

Warmup: Optimal linked list order

- Suppose we have n distinct data items
 x₁, x₂, ..., x_n in a linked list.
- Also suppose that we know the probabilities p_1 , p_2 , ..., p_n that each of these items is the item we'll be searching for.
- Questions we'll attempt to answer:
 - What is the expected number of probes before a successful search completes?
 - How can we minimize this number?
 - What about an unsuccessful search?



Examples

- $p_i = 1/n$ for each i.
 - What is the expected number of probes?
- $p_1 = \frac{1}{2}$, $p_2 = \frac{1}{4}$, ..., $p_{n-1} = \frac{1}{2^{n-1}}$, $p_n = \frac{1}{2^{n-1}}$
 - expected number of probes:

$$\sum_{i=1}^{n-1} \frac{i}{2^i} + \frac{n}{2^{n-1}} = 2 - \frac{1}{2^{n-1}} < 2$$

 What if the same items are placed into the list in the opposite order?

$$\sum_{i=2}^{n} \frac{i}{2^{n+1-i}} + \frac{1}{2^{n-1}} = n - 1 + \frac{1}{2^{n-1}}$$

- The next slide shows the evaluation of the last two summations in Maple.
 - Good practice for you? prove them by induction

Calculations for previous slide

```
> sum(i/2^i, i=1..n-1) + n/2^(n-1);

-2\left(\frac{1}{2}\right)^{n} n - 2\left(\frac{1}{2}\right)^{n} + 2 + \frac{n}{2^{(n-1)}}
> simplify(%);

-2^{(1-n)} + 2
> sum(i/2^(n+1-i), i=2..n) + 1/2^(n-1);

n-1 + \frac{1}{2^{(n-1)}}
```

What if we don't know the probabilities?

- 1. Sort the list so we can at least improve the average time for unsuccessful search
- 2. Self-organizing list:
 - Elements accessed more frequently move toward the front of the list;
 elements accessed less frequently toward the rear.
 - Strategies:
 - Move ahead one position (exchange with previous element)
 - Exchange with first element
 - Move to Front (only efficient if the list is a linked list)
- What we are actually likely to know is frequencies in previous searches.
- Our best estimate of the probabilities will be proportional to the frequencies, so we can use frequencies instead of probabilities.



Optimal Binary Search Trees

- Suppose we have n distinct data keys K₁, K₂, ..., K_n (in increasing order) that we wish to arrange into a Binary Search Tree
- Suppose we know the probabilities that a successful search will end up at K_i and the probabilities that the key in an unsuccessful search will be larger than K_i and smaller than K_{i+1}
- This time the expected number of probes for a successful or unsuccessful search depends on the shape of the tree and where the search ends up
 - Formula?
- Guiding principle for optimization?

Example

- For now we consider only successful searches, with probabilities A(0.2), B(0.3), C(0.1), D(0.4).
- What would be the worst-case arrangement for the expected number of probes?
 - For simplicity, we'll multiply all of the probabilities by 10 so we can deal with integers.
- Try some other arrangements:
 Opposite, Greedy, Better, Best?
- Brute force: Try all of the possibilities and see which is best. How many possibilities?

Aside: How many possible BST's

- Given distinct keys K₁ < K₂ < ... < K_n, how many different Binary Search Trees can be constructed from these values?
- Figure it out for n=2, 3, 4, 5
- Write the recurrence relation



Aside: How many possible BST's

- Given distinct keys K₁ < K₂ < ... < K_n, how many different Binary Search Trees can be constructed from these values?
 When n=20,
- Figure it out for n=2, 3, 4, 5
- Write the recurrence relation almost 10¹⁰
- Solution is the **Catalan number** c(n)

$$c(n) = {2n \choose n} \frac{1}{n+1} = \frac{(2n)!}{n!(n+1)!} = \prod_{k=2}^{n} \frac{n+k}{k} \approx \frac{4^n}{n^{3/2} \sqrt{\pi}}$$

• Verify for n = 2, 3, 4, 5.

Wikipedia Catalan article has $c(n) = \binom{2n}{n} \frac{1}{n+1}$



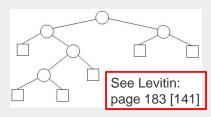
c(n) is

Optimal Binary Search Trees

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 K_n (in increasing order) that we wish to arrange into a Binary Search Tree
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- This discussion follows Reingold and Hansen, Data Structures. An excerpt on optimal static BSTS is posted on Moodle. I use a_i and b_i where Reingold and Hansen use α_i and β_i

Recap: Extended binary search tree

 It's simplest to describe this problem in terms of an extended binary search tree (EBST): a BST enhanced by drawing "external nodes" in place of all of the null pointers in the original tree



- Formally, an Extended Binary Tree (EBT) is either
 - an external node, or
 - an (internal) root node and two EBTs T₁ and T_R
- In diagram, Circles = internal nodes, Squares = external nodes
- It's an alternative way of viewing a binary tree
- The external nodes stand for places where an unsuccessful search can end or where an element can be inserted
- An EBT with n internal nodes has ____ external nodes (We proved this by induction earlier in the term)

What contributes to the expected number of probes?

- Frequencies, depth of node
- For successful search, number of probes is one more than the depth of the corresponding internal node
- For unsuccessful, number of probes is
 equal to
 the depth of the corresponding external node



Optimal BST Notation

- Keys are K₁, K₂, ..., K_n
- Let v be the value we are searching for
- For i= 1, ...,n, let a_i be the probability that v is key K_i
- For i= 1, ...,n-1, let b_i be the probability that $K_i < v < K_{i+1}$
 - Similarly, let b_0 be the probability that $v < K_1$, and b_n the probability that $v > K_n$
- Note that

$$\sum_{i=1}^{n} a_i + \sum_{i=0}^{n} b_i = 1$$

- We can also just use frequencies instead of probabilities when finding the optimal tree (and divide by their sum to get the probabilities if we ever need them). That is what we will do in anexample.
- Should we try exhaustive search of all possible BSTs?

What not to measure

- What about external path length and internal path length?
- These are too simple, because they do not take into account the frequencies.
- We need weighted path lengths.



Weighted Path Length

$$C(T) = \sum_{i=1}^{n} a_i [1 + depth(x_i)] + \sum_{i=0}^{n} b_i [depth(y_i)]$$
Note: y_0, ..., y_n are the external nodes of the tree

- If we divide this by $\Sigma a_i + \Sigma b_i$ we get the expected number of probes.
- We can also define it recursively:

•
$$C(\square) = 0$$
. If $T = 0$, then

 $C(T) = C(T_L) + C(T_R) + \Sigma a_i + \Sigma b_i$, where the summations are over all a_i and b_i for nodes in T

• It can be shown by induction that these two definitions are equivalent (a homeworkproblem,).

Example

- Frequencies of vowel occurrence in English
- : A, E, I, O, U
- a's: 32, 42, 26, 32, 12
- b's: 0, 34, 38, 58, 95, 21
- Draw a couple of trees (with E and I as roots), and see which is best. (sum of a's and b's is 390).



Strategy

- We want to minimize the weighted path length
- Once we have chosen the root, the left and right subtrees must themselves be optimal EBSTs
- We can build the tree from the bottom up, keeping track of previously-computed values



Intermediate Quantities

- Cost: Let C_{ij} (for $0 \le i \le j \le n$) be the cost of an optimal tree (not necessarily unique) over the frequencies b_i , a_{i+1} , b_{i+1} , ... a_i , b_i . Then
- $C_{ii} = 0$, and $C_{ij} = \min_{i < k \le i} (C_{i,k-1} + C_{kj}) + \sum_{t=i}^{j} b_t + \sum_{t=i+1}^{j} a_t$
- This is true since the subtrees of an optimal tree must be optimal
- To simplify the computation, we define
- W_{ii} = b_i, and W_{ij} = W_{i,j-1} + a_j + b_j for i<j.
 Note that W_{ij} = b_i + a_{i+1} + ... + a_j + b_j, and so
- $C_{ij} = 0$, and $C_{ij} = W_{ij} + \min_{i < k < i} (C_{i,k-1} + C_{kj})$
- Let R_{ij} (root of best tree from i to j) be a value of k that minimizes $C_{i,k-1} + C_{kj}$ in the above formula

Code

```
# initialize the main diagonal
for i in range (n + 1):
   R[i][i] = i
   W[i][i] = b[i]
    # Draw this cell of the table in the given window.
   drawSquare(i, i, W[i][i], C[i][i], R[i][i], win, indent, squareSize)
# Now populate each of the n upper diagonals:
for d in range(1, n+1): # fill in this diagonal
    # The previous diagonals are already filled in.
    for i in range (n - d + 1):
        j = i + d; # on the dth diagonal, j - i = d
        opt = i + 1 # until we find a better one
        for k in range(i+2, j+1):
           if C[i][k-1]+C[k][j] < C[i][opt-1]+C[opt][j]:
               opt = k
        R[i][j] = opt
        W[i][j] = W[i][j-1] + a[j] + b[j]
        C[i][j] = C[i][opt-1] + C[opt][j] + W[i][j]
        # Draw this cell of the table in the given window.
        drawSquare(i, j, W[i][j], C[i][j], R[i][j], win, indent, squareSize)
```

Results													
R00: W00: C00:	0	R01: W01: C01:	1 66 66	R02: W02: C02:		R03: W03: C03:		R04: W04: C04:		R05: W05: C05:		 Constructed by diagonals, 	
		R11: W11: C11:	1 34 0	R12: W12: C12:		R13: W13: C13:		R14: W14: C14:		R15: W15: C15:		from main diagonal	
				R22: W22: C22:	2 38 0	R23: W23: C23:		R24: W24: C24:		R25: W25: C25:		upward	
How to construct the						58	R34: W34: C34:		R35: W35: C35:		 What is the optimal tree? 		
optimal tree?							R44: W44: C44:	4 95 0	R45: W45: C45:				
Analysis of the algorithm?										W55: 2:	5 21 0		

Running time

- Most frequent statement is the comparison if C[i][k-1]+C[k][j] < C[i][opt-1]+C[opt][j]:
- How many times does it execute:

$$\sum_{d=1}^{n} \sum_{i=0}^{n-d} \sum_{k=i+2}^{i+d} 1$$

 $\begin{aligned} \text{simplify(sum(sum(sum(1,k=i+2..i+d),i=0..n-d),d=1..n));} \\ & -\frac{1}{6}n + \frac{1}{6}n^3 \end{aligned}$

Do what seems best at the moment ...

GREEDY ALGORITHMS

Greedy algorithms

- Whenever a choice is to be made, pick the one that seems optimal for the moment, without taking future choices into consideration
 - Once each choice is made, it is irrevocable
- For example, a greedy Scrabble player will simply maximize her score for each turn, never saving any "good" letters for possible better plays later
 - Doesn't necessarily optimize score for entire game
- Greedy works well for the "optimal linked list with known search probabilities" problem, and reasonably well for the "optimal BST" problem
 - But does not necessarily produce an optimal tree

Greedy Chess

- Take a piece or pawn whenever you will not lose a piece or pawn (or will lose one of lesser value) on the next turn
- Not a good strategy for this game either



Greedy Map Coloring

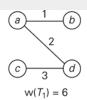
- On a planar (i.e., 2D Euclidean) connected map, choose a region and pick a color for that region
- Repeat until all regions are colored:
 - Choose an uncolored region R that is adjacent¹ to at least one colored region
 - If there are no such regions, let R be any uncolored region
 - Choose a color that is different than the colors of the regions that are adjacent to R
 - Use a color that has already been used if possible
- The result is a valid map coloring, not necessarily with the minimum possible number of colors

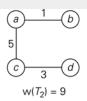
¹ Two regions are adjacent if they have a common edge



Spanning Trees for a Graph







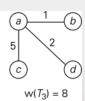
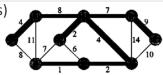


FIGURE 9.1 Graph and its spanning trees; T_1 is the minimum spanning tree



Minimal Spanning Tree (MST)

- Suppose that we have a connected network G
 (a graph whose edges are labeled by numbers,
 which we call weights)
- We want to find a tree T that
 - spans the graph (i.e. contains all nodes of G).
 - minimizes (among all spanning trees) the sum of the weights of its edges.
- Is this MST unique?



- One approach: Generate all spanning trees and determine which is minimum
- Problems:
 - The number of trees grows exponentially with N
 - Not easy to generate
 - Finding a MST directly is simpler and faster

More details soon



Huffman's algorithm

- Goal: We have a message that co9ntains n different alphabet symbols. Devise an encoding for the symbols that minimizes the total length of the message.
- Principles: More frequent characters have shorter codes. No code can be a prefix of another.
- Algorithm: Build a tree form which the codes are derived. Repeatedly join the two lowest-frequency trees into a new tree.

