

Algorithmic Speed

BBM 101 - Introduction to Programming I

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Measuring complexity

- Goals in designing programs
 1. It returns the correct answer on all legal inputs
 2. It performs the computation efficiently
- Typically (1) is most important, but sometimes (2) is also critical, e.g., programs for collision detection
- Even when (1) is most important, it is valuable to understand and optimize (2)

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Computational complexity

- How much time will it take a program to run?
- How much memory will it need to run?
- Need to balance minimizing computational complexity with conceptual complexity
 - Keep code simple and easy to understand, but where possible optimize performance

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How do we measure complexity?

- Given a function, would like to answer: “How long will this take to run?”
- Could just run on some input and time it.
- Problem is that this depends on:
 1. Speed of computer
 2. Specifics of Python implementation
 3. Value of input
- Avoid (1) and (2) by measuring time in terms of number of basic steps executed

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Measuring basic steps

- Use a **random access machine (RAM)** as model of computation
 - Steps are executed sequentially
 - Step is an operation that takes constant time
 - Assignment
 - Comparison
 - Arithmetic operation
 - Accessing object in memory
- For point (3), measure time in terms of size of input

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But complexity might depend on value of input?

```
def linearSearch(L, x):  
    for e in L:  
        if e==x:  
            return True  
    return False
```

- If x happens to be near front of L, then returns True almost immediately
- If x not in L, then code will have to examine all elements of L
- Need a general way of measuring

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Cases for measuring complexity

- **Best case:** minimum running time over all possible inputs of a given size
 - For linearSearch – constant, i.e. independent of size of inputs
- **Worst case:** maximum running time over all possible inputs of a given size
 - For linearSearch – linear in size of list
- **Average (or expected) case:** average running time over all possible inputs of a given size
- We will focus on worst case – a kind of **upper bound** on running time

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Example

```
def fact(n):  
    answer = 1  
    while n > 1:  
        answer *= n  
        n -= 1  
    return answer
```

- Number of steps
 - 1 (for assignment)
 - 5*n (1 for test, plus 2 for first assignment, plus 2 for second assignment in while; repeated n times through while)
 - 1 (for return)
- 5*n+2 steps
- But as n gets large, 2 is irrelevant, so basically 5*n steps

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Example

- What about the multiplicative constant (5 in this case)?
- We argue that in general, multiplicative constants are not relevant when comparing algorithms

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Example

```
def sqrtExhaust(x, eps):  
    step = eps**2  
    ans = 0.0  
    while abs(ans**2 - x) >= eps and ans <= max(x, 1):  
        ans += step  
    return ans
```

- If we call this on 100 and 0.0001, will take one billion iterations of the loop
 - Have roughly 8 steps within each iteration

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Example

```
def sqrtBi(x, eps):  
    low = 0.0  
    high = max(1, x)  
    ans = (high + low)/2.0  
    while abs(ans**2 - x) >= eps:  
        if ans**2 < x:  
            low = ans  
        else:  
            high = ans  
        ans = (high + low)/2.0  
    return ans
```

- If we call this on 100 and 0.0001, will take thirty iterations of the loop
 - Have roughly 10 steps within each iteration
- 1 billion or 8 billion versus 30 or 300 – it is size of problem that matters

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Measuring complexity

- Given this difference in iterations through loop, multiplicative factor (number of steps within loop) probably irrelevant
- Thus, we will focus on measuring the complexity as a function of input size
 - Will focus on the largest factor in this expression
 - Will be mostly concerned with the worst case scenario

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Asymptotic notation

- Need a formal way to talk about relationship between running time and size of inputs
- Mostly interested in what happens as size of inputs gets very large, i.e. approaches infinity

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Example

```
def f(x):  
    for i in range(1000):  
        ans = i  
    for i in range(x):  
        ans += 1  
    for i in range(x):  
        for j in range(x):  
            ans += 1
```

Complexity is $1000 + 2x + 2x^2$, if each line takes one step

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Example

- $1000 + 2x + 2x^2$
- If x is small, constant term dominates
 - E.g., $x = 10$ then 1000 of 1220 steps are in first loop
- If x is large, quadratic term dominates
 - E.g. $x = 1,000,000$, then first loop takes 0.000000005% of time, second loop takes 0.0001% of time (out of 2,000,002,001,000 steps)!

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Example

- So really only need to consider the nested loops (quadratic component)
- Does it matter that this part takes $2x^2$ steps, as opposed to say x^2 steps?
 - For our example, if our computer executes 100 million steps per second, difference is 5.5 hours versus 2.25 hours
 - On the other hand if we can find a linear algorithm, this would run in a fraction of a second
 - So multiplicative factors probably not crucial, but order of growth is crucial

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Rules of thumb for complexity

- Asymptotic complexity
 - Describe running time in terms of number of basic steps
 - If running time is sum of multiple terms, keep one with the largest growth rate
 - If remaining term is a product, drop any multiplicative constants
- Use “Big O” notation (aka Omicron)
 - Gives an upper bound on asymptotic growth of a function

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Complexity classes

- $O(1)$ denotes constant running time
- $O(\log n)$ denotes logarithmic running time
- $O(n)$ denotes linear running time
- $O(n \log n)$ denotes log-linear running time
- $O(n^c)$ denotes polynomial running time (c is a constant)
- $O(c^n)$ denotes exponential running time (c is a constant being raised to a power based on size of input)

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Constant complexity

- Complexity independent of inputs
- Very few interesting algorithms in this class, but can often have pieces that fit this class
- Can have loops or recursive calls, but number of iterations or calls independent of size of input

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Logarithmic complexity

- Complexity grows as log of size of one of its inputs
- Example:
 - Bisection search
 - Binary search of a list

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Logarithmic complexity

```
def intToStr(i):
    digits = '0123456789'
    if i == 0:
        return '0'
    result = ''
    while i > 0:
        result = digits[i%10] + result
        i = i/10
    return result
```

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Logarithmic complexity

```
def intToStr(i):
    digits = '0123456789'
    if i == 0:
        return '0'
    result = ''
    while i > 0:
        result = digits[i%10] + result
        i = i/10
    return result
```

- Only have to look at loop as no function calls
- Within while loop constant number of steps
- How many times through loop?
 - How many times can one divide i by 10?
 - $O(\log(i))$

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Linear complexity

- Searching a list in order to see if an element is present
- Add characters of a string, assumed to be composed of decimal digits

```
def addDigits(s):
    val = 0
    for c in s:
        val += int(c)
    return val
```

- $O(\text{len}(s))$

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Linear complexity

- Complexity can depend on number of recursive calls

```
def fact(n):
    if n == 1:
        return 1
    else:
        return n*fact(n-1)
```

- Number of recursive calls?
 - $\text{Fact}(n)$, then $\text{fact}(n-1)$, etc. until get to $\text{fact}(1)$
 - Complexity of each call is constant
 - $O(n)$

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Log-linear complexity

- Many practical algorithms are log-linear
- Very commonly used log-linear algorithm is merge sort
- Will return to this

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Polynomial complexity

- Most common polynomial algorithms are quadratic, i.e., complexity grows with square of size of input
- Commonly occurs when we have nested loops or recursive function calls

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Quadratic complexity

```
def isSubset(L1, L2):  
    for e1 in L1:  
        matched = False  
        for e2 in L2:  
            if e1 == e2:  
                matched = True  
                break  
        if not matched:  
            return False  
    return True
```

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Quadratic complexity

```
def isSubset(L1, L2):  
    for e1 in L1:  
        matched = False  
        for e2 in L2:  
            if e1 == e2:  
                matched = True  
                break  
        if not matched:  
            return False  
    return True
```

- Outer loop executed $\text{len}(L1)$ times
- Each iteration will execute inner loop up to $\text{len}(L2)$ times
- $O(\text{len}(L1) * \text{len}(L2))$
- Worst case when $L1$ and $L2$ same length, none of elements of $L1$ in $L2$
- $O(\text{len}(L1)^2)$

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Quadratic complexity

Find intersection of two lists, return a list with each element appearing only once

```
def intersect(L1, L2):
    tmp = []
    for e1 in L1:
        for e2 in L2:
            if e1 == e2:
                tmp.append(e1)
    res = []
    for e in tmp:
        if not(e in res):
            res.append(e)
    return res
```

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Quadratic complexity

```
def intersect(L1, L2):
    tmp = []
    for e1 in L1:
        for e2 in L2:
            if e1 == e2:
                tmp.append(e1)
    res = []
    for e in tmp:
        if not(e in res):
            res.append(e)
    return res
```

- First nested loop takes $\text{len}(L1) * \text{len}(L2)$ steps
- Second loop takes at most $\text{len}(L1)$ steps
- Latter term overwhelmed by former term
- $O(\text{len}(L1) * \text{len}(L2))$

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Exponential complexity

- Recursive functions where more than one recursive call for each size of problem
 - Towers of Hanoi
- Many important problems are inherently exponential
 - Unfortunate, as cost can be high
 - Will lead us to consider approximate solutions more quickly

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Exponential complexity

```
def genSubsets(L):
    res = []
    if len(L) == 0:
        return [[]] #list of empty list
    smaller = genSubsets(L[:-1])
    # get all subsets without last element
    extra = L[-1:]
    # create a list of just last element
    new = []
    for small in smaller:
        new.append(small+extra)
    # for all smaller solutions, add one with last element
    return smaller+new
    # combine those with last element and those without
```

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Exponential complexity

```
def genSubsets(L):
    res = []
    if len(L) == 0:
        return [[]]
    smaller = genSubsets(L[:-1])
    extra = L[-1:]
    new = []
    for small in smaller:
        new.append(small+extra)
    return smaller+new
```

- Assuming append is constant time
- Time includes time to solve smaller problem, plus time needed to make a copy of all elements in smaller problem

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Exponential complexity

```
def genSubsets(L):
    res = []
    if len(L) == 0:
        return [[]]
    smaller = genSubsets(L[:-1])
    extra = L[-1:]
    new = []
    for small in smaller:
        new.append(small+extra)
    return smaller+new
```

- But important to think about size of smaller
- Know that for a set of size k there are 2^k cases
- So to solve need $2^{n-1} + 2^{n-2} + \dots + 2^0$ steps
- Math tells us this is $O(2^n)$

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Complexity classes

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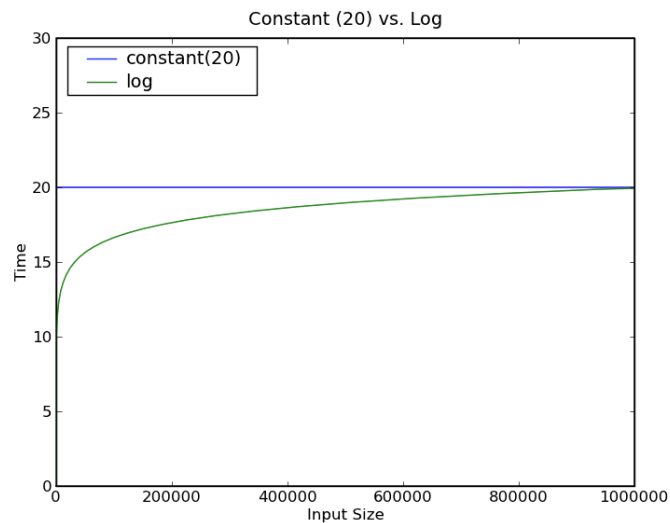
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Comparing complexities

- So does it really matter if our code is of a particular class of complexity?
- Depends on size of problem, but for large scale problems, complexity of worst case makes a difference

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Constant versus Logarithmic



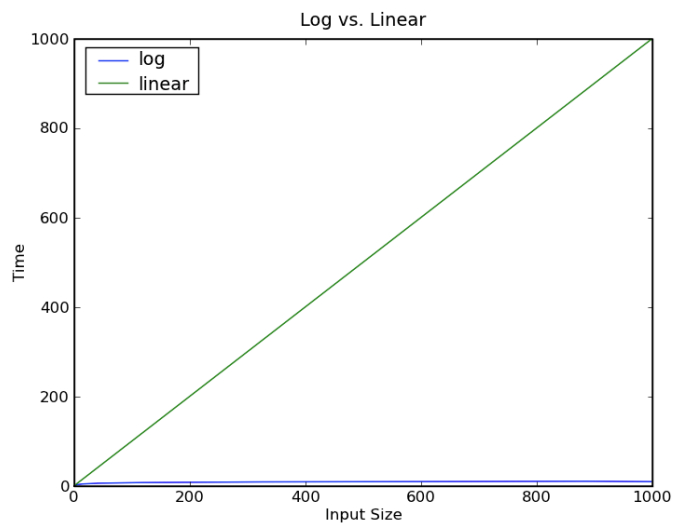
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Observations

- A logarithmic algorithm is often almost as good as a constant time algorithm
- Logarithmic costs grow very slowly

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Logarithmic versus Linear



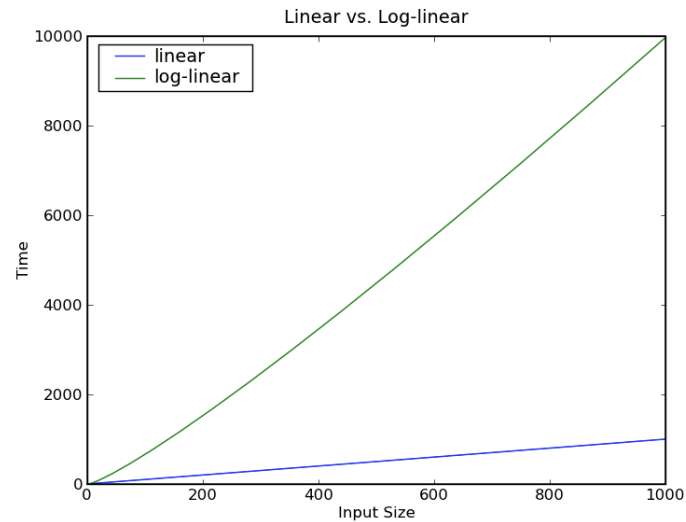
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Observations

- Logarithmic clearly better for large scale problems than linear
- Does not imply linear is bad, however

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Linear versus Log-linear



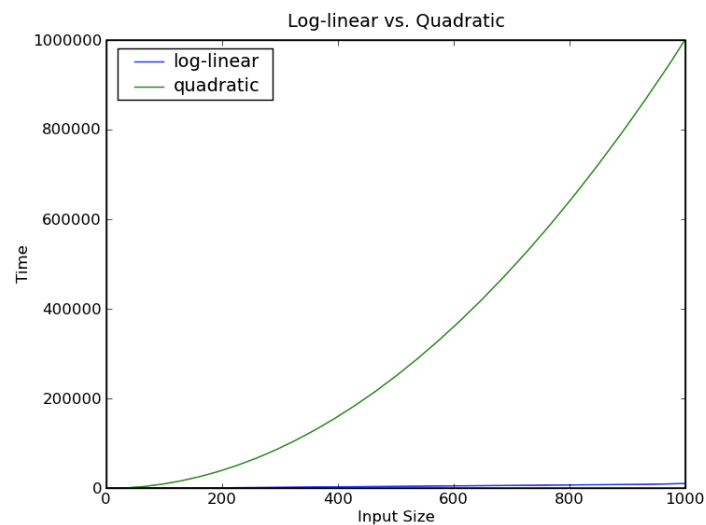
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Observations

- While $\log(n)$ may grow slowly, when multiplied by a linear factor, growth is much more rapid than pure linear
- $O(n \log n)$ algorithms are still very valuable

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Log-linear versus Quadratic



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Observations

- Quadratic is often a problem, however.
- Some problems inherently quadratic but if possible always better to look for more efficient solutions

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Quadratic versus Exponential

- Exponential algorithms very expensive
 - Right plot is on a log scale, since left plot almost invisible given how rapidly exponential grows
- Exponential generally not of use except for small problems

