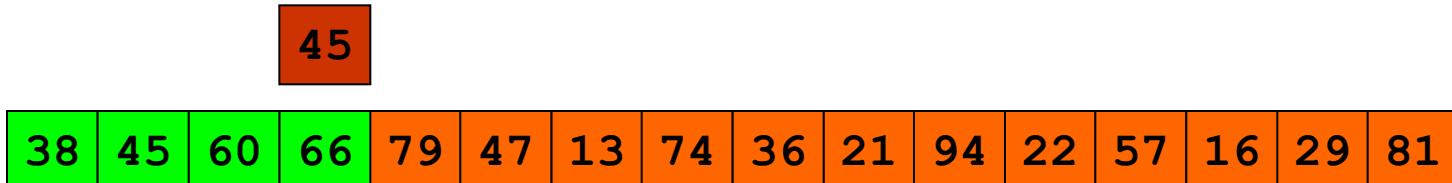
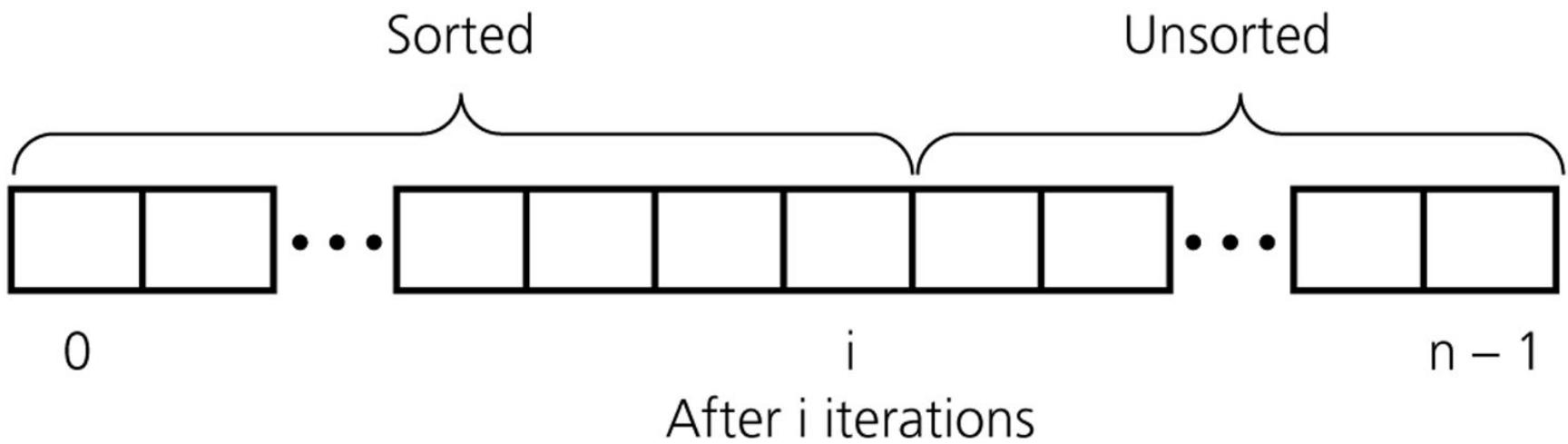


Insertion Sort

- while some elements unsorted:
 - Using linear search, find the location in the sorted portion where the 1st element of the unsorted portion should be inserted
 - Move all the elements after the insertion location up one position to make space for the new element



the fourth iteration of this loop is shown here



An insertion sort partitions the array into two regions



Initial array:

29	10	14	37	13
----	----	----	----	----

29	29	14	37	13
----	----	----	----	----

10	29	14	37	13
----	----	----	----	----

10	29	29	37	13
----	----	----	----	----

10	14	29	37	13
----	----	----	----	----

10	14	29	37	13
----	----	----	----	----

10	14	14	29	37
----	----	----	----	----

Sorted array:

10	13	14	29	37
----	----	----	----	----

Copy 10

Shift 29

Insert 10; copy 14

Shift 29

Insert 14; copy 37, insert 37 on top of itself

Copy 13

Shift 37, 29, 14

Insert 13

An insertion sort of an array of five integers



Insertion Sort Algorithm

```
public void insertionSort(Comparable[] arr) {  
    for (int i = 1; i < arr.length; ++i) {  
        Comparable temp = arr[i];  
        int pos = i;  
        // Shuffle up all sorted items > arr[i]  
        while (pos > 0 &&  
               arr[pos-1].compareTo(temp) > 0) {  
            arr[pos] = arr[pos-1];  
            pos--;  
        } // end while  
        // Insert the current item  
        arr[pos] = temp;  
    }  
}
```



Insertion Sort Analysis

```
public void insertionSort(Comparable[] arr) {  
    for (int i = 1; i < arr.length; ++i) {  
        Comparable temp = arr[i];  
        int pos = i;  
        // Shuffle up all sorted items > arr[i]  
        while (pos > 0 &&  
               arr[pos-1].compareTo(temp) > 0) {  
            arr[pos] = arr[pos-1];  
            pos--;  
        } // end while  
        // Insert the current item  
        arr[pos] = temp;  
    }  
}
```

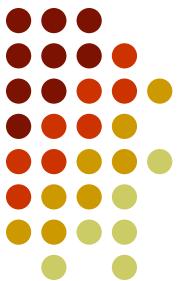
The diagram illustrates the execution flow of the insertion sort algorithm. It highlights two loops: the outer loop (for i) and the inner loop (while $pos > 0$). The outer loop is executed $n-1$ times, where n is the length of the array. The inner loop is executed i times for each iteration of the outer loop.

Insertion Sort: Number of Comparisons



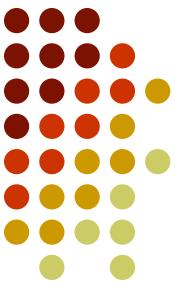
# of Sorted Elements	Best case	Worst case
0	0	0
1	1	1
2	1	2
...
$n-1$	1	$n-1$
<hr/>		$n(n-1)/2$
<hr/>		

Remark: we only count comparisons of elements in the array.



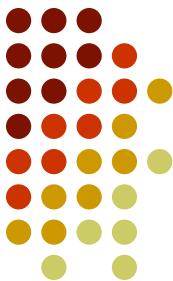
Insertion Sort: Cost Function

- 1 operation to initialize the outer loop
- The outer loop is evaluated $n-1$ times
 - 5 instructions (including outer loop comparison and increment)
 - Total cost of the outer loop: $5(n-1)$
- How many times the inner loop is evaluated is affected by the state of the array to be sorted
- Best case: the array is already completely sorted so no “shifting” of array elements is required.
 - We only test the condition of the inner loop once (2 operations = 1 comparison + 1 element comparison), and the body is never executed
 - Requires $2(n-1)$ operations.



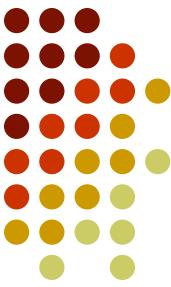
Insertion Sort: Cost Function

- Worst case: the array is sorted in reverse order (so each item has to be moved to the front of the array)
 - In the i -th iteration of the outer loop, the inner loop will perform $4i+1$ operations
 - Therefore, the total cost of the inner loop will be $2n(n-1)+n-1$
- Time cost:
 - Best case: $7(n-1)$
 - Worst case: $5(n-1)+2n(n-1)+n-1$
- What about the number of moves?
 - Best case: $2(n-1)$ moves
 - Worst case: $2(n-1)+n(n-1)/2$



Insertion Sort: Average Case

- Is it closer to the best case (n comparisons)?
- The worst case ($n * (n-1) / 2$) comparisons?
- It turns out that when random data is sorted, insertion sort is usually closer to the worst case
 - Around $n * (n-1) / 4$ comparisons
 - Calculating the average number of comparisons more exactly would require us to state assumptions about what the “average” input data set looked like
 - This would, for example, necessitate discussion of how items were distributed over the array
- Exact calculation of the number of operations required to perform even simple algorithms can be challenging
 - (for instance, assume that each initial order of elements has the same probability to occur)



Bubble Sort

- Simplest sorting algorithm
- Idea:
 - 1. Set flag = false
 - 2. Traverse the array and compare pairs of two consecutive elements
 - 1.1 If $E1 \leq E2$ -> OK (do nothing)
 - 1.2 If $E1 > E2$ then Swap($E1, E2$) and set flag = true
 - 3. repeat 1. and 2. while flag=true.



Bubble Sort

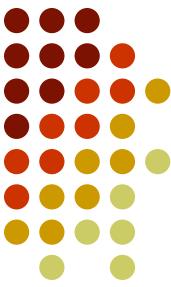
1	1	23	2	56	9	8	10	100
2	1	2	23	56	9	8	10	100
3	1	2	23	9	56	8	10	100
4	1	2	23	9	8	56	10	100
5	1	2	23	9	8	10	56	100

---- finish the first traversal ----

1	1	2	23	9	8	10	56	100
2	1	2	9	23	8	10	56	100
3	1	2	9	8	23	10	56	100
4	1	2	9	8	10	23	56	100

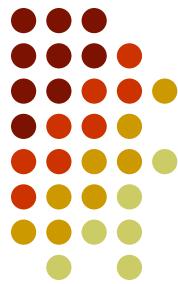
---- finish the second traversal ----

...



Bubble Sort

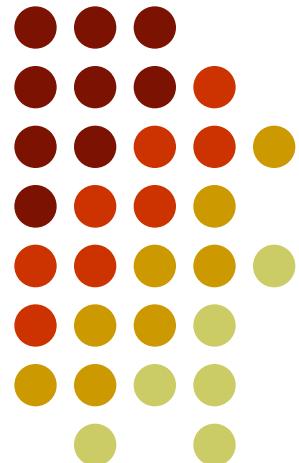
```
public void bubbleSort (Comparable[] arr) {  
    boolean isSorted = false;  
    while (!isSorted) {  
        isSorted = true;  
        for (i = 0; i<arr.length-1; i++)  
            if (arr[i].compareTo(arr[i+1]) > 0) {  
                Comparable tmp = arr[i];  
                arr[i] = arr[i+1];  
                arr[i+1] = tmp;  
                isSorted = false;  
            }  
    }  
}
```

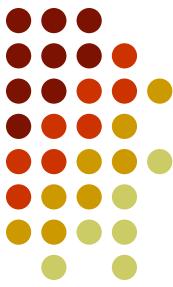


Bubble Sort: analysis

- After the first traversal (iteration of the main loop) – the maximum element is moved to its place (the end of array)
- After the i -th traversal – largest i elements are in their places
- Time cost, number of comparisons, number of moves -> Assignment 4

O Notation





O-notation Introduction

- Exact counting of operations is often difficult (and tedious), even for simple algorithms
- Often, exact counts are not useful due to other factors, e.g. the language/machine used, or the implementation of the algorithm (different types of operations do not take the same time anyway)
- O-notation is a mathematical language for evaluating the running-time (and memory usage) of algorithms



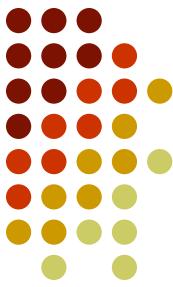
Growth Rate of an Algorithm

- We often want to compare the performance of algorithms
- When doing so we generally want to know how they perform when the problem size (n) is large
- Since cost functions are complex, and may be difficult to compute, we approximate them using O notation



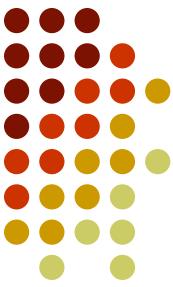
Example of a Cost Function

- Cost Function: $t_A(n) = n^2 + 20n + 100$
 - Which term dominates?
- It depends on the size of n
 - $n = 2, t_A(n) = 4 + 40 + \underline{100}$
 - The constant, 100, is the dominating term
 - $n = 10, t_A(n) = 100 + \underline{200} + 100$
 - $20n$ is the dominating term
 - $n = 100, t_A(n) = \underline{10,000} + 2,000 + 100$
 - n^2 is the dominating term
 - $n = 1000, t_A(n) = \underline{1,000,000} + 20,000 + 100$
 - n^2 is the dominating term



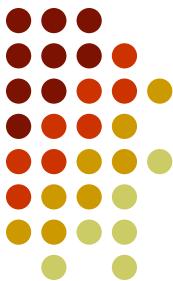
Big O Notation

- O notation approximates the cost function of an algorithm
 - The approximation is usually good enough, especially when considering the efficiency of algorithm as n gets very large
 - Allows us to estimate rate of function growth
- Instead of computing the entire cost function we only need to count the number of times that an algorithm executes its *barometer instruction(s)*
 - The instruction that is executed the most number of times in an algorithm (the highest order term)



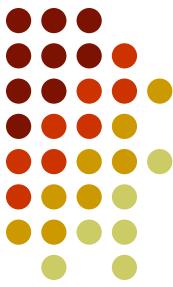
Big O Notation

- Given functions $t_A(n)$ and $g(n)$, we can say that the efficiency of an algorithm is *of order* $g(n)$ if there are positive constants c and m such that
 - $t_A(n) \leq c.g(n)$ for all $n \geq m$
- we write
 - $t_A(n)$ is $O(g(n))$ and we say that
 - $t_A(n)$ is of order $g(n)$
- e.g. if an algorithm's running time is $3n + 12$ then the algorithm is $O(n)$. If c is 3 and m is 12 then:
 - $4 * n \geq 3n + 12$ for all $n \geq 12$



In English...

- The cost function of an algorithm A, $t_A(n)$, can be approximated by another, simpler, function $g(n)$ which is also a function with only 1 variable, the data size n .
- The function $g(n)$ is selected such that it represents an *upper bound* on the efficiency of the algorithm A (i.e. an upper bound on the value of $t_A(n)$).
- This is expressed using the big-O notation: $O(g(n))$.
- For example, if we consider the time efficiency of algorithm A then “ $t_A(n)$ is $O(g(n))$ ” would mean that
 - A cannot take more “time” than $O(g(n))$ to execute or that (more than $c.g(n)$ for some constant c)
 - the cost function $t_A(n)$ grows *at most* as fast as $g(n)$



The general idea is ...

- when using Big-O notation, rather than giving a precise figure of the cost function using a specific data size n
- express the behaviour of the algorithm as its data size n grows very large
- so ignore
 - lower order terms and
 - constants



O Notation Examples

- All these expressions are $O(n)$:
 - $n, 3n, 61n + 5, 22n - 5, \dots$
- All these expressions are $O(n^2)$:
 - $n^2, 9n^2, 18n^2 + 4n - 53, \dots$
- All these expressions are $O(n \log n)$:
 - $n(\log n), 5n(\log 99n), 18 + (4n - 2)(\log(5n + 3)), \dots$