## Lecture 4: Hashing

## Review

| Data Structure | Operations $O(\cdot)$ |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Container | Static | Dynamic |  | der |
|  | build (X) | find (k) | insert (x) <br> delete (k) | $\begin{aligned} & \text { find_min() } \\ & \text { find_max() } \end{aligned}$ | find_prev (k) find_next (k) |
| Array | $n$ | $n$ | $n$ | $n$ | $n$ |
| Sorted Array | $n \log n$ | $\log n$ | $n$ | 1 | $\log n$ |

- Idea! Want faster search and dynamic operations. Can we find $(\mathrm{k})$ faster than $\Theta(\log n)$ ?
- Answer is no (lower bound)! (But actually, yes...!?)


## Comparison Model

- In this model, assume algorithm can only differentiate items via comparisons
- Comparable items: black boxes only supporting comparisons between pairs
- Comparisons are $<, \leq,>, \geq,=, \neq$, outputs are binary: True or False
- Goal: Store a set of $n$ comparable items, support $f$ ind ( $k$ ) operation
- Running time is lower bounded by \# comparisons performed, so count comparisons!


## Decision Tree

- Any algorithm can be viewed as a decision tree of operations performed
- An internal node represents a binary comparison, branching either True or False
- For a comparison algorithm, the decision tree is binary (draw example)
- A leaf represents algorithm termination, resulting in an algorithm output
- A root-to-leaf path represents an execution of the algorithm on some input
- Need at least one leaf for each algorithm output, so search requires $\geq n+1$ leaves


## Comparison Search Lower Bound

- What is worst-case running time of a comparison search algorithm?
- running time $\geq$ \# comparisons $\geq$ max length of any root-to-leaf path $\geq$ height of tree
- What is minimum height of any binary tree on $\geq n$ nodes?
- Minimum height when binary tree is complete (all rows full except last)
- Height $\geq\lceil\lg (n+1)\rceil-1=\Omega(\log n)$, so running time of any comparison sort is $\Omega(\log n)$
- Sorted arrays achieve this bound! Yay!
- More generally, height of tree with $\Theta(n)$ leaves and max branching factor $b$ is $\Omega\left(\log _{b} n\right)$
- To get faster, need an operation that allows super-constant $\omega(1)$ branching factor. How??


## Direct Access Array

- Exploit Word-RAM $O(1)$ time random access indexing! Linear branching factor!
- Idea! Give item unique integer key $k$ in $\{0, \ldots, u-1\}$, store item in an array at index $k$
- Associate a meaning with each index of array
- If keys fit in a machine word, i.e. $u \leq 2^{w}$, worst-case $O(1)$ find/dynamic operations! Yay!
- 6.006: assume input numbers/strings fit in a word, unless length explicitly parameterized
- Anything in computer memory is a binary integer, or use (static) 64-bit address in memory
- But space $O(u)$, so really bad if $n \ll u \ldots \quad$ :(
- Example: if keys are ten-letter names, for one bit per name, requires $26^{10} \approx 17.6 \mathrm{~TB}$ space
- How can we use less space?


## Hashing

- Idea! If $n \ll u$, map keys to a smaller range $m=\Theta(n)$ and use smaller direct access array
- Hash function: $h(k):\{0, \ldots, u-1\} \rightarrow\{0, \ldots, m-1\}$ (also hash map)
- Direct access array called hash table, $h(k)$ called the hash of key $k$
- If $m \ll u$, no hash function is injective by pigeonhole principle
- Always exists keys $a, b$ such that $h(a)=h(b) \rightarrow$ Collision! :(
- Can't store both items at same index, so where to store? Either:
- store somewhere else in the array (open addressing)
* complicated analysis, but common and practical
- store in another data structure supporting dynamic set interface (chaining)


## Chaining

- Idea! Store collisions in another data structure (a chain)
- If keys roughly evenly distributed over indices, chain size is $n / m=n / \Omega(n)=O(1)$ !
- If chain has $O(1)$ size, all operations take $O(1)$ time! Yay!
- If not, many items may map to same location, e.g. $h(k)=$ constant, chain size is $\Theta(n) \quad:($
- Need good hash function! So what's a good hash function?


## Hash Functions

Division (bad): $\quad h(k)=(k \bmod m)$

- Heuristic, good when keys are uniformly distributed!
- $m$ should avoid symmetries of the stored keys
- Large primes far from powers of 2 and 10 can be reasonable
- Python uses a version of this with some additional mixing
- If $u \gg n$, every hash function will have some input set that will a create $O(n)$ size chain
- Idea! Don't use a fixed hash function! Choose one randomly (but carefully)!

Universal (good, theoretically): $\quad h_{a b}(k)=(((a k+b) \bmod p) \bmod m)$

- Hash Family $\mathcal{H}(p, m)=\left\{h_{a b} \mid a, b \in\{0, \ldots, p-1\}\right.$ and $\left.a \neq 0\right\}$
- Parameterized by a fixed prime $p>u$, with $a$ and $b$ chosen from range $\{0, \ldots, p-1\}$
- $\mathcal{H}$ is a Universal family: $\operatorname{Pr}_{h \in \mathcal{H}}\left\{h\left(k_{i}\right)=h\left(k_{j}\right)\right\} \leq 1 / m \quad \forall k_{i} \neq k_{j} \in\{0, \ldots, u-1\}$
- Why is universality useful? Implies short chain lengths! (in expectation)
- $X_{i j}$ indicator random variable over $h \in \mathcal{H}: \quad X_{i j}=1$ if $h\left(k_{i}\right)=h\left(k_{j}\right), X_{i j}=0$ otherwise
- Size of chain at index $h\left(k_{i}\right)$ is random variable $X_{i}=\sum_{j} X_{i j}$
- Expected size of chain at index $h\left(k_{i}\right)$

$$
\begin{aligned}
\underset{h \in \mathcal{H}}{\mathbb{E}}\left\{X_{i}\right\}=\underset{h \in \mathcal{H}}{\mathbb{E}}\left\{\sum_{j} X_{i j}\right\}=\sum_{j} \underset{h \in \mathcal{H}}{\mathbb{E}}\left\{X_{i j}\right\} & =1+\sum_{j \neq i} \underset{h \in \mathcal{H}}{\mathbb{E}}\left\{X_{i j}\right\} \\
& =1+\sum_{j \neq i}(1) \operatorname{Pr}_{h \in \mathcal{H}}\left\{h\left(k_{i}\right)=h\left(k_{j}\right)\right\}+(0) \operatorname{Pr}_{h \in \mathcal{H}}\left\{h\left(k_{i}\right) \neq h\left(k_{j}\right)\right\} \\
& \leq 1+\sum_{j \neq i} 1 / m=1+(n-1) / m
\end{aligned}
$$

- Since $m=\Omega(n)$, load factor $\alpha=n / m=O(1)$, so $O(1)$ in expectation!


## Dynamic

- If $n / m$ far from 1 , rebuild with new randomly chosen hash function for new size $m$
- Same analysis as dynamic arrays, cost can be amortized over many dynamic operations
- So a hash table can implement dynamic set operations in expected amortized $O(1)$ time! :)

| Data Structure | Operations $O(\cdot)$ |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Container <br> build(X) | $\begin{gathered} \hline \text { Static } \\ \text { find }(k) \end{gathered}$ | Dynamic <br> insert(x) <br> delete(k) | Order |  |
|  |  |  |  | find_min() <br> find_max () | find_prev (k) <br> find_next (k) |
| Array | $n$ | $n$ | $n$ | $n$ | $n$ |
| Sorted Array | $n \log n$ | $\log n$ | $n$ | 1 | $\log n$ |
| Direct Access Array | $u$ | 1 | 1 | $u$ | $u$ |
| Hash Table | $n_{(e)}$ | $1_{(e)}$ | $1_{(a)(e)}$ | $n$ | $n$ |

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### 6.006 Introduction to Algorithms

Spring 2020
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