
CSE 373

Algorithm Analysis and Runtime Complexity

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Evaluating an algorithm

- How to know whether a given algorithm is good, efficient, etc.?
- One idea: *Implement it*, run it, time it / measure it (averaging trials)
 - Pros?
 - Find out how the system effects performance
 - Stress testing – how does it perform in dynamic environment
 - No math!
 - Cons?
 - Need to implement code (takes time)
 - Can be hard to estimate performance
 - When comparing two algorithms, all other factors need to be held constant (e.g., same computer, OS, processor, load)

Range algorithm

How efficient is this algorithm? Can it be improved?

```
// returns the range of values in the given array;
// the difference between elements furthest apart
// example: range({17, 29, 11, 4, 20, 8}) is 25
public static int range(int[] numbers) {
    int maxDiff = 0;          // look at each pair of values
    for (int i = 0; i < numbers.length; i++) {
        for (int j = 0; j < numbers.length; j++) {
            int diff = Math.abs(numbers[j] - numbers[i]);
            if (diff > maxDiff) {
                maxDiff = diff;
            }
        }
    }
    return maxDiff;
}
```

Range algorithm 2

A slightly better version:

```
// returns the range of values in the given array;
// the difference between elements furthest apart
// example: range({17, 29, 11, 4, 20, 8}) is 25
public static int range(int[] numbers) {
    int maxDiff = 0;          // look at each pair of values
    for (int i = 0; i < numbers.length; i++) {
        for (int j = i + 1; j < numbers.length; j++) {
            int diff = Math.abs(numbers[j] - numbers[i]);
            if (diff > maxDiff) {
                maxDiff = diff;
            }
        }
    }
    return maxDiff;
}
```

Range algorithm 3

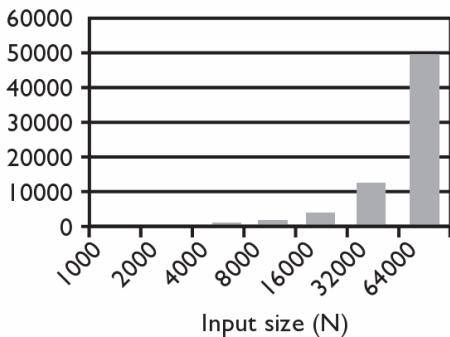
A MUCH faster version. Why is it so much better?

```
// returns the range of values in the given array;
// example: range({17, 29, 11, 4, 20, 8}) is 25
public static int range(int[] numbers) {
    int max = numbers[0];          // find max/min values
    int min = max;
    for (int i = 1; i < numbers.length; i++) {
        if (numbers[i] < min) {
            min = numbers[i];
        }
        if (numbers[i] > max) {
            max = numbers[i];
        }
    }
    return max - min;
}
```

Runtime of each version

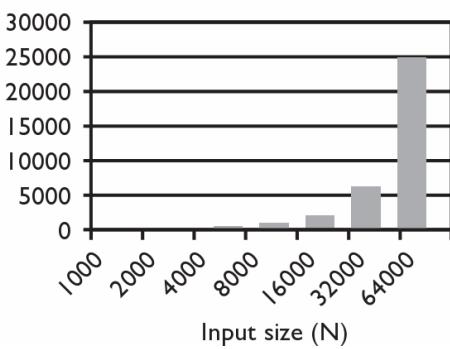
- Version 1:

N	Runtime (ms)
1000	15
2000	47
4000	203
8000	781
16000	3110
32000	12563
64000	49937



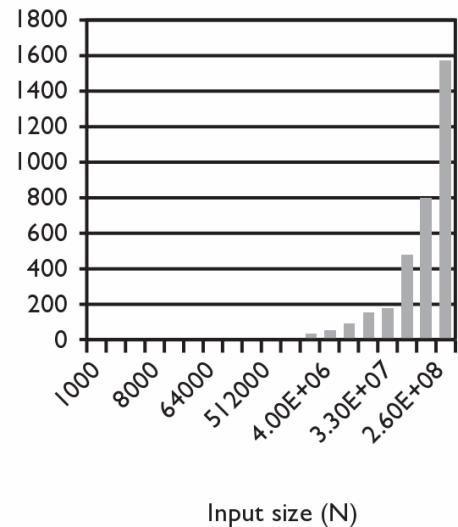
- Version 2:

N	Runtime (ms)
1000	16
2000	16
4000	110
8000	406
16000	1578
32000	6265
64000	25031



- Version 3:

N	Runtime (ms)
1000	0
2000	0
4000	0
8000	0
16000	0
32000	0
64000	0
128000	0
256000	0
512000	0
1e6	0
2e6	16
4e6	31
8e6	47
1.67e7	94
3.3e7	188
6.5e7	453
1.3e8	797
2.6e8	1578



Max subsequence sum

- Write a method `maxSum` to find the largest sum of any contiguous subsequence in an array of integers.
 - Easy for all positives: include the whole array.
 - What if there are negatives?

index	0	1	2	3	4	5	6	7	8
value	2	1	-4	10	15	-2	22	-8	5

Largest sum: $10 + 15 + -2 + 22 = 45$

- (Let's define the max to be 0 if the array is entirely negative.)
- Ideas for algorithms?

Algorithm 1 pseudocode

```
maxSum(a) :  
    max = 0.  
    for each starting index i:  
        for each ending index j:  
            sum = add the elements from a[i] to a[j].  
            if sum > max,  
                max = sum.  
  
    return max.
```

index	0	1	2	3	4	5	6	7	8
value	2	1	-4	10	15	-2	22	-8	5

Algorithm 1 code

- How efficient is this algorithm?
 - Poor. It takes a few seconds to process 2000 elements.

```
public static int maxSum1(int[] a) {  
    int max = 0;  
    for (int i = 0; i < a.length; i++) {  
        for (int j = i; j < a.length; j++) {  
            // sum = add the elements from a[i] to a[j].  
            int sum = 0;  
            for (int k = i; k <= j; k++) {  
                sum += a[k];  
            }  
            if (sum > max) {  
                max = sum;  
            }  
        }  
    }  
    return max;  
}
```

Flaws in algorithm 1

- Observation: We are redundantly re-computing sums.
 - For example, we compute the sum between indexes 2 and 5:
 $a[2] + a[3] + a[4] + a[5]$
 - Next we compute the sum between indexes 2 and 6:
 $a[2] + a[3] + a[4] + a[5] + a[6]$
 - We already had computed the sum of 2-5, but we compute it again as part of the 2-6 computation.
 - Let's write an improved version that avoids this flaw.

Algorithm 2 code

- How efficient is this algorithm?
 - Mediocre. It can process 10,000s of elements per second.

```
public static int maxSum2(int[] a) {  
    int max = 0;  
    for (int i = 0; i < a.length; i++) {  
        int sum = 0;  
        for (int j = i; j < a.length; j++) {  
            sum += a[j];  
            if (sum > max) {  
                max = sum;  
            }  
        }  
    }  
    return max;  
}
```

A clever solution

- *Claim 1* : The max range cannot start with a negative-sum range.

i	...	j	j+1	...	k
< 0		sum(j+1, k)			
sum(i, k) < sum(j+1, k)					

- *Claim 2* : If $\text{sum}(i, j-1) \geq 0$ and $\text{sum}(i, j) < 0$, any max range that ends at $j+1$ or higher cannot start at any of i through j .

i	...	j-1	j	j+1	...	k
≥ 0		< 0		sum(j+1, k)		
< 0			sum(j+1, k)			
		sum(?, k) < sum(j+1, k)				

- Together, these observations lead to a very clever algorithm...

Algorithm 3 code

- How efficient is this algorithm?
 - Excellent. It can handle many millions of elements per second!

```
public static int maxSum3(int[] a) {  
    int max = 0;  
    int sum = 0;  
    int i = 0;  
    for (int j = 0; j < a.length; j++) {  
        if (sum < 0) { // if sum becomes negative, max range  
            i = j; // cannot start with any of i - j-1,  
            sum = 0; // (Claim 2) so move i up to j  
        }  
        sum += a[j];  
        if (sum > max) {  
            max = sum;  
        }  
    }  
    return max;  
}
```

Analyzing efficiency

- **efficiency:** A measure of the use of computing resources by code.
 - most commonly refers to run time; but could be memory, etc.
- Rather than writing and timing algorithms, let's *analyze* them. Code is hard to analyze, so let's make the following assumptions:
 - Any *single Java statement* takes a constant amount of time to run.
 - The runtime of a *sequence* of statements is the sum of their runtimes.
 - An *if/else*'s runtime is the runtime of the if test, plus the runtime of whichever branch of code is chosen.
 - A *loop*'s runtime, if the loop repeats N times, is N times the runtime of the statements in its body.
 - A *method call*'s runtime is measured by the total of the statements inside the method's body.

Runtime example

```
statement1;  
statement2; } 2  
  
for (int i = 1; i <= N; i++) {  
    statement3;  
    statement4;  
    statement5;  
    statement6;  
}  
  
for (int i = 1; i <= N; i++) {  
    for (int j = 1; j <= N/2; j++) {  
        statement7;  
    } } }  
}
```

The diagram illustrates the runtime analysis of the given code. Braces on the left side group statements:

- statement1 and statement2 are grouped by a brace labeled "2".
- The entire for loop body (from "for" to the innermost brace) is grouped by a brace labeled "4N".
- The entire code block (including both for loops) is grouped by a large brace labeled $\frac{1}{2} N^2 + 4N + 2$.

- How many statements will execute if $N = 10$? If $N = 1000$?

Algorithm growth rates

- We measure runtime in proportion to the input data size, N .
 - **growth rate:** Change in runtime as N changes.
- Say an algorithm runs $0.4N^3 + 25N^2 + 8N + 17$ statements.
 - Consider the runtime when N is *extremely large* .
(Almost any algorithm is fine if N is small.)
 - We ignore constants like 25 because they are tiny next to N .
 - The highest-order term (N^3) dominates the overall runtime.
 - We say that this algorithm runs "on the order of" N^3 .
 - or **$O(N^3)$** for short ("Big-Oh of N cubed")

Growth rate example

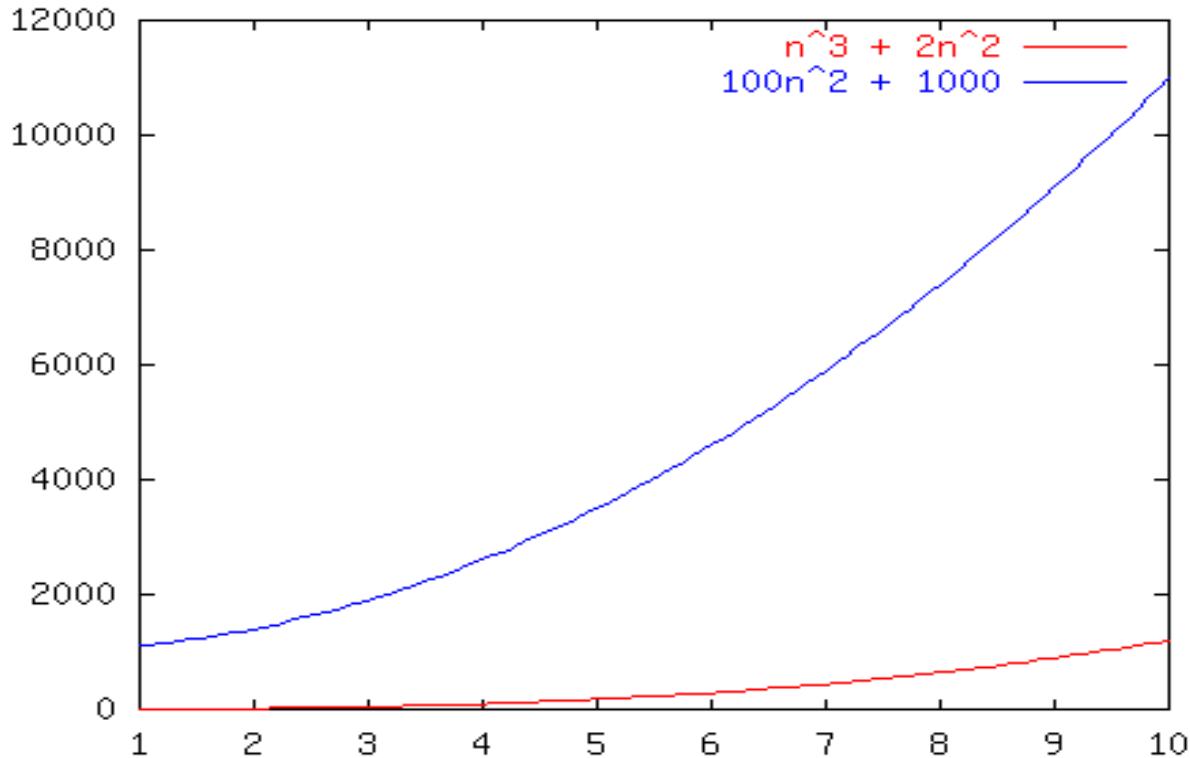
Consider these graphs of functions.

Perhaps each one represents an algorithm:

$$N^3 + 2N^2$$

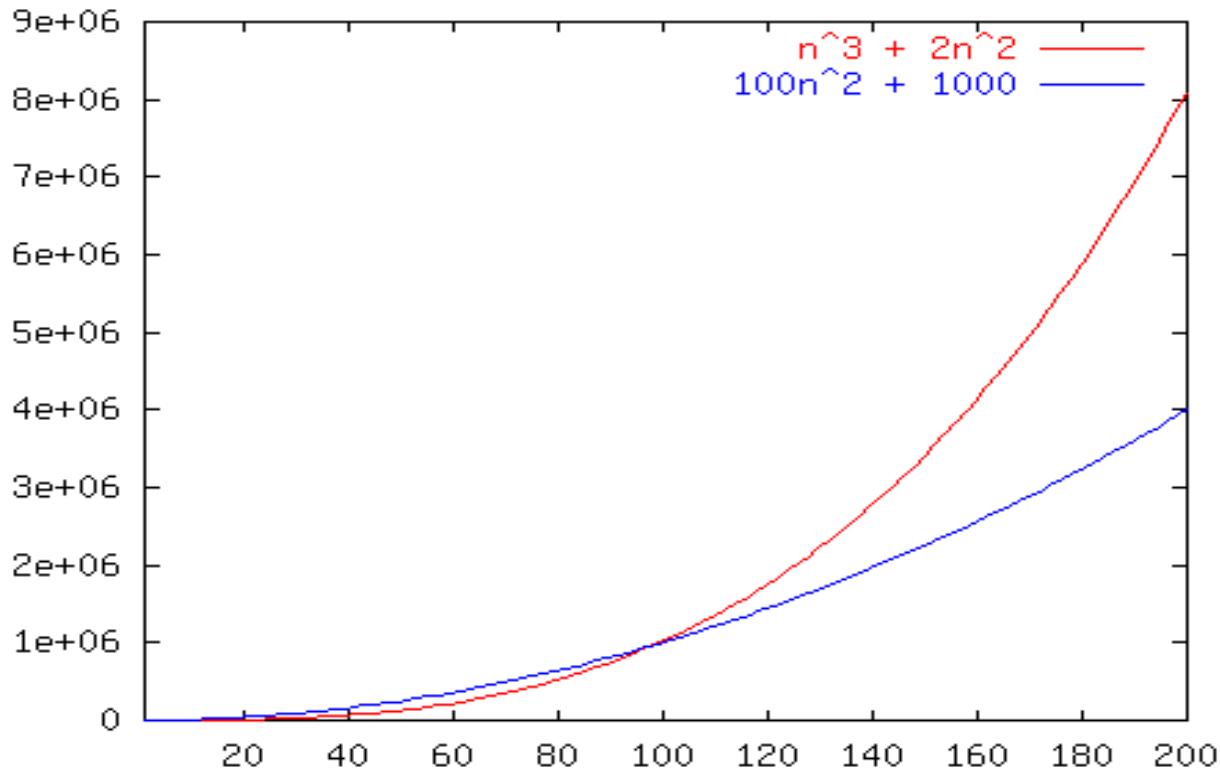
$$100N^2 + 1000$$

- Which is better?



Growth rate example

- How about now, at large values of N ?



Complexity classes

- **complexity class:** A category of algorithm efficiency based on the algorithm's relationship to the input size N .

Class	Big-Oh	If you double N , ...	Example
constant	$O(1)$	unchanged	10ms
logarithmic	$O(\log_2 N)$	increases slightly	175ms
linear	$O(N)$	doubles	3.2 sec
log-linear	$O(N \log_2 N)$	slightly more than doubles	6 sec
quadratic	$O(N^2)$	quadruples	1 min 42 sec
cubic	$O(N^3)$	multiplies by 8	55 min
...
exponential	$O(2^N)$	multiplies drastically	$5 * 10^{61}$ years

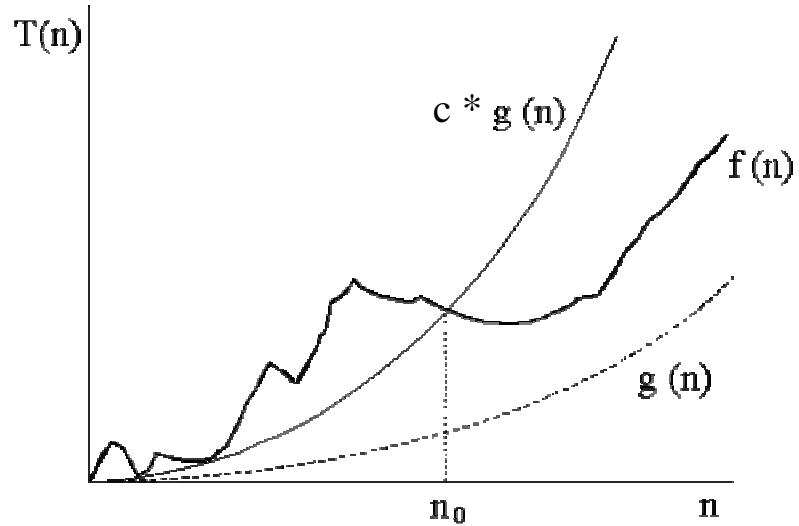
Java collection efficiency

Method	ArrayList	LinkedList	Stack	Queue	TreeSet /Map	[Linked] HashSet /Map	Priority Queue
add or put	O(1)	O(1)	O(1)*	O(1)*	O(log N)	O(1)	O(log N)*
add at index	O(N)	O(N)	-	-	-	-	-
contains/ indexOf	O(N)	O(N)	-	-	O(log N)	O(1)	-
get/set	O(1)	O(N)	O(1)*	O(1)*	-	-	O(1)*
remove	O(N)	O(N)	O(1)*	O(1)*	O(log N)	O(1)	O(log N)*
size	O(1)	O(1)	O(1)	O(1)	O(1)	O(1)	O(1)

- * = operation can only be applied to certain element(s) / places

Big-Oh defined

- Big-Oh is about finding an *asymptotic upper bound*.
- Formal definition of Big-Oh:
 $f(N) = O(g(N))$, if there exists positive constants c , N_0 such that
 $f(N) \leq c \cdot g(N)$ for all $N \geq N_0$.
 - We are concerned with how f grows when N is large.
 - not concerned with small N or constant factors
 - Lingo: " $f(N)$ grows no faster than $g(N)$."



Big-Oh questions

- $N + 2 = O(N)$?
 - yes
- $2N = O(N)$?
 - yes
- $N = O(N^2)$?
 - yes
- $N^2 = O(N)$?
 - no
- $100 = O(N)$?
 - yes
- $N = O(1)$?
 - no
- $214N + 34 = O(N^2)$?
 - yes

Preferred Big-Oh usage

- Pick the tightest bound. If $f(N) = 5N$, then:

$$f(N) = O(N^5)$$

$$f(N) = O(N^3)$$

$$f(N) = O(N \log N)$$

$$f(N) = O(N) \quad \leftarrow \text{preferred}$$

- Ignore constant factors and low order terms:

$$f(N) = O(N), \quad \text{not } f(N) = O(5N)$$

$$f(N) = O(N^3), \quad \text{not } f(N) = O(N^3 + N^2 + 15)$$

- Wrong: $f(N) \leq O(g(N))$
- Wrong: $f(N) \geq O(g(N))$
- Right: $f(N) = O(g(N))$

A basic Big-Oh proof

- *Claim:* $2N + 6 = O(N)$.
- *To prove:* Must find c, N_0 such that for all $N \geq N_0$,
$$2N + 6 \leq c \cdot N$$

- *Proof:* Let $c = 3, N_0 = 6$.

$$2N + 6 \leq 3 \cdot N$$

$$6 \leq N$$

Math background: Exponents

- Exponents:
 - X^Y , or "X to the Y^{th} power";
X multiplied by itself Y times
- Some useful identities:
 - $X^A \cdot X^B = X^{A+B}$
 - $X^A / X^B = X^{A-B}$
 - $(X^A)^B = X^{AB}$
 - $X^N + X^N = 2X^N$
 - $2^N + 2^N = 2^{N+1}$

Math background: Logarithms

- Logarithms
 - *definition:* $X^A = B$ if and only if $\log_X B = A$
 - *intuition:* $\log_X B$ means:
"the power X must be raised to, to get B"
 - In this course, a logarithm with no base implies base 2.
 $\log B$ means $\log_2 B$
- Examples
 - $\log_2 16 = 4$ (because $2^4 = 16$)
 - $\log_{10} 1000 = 3$ (because $10^3 = 1000$)

Logarithm bases

- Identities for logs with addition, multiplication, powers:
 - $\log(A \cdot B) = \log A + \log B$
 - $\log(A/B) = \log A - \log B$
 - $\log(A^B) = B \log A$
- Identity for converting bases of a logarithm:

$$\log_A B = \frac{\log_C B}{\log_C A}$$

- example:
$$\begin{aligned}\log_4 32 &= (\log_2 32) / (\log_2 4) \\ &= 5 / 2\end{aligned}$$
- Practically speaking, this means all \log_c are a constant factor away from \log_2 , so we can think of them as equivalent to \log_2 in Big-Oh analysis.

More runtime examples

- What is the exact runtime and complexity class (Big-Oh)?

```
int sum = 0;  
for (int i = 1; i <= N; i += c) {  
    sum++;  
}
```

- Runtime = $N / c = O(N)$.

```
int sum = 0;  
for (int i = 1; i <= N; i *= c) {  
    sum++;  
}
```

- Runtime = $\log_c N = O(\log N)$.

Binary search

- **binary search** successively eliminates half of the elements.
 - *Algorithm:* Examine the middle element of the array.
 - If it is too big, eliminate the right half of the array and repeat.
 - If it is too small, eliminate the left half of the array and repeat.
 - Else it is the value we're searching for, so stop.
 - Which indexes does the algorithm examine to find value **42**?
 - What is the runtime complexity class of binary search?

index	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
value	-4	2	7	10	15	20	22	25	30	36	42	50	56	68	85	92	103
	 min									 mid						 max	

Binary search runtime

- For an array of size N , it eliminates $\frac{1}{2}$ until 1 element remains.
 $N, N/2, N/4, N/8, \dots, 4, 2, 1$
 - How many divisions does it take?
- Think of it from the other direction:
 - How many times do I have to multiply by 2 to reach N ?
 $1, 2, 4, 8, \dots, N/4, N/2, N$
 - Call this number of multiplications " x ".
 $2^x = N$
 $x = \log_2 N$
- Binary search is in the **logarithmic** ($O(\log N)$) complexity class.

Math: Arithmetic series

- Arithmetic series notation (*useful for analyzing runtime of loops*):

$$\sum_{i=j}^k Expr$$

- the sum of all values of *Expr* with each value of *i* between *j--k*

- Example:

$$\sum_{i=0}^4 2i + 1$$

$$\begin{aligned}&= (2(0) + 1) + (2(1) + 1) + (2(2) + 1) + (2(3) + 1) + (2(4) + 1) \\&= 1 + 3 + 5 + 7 + 9 \\&= 25\end{aligned}$$

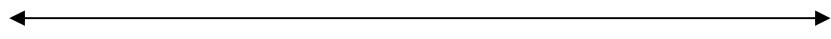
Arithmetic series identities

- sum from 1 through N inclusive:

$$\sum_{i=1}^N i = \frac{N(N+1)}{2} = O(N^2)$$

- Intuition:

- sum = $1 + 2 + 3 + \dots + (N-2) + (N-1) + N$
- sum = $(1 + N) + (2 + N-1) + (3 + N-2) + \dots$



// rearranged
// $N/2$ pairs total

- sum of squares:

$$\sum_{i=1}^N i^2 = \frac{N(N+1)(2N+1)}{6} = O(N^3)$$

Series runtime examples

- What is the exact runtime and complexity class (Big-Oh)?

```
int sum = 0;
for (int i = 1; i <= N; i++) {
    for (int j = 1; j <= N * 2; j++) {
        sum++;
    }
}
```

- Runtime = $N \cdot 2N = O(N^2)$.

```
int sum = 0;
for (int i = 1; i <= N; i++) {
    for (int j = 1; j <= i; j++) {
        sum++;
    }
}
```

- Runtime = $N(N + 1) / 2 = O(N^2)$.