Computer Science 20
Programming Methods

- Pre-requisites: CS 10 and Math 3B
- Main emphasis: learn about data structures
  - Including related topics, such as abstraction, specialized algorithms, and efficiency issues
- A main goal: increase your programming skills
  - In Java, as well as the design and application of object-oriented solutions to problems
  - Requires *practice* – and a commitment of time/effort

Stuff you should already know

- *Catch up by yourself* if necessary on any of these:
  - How to write/execute a Java *application*
  - Comments, primitive data types, basic operators, arithmetic, assignment, type casting for primitive types
  - Control structures – `if/else`, `switch`, `while`, `for`, `do/while`, conditional operator
  - Writing/using classes, and method basics – including parameters, scope and duration rules, and overloading
  - Other *elementary* Java or programming topics
- Tip: keep your CS 10 (or other Java) book handy

What CS 20 will reinforce (to start)

- Basics of objects and references
- Strings and arrays
- Exception handling
- Input and output
- Some OOP concepts and related Java issues
  - Class design and javadocs
  - Methods of `class Object`
  - Inheritance and polymorphism
  - Abstract classes and interfaces

Approximate schedule
(generally follows Dale/Joyce/Weems text)

1. Reinforce important Java and OOP topics
2. Complexity concepts, correctness and testing
3. Data abstraction ideas, and start priority queues
4. Stacks, Recursion, and 1st midterm exam
5. Queues, and Lists
6. Trees, including heaps and faster priority queues
7. Binary search trees, and 2nd midterm exam
8. Sorting algorithms
9. Searching algorithms, and hash tables
10. Maybe more *as time permits*

Requirements

- Students are *required* to monitor the course's web pages, starting at http://www.cs.ucsb.edu/~mikec/cs20
- Assignments – 30%
  - Weekly written homeworks and bi-weekly programming projects
  - Must work *individually* unless explicitly told otherwise
- Three exams – each 20%
- Attendance – 10%

To do *this week*

- Read chapters 1 and 2 in Dale/Joyce/Weems text
  - In general, try to read ahead of the lectures
  - Also Section 9.1, and browse Appendices as necessary
- Verify CSIL access
  - Need account @engineering.ucsb.edu (@cs is alias) – apply online if don't already have one
  - Change password if required – sign on and acclimate
- Attend class – inc. discussion section Thursday
- Questions?

What is a reference?

- Actually a reference variable
  - A variable that can store a memory address
  - Refer to objects or `null`, but not primitive types
- Very few operations allowed for references
  - Just assignment with = or equality test with ==
  - Only exception is + for Strings
- Mostly references are used to operate on objects
  - Access internal field or call a method with `.` operator
  - Type conversion with `(cast)`, or test with `instanceof`

Dealing with objects

- Declaring and creating – 2 discrete steps
- Garbage collection – behind the scenes
- `=` – copies a reference – creates alias
- `==` – true if references are aliases
  - Use `equals` (if overridden for the class) to compare objects
- Parameters – always *copies* – even for references
  - But alias can be used to operate on the object
- No operator overloading allowed
  - Reason: what you see is what you get with Java (except for String `+` and `+=` operators)

Strings

- Immutable objects – means safe to share references
- `+` concatenates if either is string: `5 + "a"` → `"5a"`
- Comparing strings requires methods, not ==, <, …
  - `s1.equals(s2)` – overridden `Object` method – true if all same characters in same order
  - `s1.compareTo(s2)` – from `interface Comparable` – returns `int`
- Converting from/to other types
  - `String.valueOf(x)` – overloaded many times
  - Other direction less standard – `Integer.parseInt(s)`

More string things

- StringBuffer and StringBuilder – mutable strings
  - `StringBuilder b = new StringBuilder(`aString`);`
  - `b.append(`anotherString`);`
  - Also `b.insert`, `b.setCharAt`, `b.reverse`, …
  - `b.toString()` – creates String when done
- StringTokenizer – handy way to break up a string
  - `StringTokenizer t = new StringTokenizer(`aString`);`
    `while (t.hasMoreTokens())`
    `{   String word = t.nextToken();` … `}`
- See online documentation for class String, and others

Arrays

- Built-in data structures – a.k.a. collections
- Entities (array elements) are *all the same type*
  - Access each entity by array indexing operator – `[]`
- Declare, create, and assign values – 3 distinct steps
  1. Declare array variable: `int[] a;` // type restricted to `int`
  2. Create array object: `a = new int[5];` // size is fixed at 5
  3. Assign values: `for (int i = 0; i < 5; i++) a[i] =` …
- Treat whole array like any other `Object`
  - `int[] b = a;` // creates an alias – not a copy of array
  - `someMethod(a);` // passes alias – `a` can be changed
  - An instance variable (`a.length`), and inherited methods!

Preview: better collections

- java.util.ArrayList – an array-like structure
  - *Expands dynamically*, so no need to set fixed size
    `ArrayList<Integer> a = new ArrayList<Integer>();`
  - Note use of Java 5 generic type – `Integer` in this case
- Must *wrap* primitive types:
  `a.add(new Integer(7));`
  `a.add(17);` // or rely on "autoboxing"
- Unwrap on retrieval:
  `int i = ( (Integer) a.get(0) ).intValue();`
  `int j = a.get(1);` // or rely on "auto un-boxing"
- Overrides Object methods – to make more sense

How *complex* is that algorithm?

- *Count* the steps to find out
- Note that execution time depends on many things
  - Hardware features of particular computer
    - Processor type and speed
    - Available memory (cache and RAM)
    - Available disk space, and disk read/write speed
  - Programming language features
  - Language compiler/interpreter used
  - Computer's operating system software
- So execution times for algorithms differ for different systems – but complexity is more basic

A detailed computer model

- Assume constant times for various operations
  - T_{fetch} – time to fetch an operand from memory
  - T_{store} – time to store an operand in memory
  - T_{+}, T_{-}, T_{*}, $T_{\div}$, $T_{<}$, … – times to perform simple arithmetic operation or comparison
  - T_{call}, T_{return} – times to call and return from methods
  - $T_{[\cdot]}$ – time to calculate array element's address
- e.g., time to execute `y = x` is $T_{fetch} + T_{store}$
  - Note: `y = 1` takes same time – 1 is stored somewhere

More counting steps

- `y = y + 1` → $2T_{fetch}+T_{+}+T_{store}$
  - Same as time for `y += 1`, `y++`, and `++y`
- `y = f(x)` → $T_{fetch}+2T_{store}+T_{call}+T_{f(x)}$
- Method example – `public int sumSeries(int n)`:

```
int result = 0;     → Tfetch+Tstore
for (int i = 1;     → Tfetch+Tstore
         i <= n;    → (2Tfetch+T<) * (n+1)
         i++)       → (2Tfetch+T+ +Tstore) * n
    result += i;    → (2Tfetch+T+ +Tstore) * n
return result;      → Tfetch+Treturn
```

Let $t_1 = 5T_{fetch}+2T_{store}+T_{<}+T_{return}$ and $t_2 = 6T_{fetch}+2T_{store}+T_{<}+2T_{+}$ → then total time for method is $t_1 + t_2 n$

Things to notice about counts

- Very tedious – even for simple algorithms
- Operation times are constant only for particular computer/compiler/… situations
- The size of the problem matters the most
- e.g., total of $t_1 + t_2 n$ from previous slide
  - t_1 and t_2 vary, depending on platform
  - The second term dominates if n is large
- So is there a better way to compare algorithms?

Algorithm analysis

- Really want to compare *just the algorithms*
  - i.e., holding constant things that don't matter
  - Question becomes – which algorithm is more efficient on *any computer in any language*?
- Solution – 'O' notation
  - Simplest is worst case analysis – Big-Oh
    - Provides an upper bound on expected running time
  - Others include Little-Oh, Big Ω (omega), and Big Θ (theta) – all useful, but not as commonly used

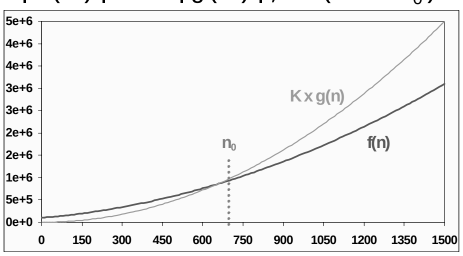
Big-Oh notation

- Strips problem of inconsequential details
  - All but the "dominant" term are ignored
    - e.g., say algorithm takes $3n^2 + 15n + 100$ steps, for a problem of size n
    - Note: as n gets large, first term ($3n^2$) dominates, so okay to ignore the other terms
  - Constants associated with processor speed and language features are ignored too
    - In above example, ignore the `3`
- So this example algorithm is $O(n^2)$
  - Pronounced "Oh of n-squared"
    - Belongs to the "quadratic complexity" class of algorithms

Formally, `f(n)` is `O(g(n))` if

$\exists$ two positive constants (K, n_0), such that

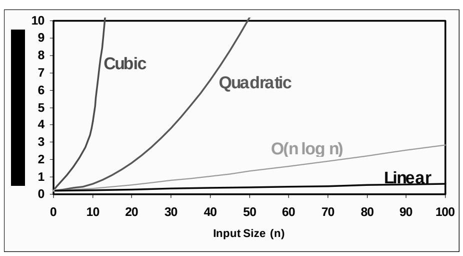
$$|f(n)| \leq K|g(n)|, \forall (n \geq n_0)$$



'O' and related notation

- Big-Oh – upper bound on running time
  - f(n) is O(g(n)) if there are positive constants, c and n_0, such that $f(n) \leq cg(n)$ when $n \geq n_0$
- Big Ω – lower bound on running time
  - f(n) is $\Omega(g(n))$ if … $f(n) \geq cg(n)$ when $n \geq n_0$
- Big Θ – both an upper *and* lower bound
  - f(n) is $\Theta(g(n))$ iff f(n) is O(g(n)) and f(n) is $\Omega(g(n))$
- Little-Oh – a "strictly-less" than upper bound
  - f(n) is o(g(n)) iff f(n) is O(g(n)) and f(n) is not $\Theta(g(n))$

Some complexity classes



- Linear - `O(n)`; Quadratic - $O(n^2)$; Cubic - $O(n^3)$
  - Also slower than cubic – e.g., Exponential - $O(2^n)$
  - And faster than linear – `O(log n)`, and Constant - `O(1)`

Applies to large problems only

- Big-Oh measures asymptotic complexity
  - Mostly irrelevant for small problems
  - But some algorithms become impractical as n grows, even if n isn't very large
- For example, imagine n = 256
  - And say a linear algorithm takes 256 microseconds
  - Cubic time is 16.8 seconds
  - Exponential time (base 2) is 3.7×10^{63} years!!!

(See related calculations on next slide.)

Big O	Microsec.	Millisec.	Seconds	Years
O(n)	256			
O(log n)	8			
O(n log n)	2,048	2.05		
O(n^2)	65,536	65.54		
O(n^3)	16,777,216	16,777	16.8	
O(2^n)	1.158E+77	1.158E+74	1.158E+71	3.7E+63

Algorithm analysis example

```
double[] prefixAverages1(double[] x) →
  double[] result = new double[x.length];
  for (int i=0; i<x.length; i++)
  {  double sum = 0; // happens n times
     for (int j=0; j<=i; j++)
          sum += x[i]; // happens n(n+1)/2 times
     result[i] = sum / (i+1); // n times
  }return result; // happens once
```

- Running time dominated by *nested* for loops
  - Approximate total is (n + n(n+1)/2 + n + 1) → so $O(n^2)$

Improved algorithm

```
double[] prefixAverages2(double[] x) →
  double[] result = new double[x.length];
  double runningSum = 0; // O(1)
  for (int i=0; i<x.length; i++)
  {   runningSum += x[i]; // O(n)
      result[i] = runningSum/(i+1);// also O(n)
  }return result; // O(1)
```

- Just one for loop this time – max term is O(n)
  - So overall complexity is O(n)

Runtime analysis

- Use to *complement (not replace)* algorithm analysis
  - Calculate elapsed clock time for operations

    ```
    long startTime = System.currentTimeMillis();
    {…} // operation to time here
    long finishTime = System.currentTimeMillis();
    long elapsedTime = finishTime - startTime;
    ```
  - Java 1.5 addition: `long instant = System.nanoTime();`
    - 1 millisecond → 1,000,000 nanoseconds !!!
- e.g., Timing_Random.java (Collins text, pp. 88-89)
- Of course results are infected by competing processes
  - Also by machine, compiler and system characteristics
  - But often can crudely estimate Big O anyway – Collins lab 4

What Big-Oh doesn't cover

- Small problems
  - Often dominated by lesser terms or constants
- What to count?
  - Comparisons? Assignments? Reads? Writes?
    - Some operations take longer than others
  - So usually just count iterations – see CountSteps.java
- Notice the definition is not restrictive
  - e.g., an algorithm that is O(n) is also O(n^2), etc.
  - So *agree* to express bound as tightly as possible, and to not include lesser terms in g(n)