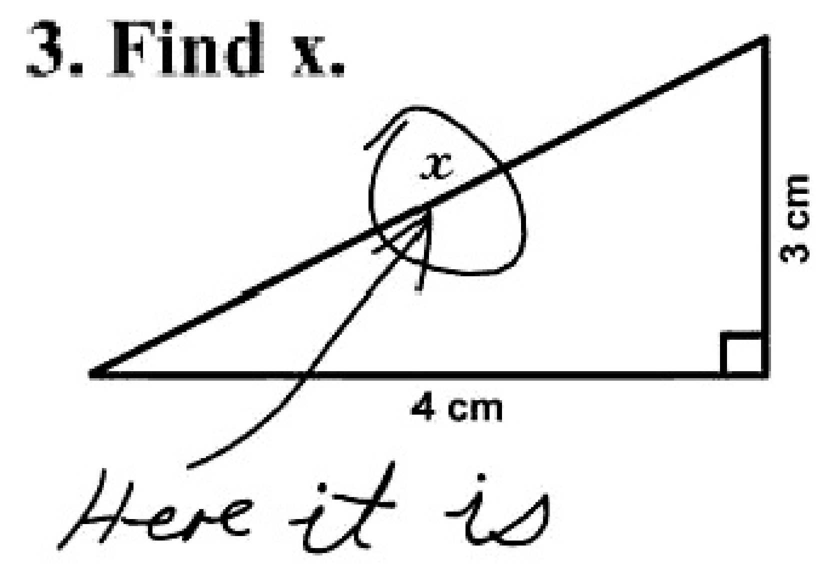


SEARCHING, SORTING, AND ASYMPTOTIC COMPLEXITY

Lecture 12
CS2110 – Fall 2009

Announcements

- Prelim 1
  - Thursday, October 15,
    7:30 - 9pm, G01 Uris
  - Topics
    - all material up to (but not including) searching and sorting (this week's topics)
    - including interfaces & inheritance
- Exam conflicts
  - A number of people will take P1 on the same day but from 6:00-6:30 (still Uris G01)
  - Email me ASAP if you have a conflict but can't solve it this way!
- A3 due Friday, October 10, 11:59pm
- Review sessions:

What Makes a Good Algorithm?

- Suppose you have two possible algorithms or data structures that basically do the same thing; which is *better*?

- Well… what do we mean by *better*?
  - Faster?
  - Less space?
  - Easier to code?
  - Easier to maintain?
  - Required for homework?

- How do we measure time and space for an algorithm?

Sample Problem: Searching

Determine if a *sorted* array of integers contains a given integer

First solution: Linear Search (check each element)

```
static boolean find(int[] a, int item) {
    for (int i = 0; i < a.length; i++) {
        if (a[i] == item) return true;
    }
    return false;
}
```

```
static boolean find(int[] a, int item) {
    for (int x : a) {
        if (x == item) return true;
    }
    return false;
}
```

Sample Problem: Searching

Second solution: *Binary Search*

```
static boolean find (int[] a, int item) {
    int low = 0;
    int high = a.length - 1;
    while (low <= high) {
        int mid = (low + high)/2;
        if (a[mid] < item)
            low = mid + 1;
        else if (a[mid] > item)
            high = mid - 1;
        else return true;
    }
    return false;
}
```

Linear Search vs Binary Search

- Which one is better?
  - Linear Search is easier to program
  - But Binary Search is faster… isn't it?
- How do we measure to show that one is faster than the other
  - Experiment?
  - Proof?
  - Which inputs do we use?

Simplifying assumption #1: Use the *size* of the input rather than the input itself

- For our sample search problem, the input size is n+1 where n is the array size

Simplifying assumption #2: Count the number of "*basic steps*" rather than computing exact times

One Basic Step = One Time Unit

- Basic step:
  - input or output of a scalar value
  - accessing the value of a scalar variable, array element, or field of an object
  - assignment to a variable, array element, or field of an object
  - a single arithmetic or logical operation
  - method invocation (not counting argument evaluation and execution of the method body)

For a conditional, count number of basic steps on the branch that is executed

For a loop, count number of basic steps in loop body times the number of iterations

For a method, count number of basic steps in method body (including steps needed to prepare stack-frame)

Runtime vs Number of Basic Steps

- But is this cheating?
  - The runtime is not the same as the number of basic steps
  - Time per basic step varies depending on computer, on compiler, on details of code…
- Well…yes, in a way
  - But the number of basic steps is *proportional* to the actual runtime

Which is better?

- n or n^2 time?
- 100 n or n^2 time?
- 10,000 n or n^2 time?

As n gets large, multiplicative constants become less important

Simplifying assumption #3: Ignore multiplicative constants

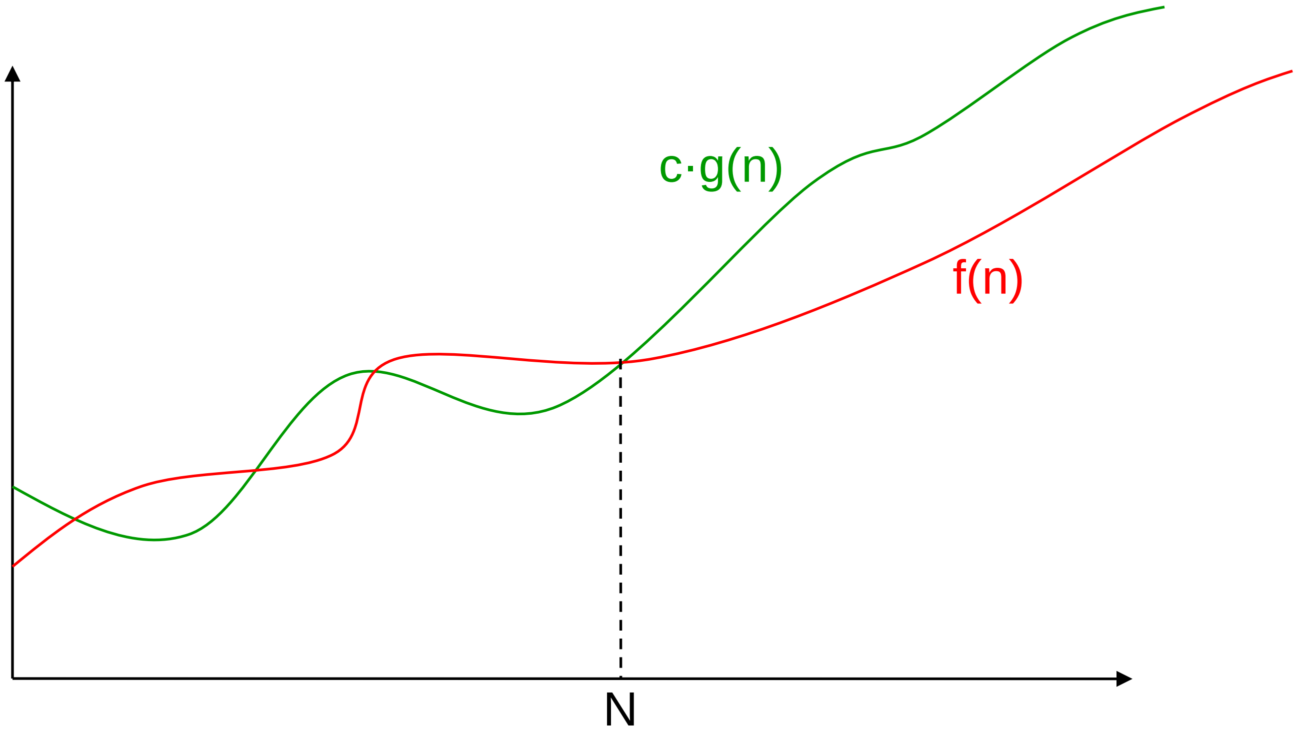
Using Big-O to Hide Constants

- We say f(n) is *order of* g(n) if f(n) is bounded by a constant times g(n)
- Notation: f(n) is O(g(n))
- Roughly, f(n) is O(g(n)) means that f(n) grows like g(n) or slower, to within a constant factor
- "Constant" means fixed and independent of n

- Example: $(n^2 + n)$ is $O(n^2)$
- We know $n \le n^2$ for $n \ge 1$
- So $n^2 + n \le 2\, n^2$ for $n \ge 1$
- So by definition, $n^2 + n$ is $O(n^2)$ for c=2 and N=1

Formal definition: f(n) is O(g(n)) if there exist constants c and N such that for all $n \ge N$, $f(n) \le c \cdot g(n)$

A Graphical View



- To prove that f(n) is O(g(n)):
  - Find an N and c such that f(n) δ c g(n) for all nεN
  - We call the pair (c, N) a *witness pair* for proving that f(n) is O(g(n))

Big-O Examples

Claim: $100\,n + \log n$ is $O(n)$

We know $\log n \leq n$ for $n \geq 1$

So $100\,n + \log n \leq 101\,n$

for $n \geq 1$

So by definition,

$100\,n + \log n$ is $O(n)$

for $c = 101$ and $N = 1$

Claim: $\log_B n$ is $O(\log_A n)$

since $\log_B n$ is $(\log_B A)(\log_A n)$

Question: Which grows faster: n or $\log n$?

Big-O Examples

- Let $f(n) = 3n^2 + 6n - 7$
  - $f(n)$ is $O(n^2)$
  - $f(n)$ is $O(n^3)$
  - $f(n)$ is $O(n^4)$
  - …
- $g(n) = 4\ n \log n + 34\ n - 89$
  - $g(n)$ is $O(n \log n)$
  - $g(n)$ is $O(n^2)$
- $h(n) = 20 \cdot 2^n + 40n$
  - $h(n)$ is $O(2^n)$
- $a(n) = 34$
  - $a(n)$ is $O(1)$

Only the *leading* term (the term that grows most rapidly) matters

Problem-Size Examples

- Suppose we have a computing device that can execute 1000 operations per second; how large a problem can we solve?

	1 second	1 minute	1 hour
n	1000	60,000	3,600,000
$n \log n$	140	4893	200,000
n^2	31	244	1897
$3n^2$	18	144	1096
n^3	10	39	153
2^n	9	15	21

Commonly Seen Time Bounds

O(1)	constant	excellent
O(log n)	logarithmic	excellent
O(n)	linear	good
O(n log n)	n log n	pretty good
$O(n^2)$	quadratic	OK
$O(n^3)$	cubic	maybe OK
$O(2^n)$	exponential	too slow

Worst-Case/Expected-Case Bounds

- We can't possibly determine time bounds for all possible inputs of size n
- Simplifying assumption #4: Determine number of steps for either
  - worst-case or
  - expected-case

Worst-case

- Determine how much time is needed for the *worst possible* input of size n

Expected-case

- Determine how much time is needed *on average* for all inputs of size n

Our Simplifying Assumptions

- Use the size of the input rather than the input itself – n
- Count the number of "basic steps" rather than computing exact times
- Multiplicative constants and small inputs ignored (order-of, big-O)
- Determine number of steps for either
  - worst-case
  - expected-case
- These assumptions allow us to analyze algorithms effectively

Worst-Case Analysis of Searching

Linear Search

```
static boolean find (int[] a, int item)
    {
   for (int i = 0; i < a.length; i++) {
      if (a[i] == item) return true;
   }
   return false;
}
```

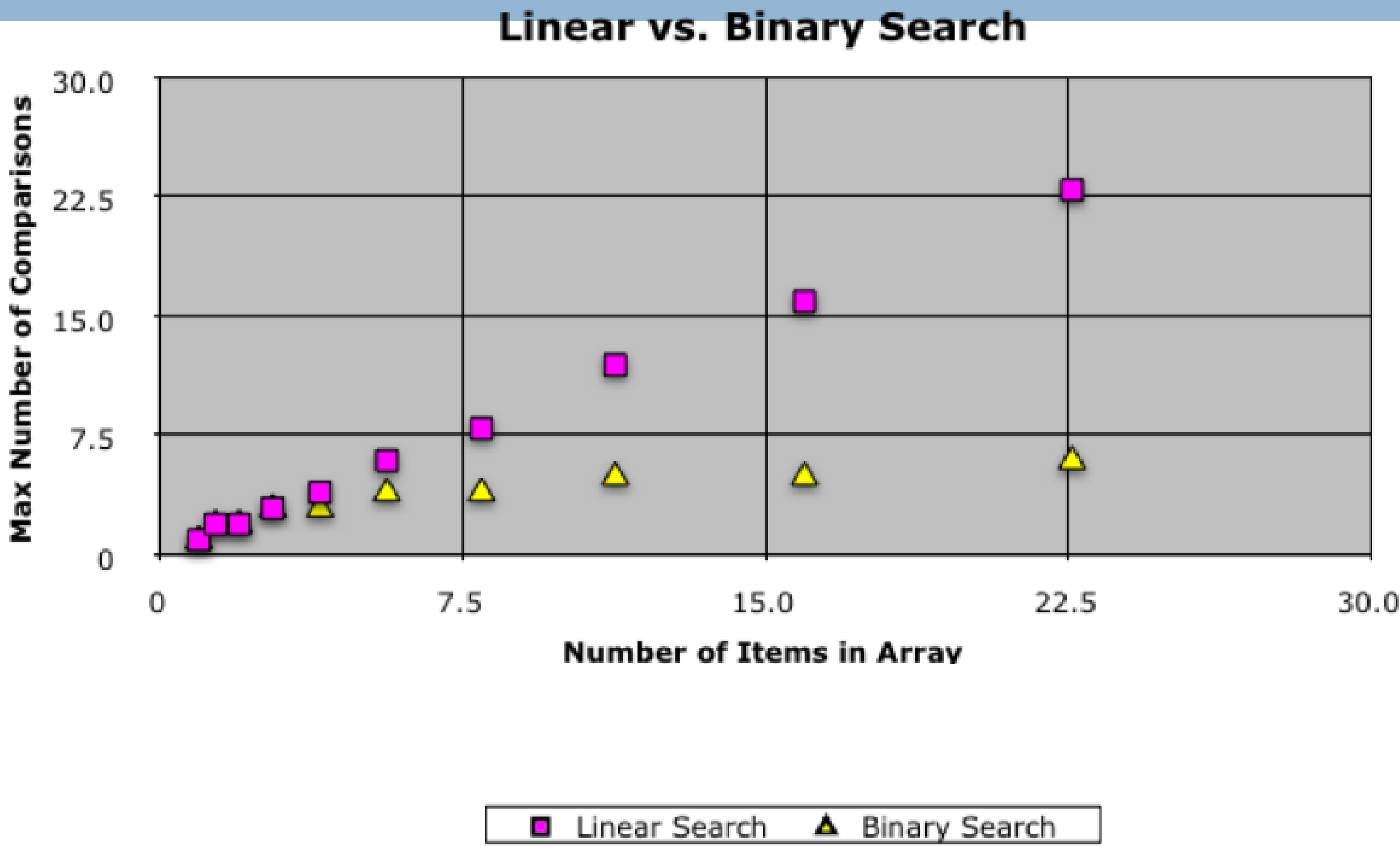
worst-case time = O(n)

Binary Search

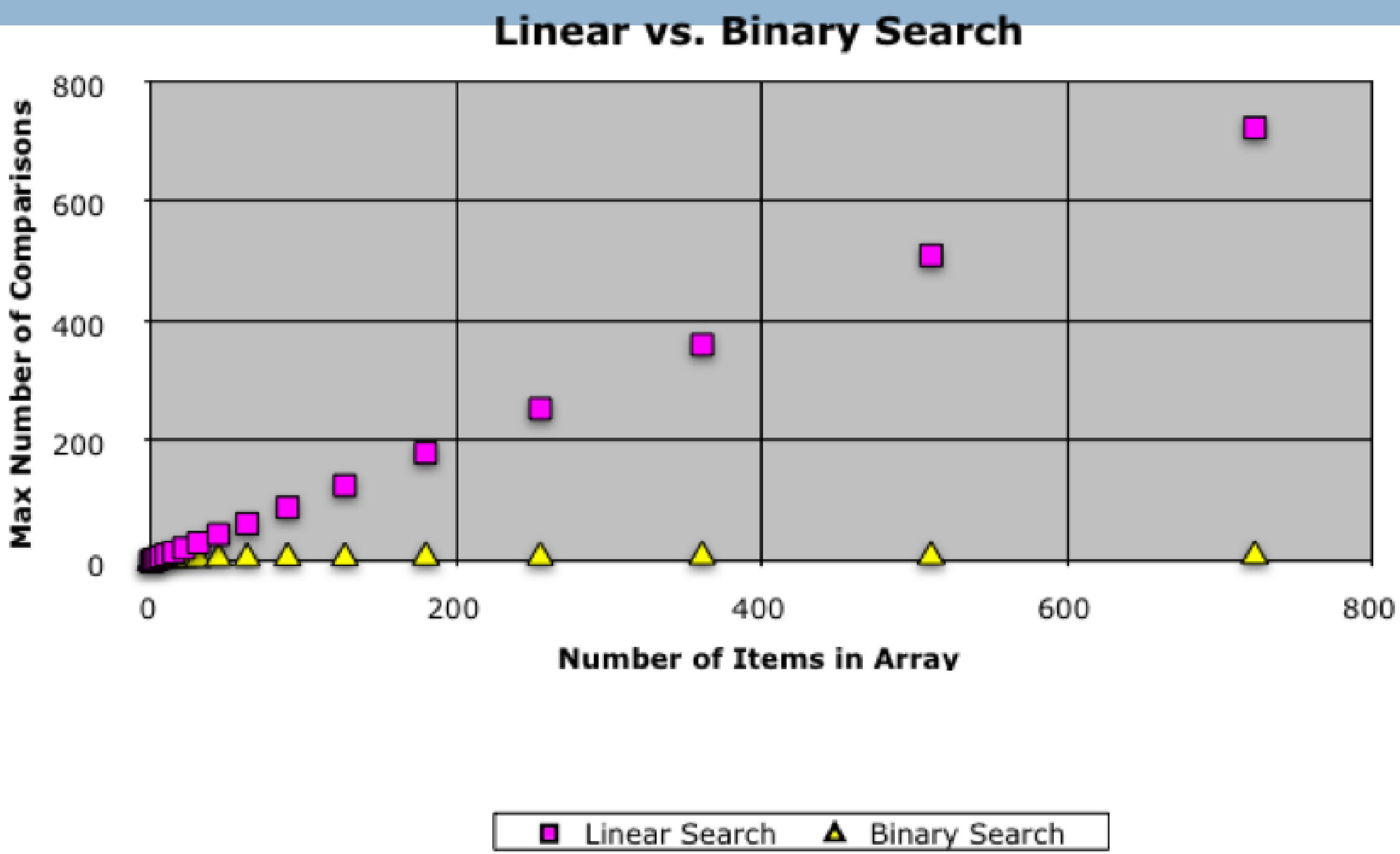
```
static boolean find (int[] a, int item) {
   int low = 0;
   int high = a.length - 1;
   while (low <= high) {
      int mid = (low + high)/2;
      if (a[mid] < item)
         low = mid+1;
      else if (a[mid] > item)
         high = mid - 1;
      else return true;
   }
   return false;
}
```

worst-case time = O(log n)

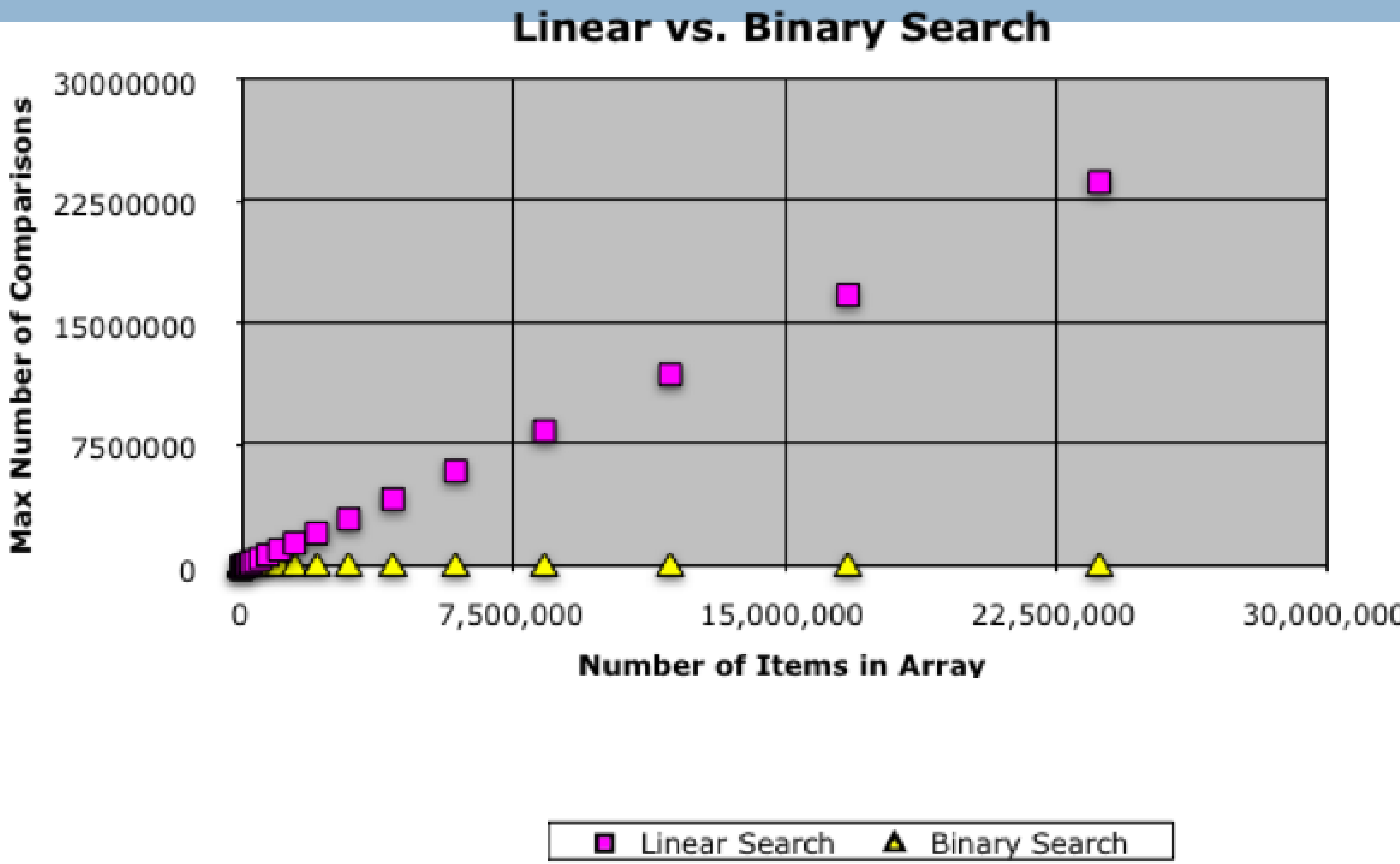
Comparison of Algorithms



Comparison of Algorithms



Comparison of Algorithms



Analysis of Matrix Multiplication

- Code for multiplying n-by-n matrices A and B:

  By convention, matrix problems are measured in terms of n, the number of rows and columns

  - Note that the input size is really $2n^2$, not n
  - Worst-case time is $O(n^3)$
  - Expected-case time is also $O(n^3)$

```
for (i = 0; i < n; i++)
        for (j = 0; j < n; j++) {
                C[i][j] = 0;
     for (k = 0; k < n; k++)
                        C[i][j] += A[i][k]*B[k][j];
   }
```

Remarks

- Once you get the hang of this, you can quickly zero in on what is relevant for determining asymptotic complexity
  - For example, you can usually ignore everything that is not in the innermost loop. Why?
- Main difficulty:
  - Determining runtime for recursive programs

Why Bother with Runtime Analysis?

- Computers are so fast these days that we can do whatever we want using just simple algorithms and data structures, right?
- Well...not really – data-structure/algorithm improvements can be a *very big* win
- Scenario:
  - A runs in n^2 msec
  - A' runs in $n^2/10$ msec
  - B runs in 10 n log n msec

Problem of size $n=10^3$

- A: 10^3 sec ≈ 17 minutes
- A': 10^2 sec ≈ 1.7 minutes
- B: 10^2 sec ≈ 1.7 minutes

Problem of size $n=10^6$

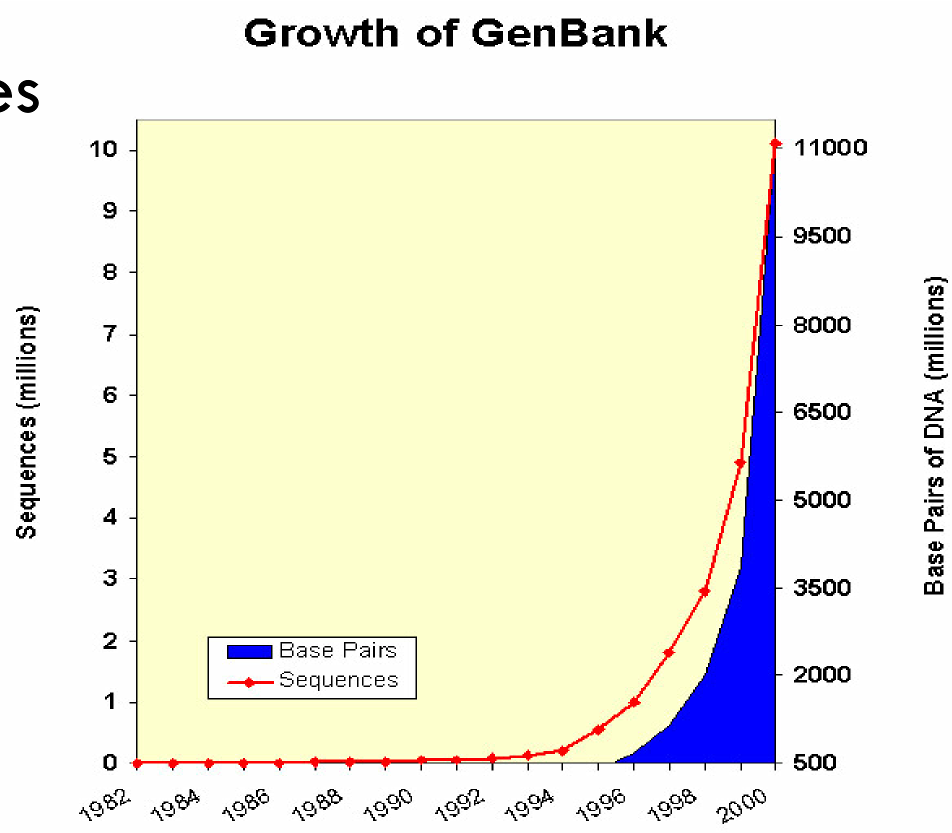
- A: 10^9 sec ≈ 30 years
- A': 10^8 sec ≈ 3 years
- B: $2 \cdot 10^5$ sec ≈ 2 days

1 day = 86,400 sec ≈ 10^5 sec

1,000 days ≈ 3 years

Algorithms for the Human Genome

- Human genome
  = 3.5 billion nucleotides
  ~ 1 Gb
- @1 base-pair instruction/μsec
  - $n^2 \rightarrow$ 388445 years
  - $n \log n \rightarrow$ 30.824 hours
  - $n \rightarrow$ 1 hour



Limitations of Runtime Analysis

- Big-O can hide a very large constant
  - Example: selection
  - Example: small problems

- The specific problem you want to solve may not be the worst case
  - Example: Simplex method for linear programming

- Your program may not be run often enough to make analysis worthwhile
  - Example: one-shot vs. every day
  - You may be analyzing and improving the wrong part of the program
- Very common situation
- Should use profiling tools

Summary

- Asymptotic complexity
  - Used to measure of time (or space) required by an algorithm
  - Measure of the *algorithm*, not the *problem*
- Searching a sorted array
  - Linear search: O(n) worst-case time
  - Binary search: O(log n) worst-case time
- Matrix operations:
  - Note: n = number-of-rows = number-of-columns
  - Matrix-vector product: O(n^2) worst-case time
  - Matrix-matrix multiplication: O(n^3) worst-case time
- More later with sorting and graph algorithms