Data Structures and Algorithms

Live Class 4: Complexity

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Today

- ► Search algorithms
- ► How to analyse algorithm complexity
 - "How does my code slow as my data grows?"

Announcements

Tutors on the chat on the Hub:

- Weekdays 9-11am, 1-3pm, 5-7pm; weekends 9-11am, 1-3pm
- Help, advice, support, guidance, comfort
- Rooms for Session 3 and 4 questions

Guessing game

A friend is thinking of a number between 1-100 and you have to guess it.

Whenever you make a guess, the friend tells you whether it is correct, too high, or too low.

How many guesses will you need?

Search algorithms

Search for the word "swagger"?





What is the worst we could do?

If the answers were "yes" and "no"?

Linear search - worst case: go through everything

If the answers are "too low" and "too high"?

- ► Each time, discard half or remaining numbers
- Binary search worst case?

Logarithms

Exponentials:
$$2^4 = 2 \times 2 \times 2 \times 2 = 16$$

Logarithm flips the exponential:

- $\log_2 16 = 4$
- "How many 2s do we multiply to get 16?"
- ► "How many times do we divide 16 by 2 to get to 1?"

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Guess the number from 1 to n:

- ► Linear search: at most *n* guesses
- ▶ Binary search: at most log₂(n) guesses

Algorithm design: searching a list

Suppose we have a list L. We want to check whether it contains the number 13.

What are computers good at?

1. Performing simple calculations

- Arithmetic operations
- Comparisons
- Assignments
- Accessing memory

2. Remembering the results

Goals in designing algorithms

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Efficiency:

- ► How much time will our computation take?
- ► How much memory will it need?

Example: linear search

Is x in list A?

```
1  def linear_search(A, x):
2    for elem in A:
3        if elem == x:
4         return True
5    return False
```

Efficiency:

- ► How much time will our computation take?
- ► How much memory will it need?

How much time will it take?

Simple: run and time it? But time depends on

- 1. Speed of computer
- 2. Specifics of implementation
- 3. Value of input

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For 3, measure number of steps depending on the size of input

Complexity and input

Searching for an item in a list?

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def linear_search(A, x):
    # A is a list of length n

for elem in A:
    if elem == x:
    return True

return False
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Complexity and input

Searching for an item in a list?

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def linear_search(A, x):
    # A is a list of length n
for elem in A:
    if elem == x:
    return True
return False
```

- x could be the first element of A
- x could not be in A
- ► How to give a general complexity measure?

Complexity cases

Cases for given input size (length of A):

- ▶ Best case minimum time
- ► Worst case maximum time
- Average case average or expected time over all possible inputs

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Principle: focus on worst-case analysis

- Upper bound on running time
- Bonus: usually easier to analyze

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- As n gets large, 2 is irrelevant
- Arguably, so is 5
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Principle: ignore constant factors and lower-order terms

- These depend on computer and program implementation
- They do not matter for large inputs
- Simplifies comparisons

```
def f(x):
                           # Let's assume x is integer
      ans = 0
                           # 1 step
      for i in range(100):
        ans += 1
                          # 200 steps
      for i in range(x):
         ans += 1
                          # 2*x
      for i in range(x):
          for j in range(x):
           ans -= 1 # 2*x^2
      return ans
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Steps: $202 + 2x + 2x^2$

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- ▶ $x \text{ large} \rightarrow \text{last loop dominates } (x = 10^6)$

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- ▶ $x \text{ large} \rightarrow \text{last loop dominates } (x = 10^6)$
- Only need to consider last (nested) loop for large x
- ▶ Does the 2 in $2x^2$ matter? For large x, order of growth much more important

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Formal way to describe this approach:

Big-O notation: upper bound on worst-case running time

Big-O: bound on runtime growth rate

Let T(n) be the number of steps taken for input size n:

• Example: $T(n) = 202 + 2n + 2n^2$

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Big-O: bound on runtime growth rate

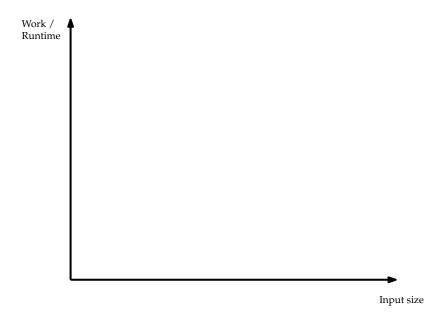
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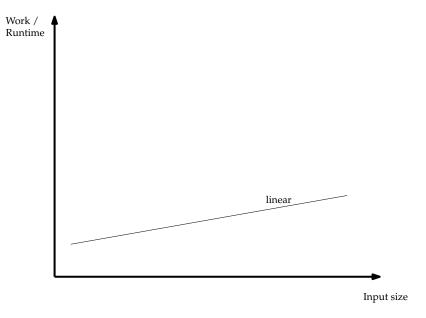
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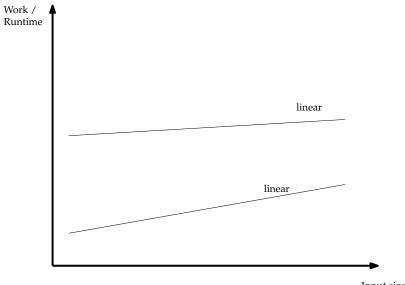
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Example: T(n) is $O(n^2)$ if for all large enough n, T(n) is bounded above by a constant multiple of $f(n) = n^2$

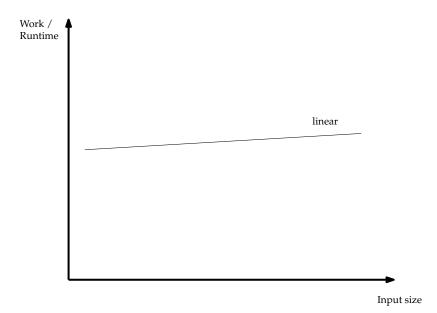
- ▶ Gist: for high values of n, does f(n) "grow at least as quickly"?
 - $ightharpoonup cf(n) = cn^2$? (for any constant c)
 - $T(n) = 202 + 2n + 2n^2$?
- ▶ What if f(n) = n, that is O(n)?

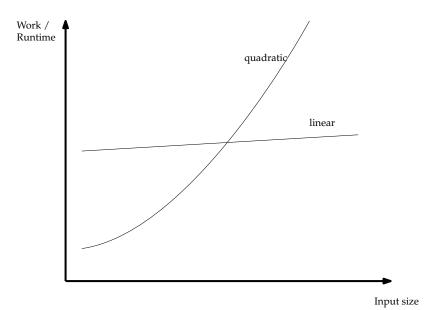






Input size





Big O tells us how fast the algorithm is

Fast algorithm: worst-case running time grows slowly with input size

- ► O(1): constant running time primitive operations
- $ightharpoonup O(\log n)$: logarithmic running time
- ► O(n): linear running time linear search
- \triangleright $O(n \log n)$: log-linear time
- \triangleright $O(n^c)$: polynomial running time
- \triangleright $O(c^n)$: exponential running time
- \triangleright O(n!): factorial running time

Go to menti.com

```
def fun_function(n):
    val = 0
    for i in range(n):
        val += 1
    for i in range(1000):
        val += 6
    return val
```

- A. Constant time O(1)
- B. Linear time O(n)
- C. Quadratic time $O(n^2)$
- D. None of the above
- E. I don't know

```
def fun_function(n):
    val = 0
    for i in range(n):
        val += 2
        for i in range(1000):
            val += 5
    return val
```

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```
def fun_function(n):
    val = 0
    for i in range(n):
        val += 2
    for i in range(n):
        val += 1
        for i in range(700):
        val += 5
    return val
```

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```
def fun_function(n):
    val = 0
    for i in range(5, 30):
        val += 2
    for i in range(3):
        val += 1
        for i in range(700):
        val -= 2
    return val
```

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- B. Linear time O(n)
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Algorithm for finding *x* in sorted list *L*:

- Pick an index i roughly dividing L in half
- If L[i] == x, return True (if nothing left to search return False)
- ► If not:
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First iteration

9	24	32	56	57	59	61	99
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$$L[i] = 24 \rightarrow \text{return True}$$

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- ▶ Complexity O(log n)!

Sorting algorithms

So if we have an unsorted list, should we sort it first?

- ► Suppose complexity *O*(*sort*(*n*))
- Is it less work to sort and do a binary search than do a linear search?
- ▶ In other words: is $sort(n) + \log(n) < n$?
- ► No...

In practice: what if we need to search repeatedly, say *k* times?

- ▶ Is $sort(n) + k \log(n) < kn$?
- Depends on k...

Complexity matters

You're planning a trip around the world visiting 10 cities. What's the cheapest route?

Check all alternative routes?

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You're planning a trip around the world visiting 10 cities. What's the cheapest route?

Check all alternative routes?

- ► There are $10 \times 9 \times 8 \times \cdots \times 2 \times 1 = 3628800$ possible routes
- ► Factorial complexity *O*(*n*!)
- ▶ Travelling salesperson problem

Review

Measuring algorithm time complexity:

- Number of basic steps taken
- Worst-case analysis
- Focus on large inputs

Searching and sorting (next session) are canonical algorithms problems

Review exercises:

- Big O practice
- Search algorithms