mathcal{O}(d \log_d n)$).

Dec-Key: decrease the key (assumes $\Delta \geq 0$) then heapify up. **Init:** iterate over internal nodes bottom-up, and heapify-down each one.

HeapSort: create a min-heap from input, the do delete-min and put the deleted element at the last position of the array. Repeat n times. At the we get a reversely-sorted array (using min-heaps).

(5.2) Binomial Trees

Definition 17. B_k is a binomial tree of degree k if



Theorm 16. (1) The root of B_k has k children (2) B_k contain 2^k nodes (3) its depth is k (4) $\binom{k}{i}$ of the nodes of B_k are at level i .

Definition 18. A *binomial min-heap* is a list of heap-ordered binomial trees, at most one of each degree, and a pointer to the root with the minimal key.

note: usually the trees are saved using a linked list.

Lemma 6. There are at most $\lfloor \log n \rfloor + 1$ trees.

Link: if two binomial trees x, y has the same degree, linking could be preformed in $\mathcal{O}(1)$ by attaching y as a child of x and replacing the roots if needed.

Insert: insertion could be done the same way as binary incrementing, where linking \equiv carrying.

Dec-Key: just heapify up as before.

Meld: link trees with the same degree, like binary addition. **Del-Min:** the children of the deleted root are a binomial heap, Meld them into the main tree.

Lazy Binomial Trees adds just B_0 -s (allows melding in $\mathcal{O}(1)$), and consolidates when runs delete-min.

Consolidating (on del-min) is the process of taking the nodes and adding them into respected bins (numbered $0 \dots \lfloor \log n \rfloor$), and when two trees are in the same bin – linking them together and moving them into the next bin.

Definition 19. T_0 is #trees before Del-Min, T_1 after Del-Min, and L is the total #Links through consolidating.

Lemma 7. $L \leq T_0 + \log n$ (we have at most $\lfloor \log n \rfloor$ trees exposed on Del-Min)

Theorm 17. The cost of consolidating is $T_0 - 1 + \log n + L = \Theta(T_0 + \log n)$.

Theorm 18. Using $\Phi = \#trees$ we get $\Delta \Phi = T_1 - T_0$ hence amort. cost of consolidating is $\mathcal{O}(\log n)$.

Lemma 8. incrementing a binary number has an amortized bound of $\mathcal{O}(1)$.

(5.3) Fibonazi Heaps

(6.0) Sorting

(6.1) Comparison-based sorting

Theorm 19. insertion sort with $I > n$ inversions ($I \leq \binom{2n}{2}$) takes $\mathcal{O}\left(n \log \frac{I}{n}\right)$.

Definition 20. *stable sort* is a sorting algo. the preserves order of items with the same key.

Definition 21. a comparison-based algo. uses only two-key comparisons to decide on key position.

assumption. two keys can be compared in $\mathcal{O}(1)$, and an item can be moved in $\mathcal{O}(1)$.

Theorem 20. the *W.C.* and average case of any comparison-base sorting algo. runs in $\Omega(n \log n)$

Lemma 9. comparison trees are a full binary tree, and has $\geq n!$ leafs.

Theorem 21. the worst/best/average case in the comparison-based model is the max/min/average depths of the leafs.

(6.2) **Other sorting algos.**
HeapSort: see 5.1. **Count sort.** For dataset A , assumes $\exists R \forall a \in A \leq R$ constant. Counts each element $a \in A$, takes a cumulative sum (a_i), then for all $a \in A$ puts a in a_i and decreases $a_i \leftarrow a_i - 1$. Takes $\mathcal{O}(n + R)$. Stable sort.

Count sort. similar to count sort, takes R bins and throws A into them, then collects them.

Radix sort. For a dataset A sized n , assumes $a \in A$ contains exactly d digit and each digit is bounded by b . Preforms count sort on the LSD \rightarrow MSD. [note: relies on count sort being stable]. Takes $\mathcal{O}(d(n + b))$.

Theorem 22. Radix sort is enough to make IBM.

(6.3) **QuickSort**
Homuto's Partition.
Hoare's Partition.

Theorem 23. *W.C.* of quicksort if $\binom{n}{2} = \mathcal{O}(n^2)$.

Theorem 24. Average case of quicksort is $2(n + 1)H_n - 4n \approx 1.39n \log n$.

(7.0).....**Probability**

Definition 22. an *Experiment* is a case where we the result is uncertain.

Definition 23. the *Sample Space* is the set of all the expected outcomes of a given experiment.

Definition 24. an *Event* is a subset of the sample space. A singleton subset called a *simple event*.

Definition 25. *Disjoint Events* are events A, B that fulfills $A \cap B = \emptyset$.

Definition 26. a *Probability Function* is a function $P: S \rightarrow [0, 1]$ for S sample space, so that $\forall E, F$ disjoint: $P(E \cup F) = P(E) + P(F)$ and $P(S) = 1$.

Theorem 25. for disjoint events $(F_i)_{i=1}^n$, if $\bigcup F_i = E$ then $\forall E: P(E) = \sum_{i=0}^n P(E \mid F_i) \cdot P(F_i)$.

(11.0).....

Lists						
let mid := min{i, n - i} + 1						
	Ins/Del-Last	Ins/Del-First	Ins(i)	Retrieve(i)	Concat(n_1, n_2)	Split(i)
Arrays	$\mathcal{O}(1)$	$\mathcal{O}(n + i)$	$\mathcal{O}(n - i + 1)$	$\mathcal{O}(1)$	$\mathcal{O}(n_2 + 1)$	$\mathcal{O}(n - i + 1)$
Circular Arr.	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(\text{mid})$	$\mathcal{O}(1)$	$\mathcal{O}(\min\{n_1, n_2\})$	$\mathcal{O}(\text{mid})$
D-Linked	$\mathcal{O}(1)$	$\mathcal{O}(1)$	$\mathcal{O}(\text{mid})$	$\mathcal{O}(\text{mid})$	$\mathcal{O}(1)$	$\mathcal{O}(\text{mid})$
AVL List	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log i + 1)$	$\mathcal{O}(\log(n_1 + n_2))$	$\mathcal{O}(\log n)$

(in a lazy doubly-linked list, amortized del./ins. $\mathcal{O}(1)$ and ret. $\mathcal{O}(i + 1)$)

Definition 27. events E, F are independent if $P(E \cap F) = P(E) \cdot P(F)$ (iff $P(E \mid F) = P(E)$).

Definition 28. a *Random Variable* if a function $X: S \rightarrow \mathbb{R}$.

Definition 29. $X = x$ is the event on which $X(E) = x$, and its probability noted as $P(X = x)$.

Definition 30. the *Expectation* of a random variable X is $\mathbb{E}[x] = \sum_x x \cdot P(X = x)$.

Theorem 26. the expectation is linear for all constants, and additive for all random variables.

Definition 31. a random variable I is called an *Indicator of an event A* if $I = \begin{cases} 1 & \text{if } A \text{ occurs} \\ 0 & \text{if } A^c \text{ occurs} \end{cases}$

Lemma 10. $\mathbb{E}[I] = P(A)$.

Definition 32. *Uniform Distribution* of a random variable X occurs when $\exists c: \forall x \in \mathbb{R}: P(X = x) = c$.

Definition 33. *Geometric Distribution* satisfies $P(x = k) = (1 - p)^{k-1}p$, hence $\mathbb{E}[X] = \sum_{k=1}^{\infty} k(1 - p)^{k-1}p = \frac{1}{p}$.

note: geometric dist. is equal to having the probability of succession p and for failure $p - 1$, and P is a rand. var. that is equal to the number of required experiments to get to an solution.

Theorem 27 (The Tail Formula). $\sum_{i=0}^m i \cdot P[X = i] = \sum_{i=1}^m P(X \geq i)$

(8.0).....**Selection**

Definition 34. given n numbers, **Select**(n) is defined to return the k^{th} smallest key.

This equals for the item in position k , assuming the array was sorted.

Definition 35. Dynamic settings assumes one-time building cost (e.g. **Tree-Select**).

Definition 36. Static settings is not a dynamic setting

Theorem 28. Using min-heap + supporting heap the selection problem is solvable is $\mathcal{O}(n + k \log k)$.

Theorem 29. The expected number of items removed during each quickselect run is $\mathbb{E}[\#\text{removed}] = \frac{k}{2} \cdot \frac{k}{n} + \frac{n-k}{2} \cdot \frac{n-k}{n} \geq \frac{n}{4}$.

Theorem 30. The expected runtime of quickselect is $\mathcal{O}(n)$.

Theorem 31. MedofMed cost is *W.C.* $\mathcal{O}(n)$.

(9.0).....**Hashing**

Direct Addressing. Create a bit vector with the universe size. e.g. $\text{Insert}(D, x)$ iff $D[x.\text{key}] \leftarrow x$ etc.

(9.1) **Chaining**

Lemma 11. There are $|m|^{|U|}$ hashes in $h \in U \rightarrow [m]$, hence takes $|U| \log m$ to store.

Chaining. each cell points to a linked list of items.

Definition 37. $\alpha := \frac{n}{m}$ where n is the universe, and m is the table size, and called the *load factor*.

Lemma 12. the probability of a random two specific insertions colliding is geometric.

Theorem 32. the expected number of values in each cell is α .

Theorem 33. when $n = \Theta(m)$, with probability $\geq 1 - \frac{1}{n}$, each cell contains at most $\mathcal{O}\left(\frac{\log n}{\log n \log n}\right)$ elements.

Theorem 34. Assuming the keys are distributed ideally (uniformly and independently), and assuming n keys were previously inserted, the expected complexity during search is $\alpha + 1$ for unsuccessful and $\frac{\alpha}{2} + 1$ for a successful search.

(9.2) **Open Addressing**

Open Addressing. let $h: U \times [m] \rightarrow [m]$ be a hash function, we'll insert the key k in the first free position in the probing sequence.

Note: make sure to use special marking (not null) for deleted items.

Theorem 35. Under ideal conditions ($\forall k \in [n]: P\left(\left(h(k, i)_{i=0}^{m-1}\right) = \frac{1}{m}\right)$), the expected time for unsuccessful search is $\frac{1}{1-\alpha}$ and fo successful search $\frac{1}{\alpha} \ln \frac{1}{1-\alpha}$.

Theorem 36. under linear probing, unsuccessful search takes $\frac{1}{2} \left(1 + \left(\frac{1}{1-\alpha}\right)^2\right)$ and successful search $\frac{1}{2} \left(1 + \frac{1}{1-\alpha}\right)$.

Note: under linear probing, we can delete by recursively checking if item j can me moved to deleted cell i for all $h'(T[j]) \in [j + 1, i]$.

Definition 38. *Linear Probing* is a hash func $h(k, i) := (h'(k) + i) \bmod m$ (less cache misses + easy to calculate).

Definition 39. *Quadratic Probing* is a hash func $h(k, i) := (h'(k) + ic_1 + c_2i^2) \bmod m$.

Definition 40. *Double Probing* is a hash func $h(k, i) := (h'(k) + ih''(k)) \bmod m$.

(9.3) **Hash Families**

Definition 41. hash family is *Universal* if $\forall k_1 \neq k_2 \in U: P_{h \in H}(h(k_1) = h(k_2)) \leq \frac{1}{m}$.

Theorem 37. For all p prime, $h_{a,b}: [p] \rightarrow [m]$ defined as $h_{a,b}(x) = ((ax + b) \bmod p) \bmod m$, and $H_{p,m} := \{h_{a,b} \mid a \in [1, p], b \in [0, p)\}$ is a universal hash family.

Theorem 38. for each p prime, let $x_1 \neq x_2 \in [p]$. Then $\forall y_1 \neq y_2 \in [p] \exists! a, b \in [p], a \neq 0: y_1 \equiv_p ax_1 + b \wedge y_2 \equiv_p ax_2 + b$.

Theorem 39. for a table $m = 2^k$ so $h_a: U = [2^w] \rightarrow [2^k]$ where w is computer word size, h_a defined as $\left\lfloor \frac{ax \bmod 2^w}{2^{w-k}} \right\rfloor$, and H is almost universal.

Definition 42. if $\forall k_1 \neq k_2 \in U: P_{h \in H}(h(k_1) = h(k_2)) \leq \frac{2}{m}$ then U is called almost universal.

Theorem 40. using universal hash family, $\mathbb{E}[\text{collisions}] \leq \frac{\binom{n}{2}}{m}$.

(9.4) **Perfect Hashing**
Content...

(10.0).....**Other**

Reduction. reduction (in our case) is the process of showing the a problem is at least as hard as another problem.

Information Bound. a bound derive by an argument that the algo. has to read a specified amount of the input, in order to get a decision. Notice that in comparison, reading isn't counted.

$$\sum_{i=1}^k \binom{k}{i} = 2^k$$
$$\binom{k}{i} = \binom{k-1}{i} + \binom{k-1}{i-1}$$

Theorem 41. merging k sorted arrays with the total of n items can be done in $\mathcal{O}(n \lfloor k \rfloor)$

.....**Complexity Tables**

Priority Queues							
	Insert	Minimum	Delete-Min	Dec.-Key	Delete	Meld	Init
AVL tree	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(n)$	$\mathcal{O}(n \log n)$
Binary Heap	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(n)$	$\mathcal{O}(n)$
W.C Binomial Heap	$\mathcal{O}(\log n)^{(*)}$	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(n)$
Lazy Amort.							
Binomial Stack	$\mathcal{O}(1)_{W.C.}$	$\mathcal{O}(1)_{W.C.}$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$	$\mathcal{O}(n)$
Amort. Fib. Heap:	$\mathcal{O}(1)_{W.C.}$	$\mathcal{O}(1)_{W.C.}$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$	$\mathcal{O}(\log n)$	$\mathcal{O}(1)$	

^{*}amortized $\mathcal{O}(1)$ for a sequence of operations from the same type.