

March 10, 2014

(日)

### Outline

performance

big-oh



# wrapper/node binary tree

instead of single tree class, separate node and bst classes:

・ロト ・ 一下・ ・ ヨト・・

Add a condition: data in left subtree is less than that in the root, which in turn is less than that in right subtree. Now search is more efficient...

class BST: """Binary search tree."""

def \_\_init\_\_(self: 'BST', root: BTNode=None) -> None: """Create BST with BTNode root.""" self.\_root = root aloo, possibly, fecord Size other fealures.

Computer Science

うして ふゆう ふほう ふほう ふしつ



## recall list searching

Inen (Leven Search) that is if hist has length that we expects # of step You've already seen algorithms for seeing whether an element is contained in a list:

[97, 36, 48, 73, 156, 947, 56, 236]

What is the performance of these algorithms in terms of list size? What about the analogous algorithm for a tree? > binary search log h

(Ig n)

# BST efficiency?

Binary search of a list allowed us to ignore (roughly) half the list. Searching a binary search tree allows us to ignore the left or right subtree — nearly half in a well-balanced tree. If we're searching the tree rooted at node n for value v, then one of three situations are possible: le n pertormance

- $\blacktriangleright$  node *n* has value *v*
- $\triangleright$  v is less than node n's value, so we should search to the left
- $\triangleright$  v is more than node n's value, so we should search to the right

(日)、(四)、(日)、(日)

### performance...

We want to measure **algorithm** performance, independent of hardware, programming language, random events

Focus on the size of the input, call it n. How does this affect the resources (e.g. processor time) required for the output? If the relationship is linear, our algorithm's complexity is  $\mathcal{O}(n)$  roughy proportional to the input size n.

## running time analysis

algorithm's behaviour over large input (size n) is common way to compare performance — how does performance vary as n changes?

constant:  $c \in \mathbb{R}^+$  (some positive number)  $\rightarrow$ logarithmic: clog n -> binaly Search linear: cn (probably not the same  $c) \rightarrow linear Search$ quadratic:  $cn^2$ cubic:  $cn^3$ exponential:  $c2^n$ horrible: cnn or cn! > bogosor 1, matrix

Computer Science

A D N A B N A B N

## running time analysis

abstract away difference between similar worst-case performance, e.g.

- one algorithm runs in  $(0.3365n^2 + 0.17n + 0.32)\mu s$
- another algorithm runs in  $(0.47n^2 + 0.08n)\mu s$
- ▶ in both cases doubling n quadruples the run time. We say both algorithms are O(n<sup>2</sup>) or "order n<sup>2</sup>" or "oh-n-squared" behaviour.

A D F A D F A D F A D F

ъ

#### asymptotics

If any reasonable implementation of an algorithm, on any reasonable computer, runs in number of steps no more than cg(n) (some constant c), we say the algorithm is  $\mathcal{O}(g(n))$ . Graphing various examples where  $g(n) = n^2$  shows how we ignore the constant c as n gets large (say  $7n^2$ ,  $2n^2 + 1$  versus 43n + 2, n = 1297).



### case: $\lg n$

this is the number of times you can divide n in half before reaching 1.

- refresher:  $a^b = c$  means  $\log_a c = b$ .
- this runtime behaviour often occurs when we "divide and conquer" a problem (e.g. binary search)
- we usually assume lg n (log base 2), but the difference is only a constant:

$$2^{\log_2 n} = n = 10^{\log_{10}} n \Longrightarrow \log_2 n = \log_2 10 imes \log_{10} n$$

イロト 不得下 イヨト イヨト

ъ

• so we just say  $\mathcal{O}(\lg n)$ .

## hierarchy

Since big-oh is an **upper-bound** the various classes fit into a hierarchy:

 $\mathcal{O}(1)\subseteq\mathcal{O}(\lg n)\subseteq\mathcal{O}(n)\subseteq\mathcal{O}(n^2)\subseteq\mathcal{O}(n^3)\subseteq\mathcal{O}(2^n)\subseteq\mathcal{O}(n^n)$ 

