Putting the Science Back into Computer Science

Robert Sedgewick Princeton University

The scientific method

is essential in applications of computation

A personal opinion formed on the basis of decades of experience as a

- CS educator
- author
- algorithm designer
- software engineer
- Silicon Valley contributor
- CS researcher



LGORITHM

Personal opinion . . . or unspoken consensus?

Fact of life in applied computing: performance matters

in a large number of important applications

Example: quadratic algorithms are useless in modern applications

- millions or billions of inputs
- 10¹² nanoseconds is 15+ minutes
- 10¹⁸ nanoseconds is 31+ years



- Bose-Einstein model
- String matching for genomics
- Natural language analysis
- N-body problem
- · ·
- .
- . [long list]

Lessons:

- 1. Efficient algorithms enable solution of problems that could not otherwise be addressed.
- 2. Scientific method is essential in understanding program performance

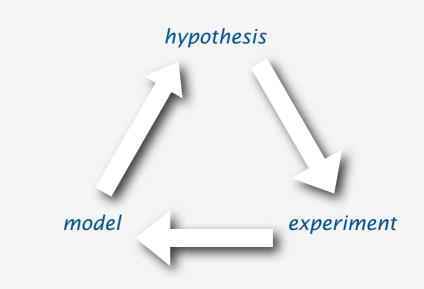
Important lessons for

- beginners
- software engineers
- scientists
- everyone]

is essential in understanding program performance

Scientific method

- create a model describing natural world
- use model to develop hypotheses
- run experiments to validate hypotheses
- refine model and repeat



1950s: uses scientific method



2000s: uses scientific method?



Algorithm designer who does not experiment gets lost in abstraction

Software developer who ignores cost risks catastrophic consequences

Problem: write a program to generate random numbers

model: classical probability and statistics hypothesis: frequency values should be uniform weak experiment:

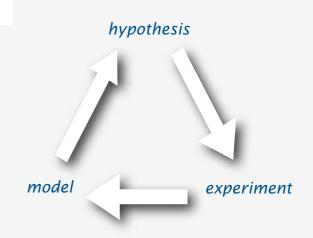
- generate random numbers
- check for uniform frequencies

better experiment:

- generate random numbers
- use $\chi^{_2}$ test to check frequency values against uniform distribution

better hypotheses/experiments still needed

- many documented disasters
- active area of scientific research
- applications: simulation, cryptography
- connects to core issues in theory of computation



int k = 0;while (true) System.out.print(k++ % V); 012345678901234567... random? int k = 0;

while (true) { k = k*1664525 + 1013904223);System.out.print(k % V);

textbook algorithm that flunks χ^2 test

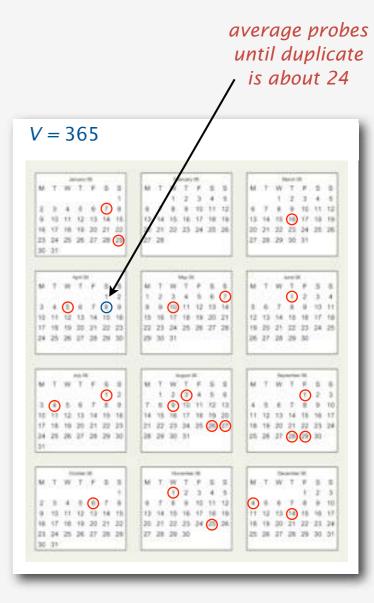
- Q. Is a given sequence of numbers random?A. No.
- Q. Does a given sequence exhibit some property that random number sequences exhibit?

Birthday paradox Average count of random numbers generated until a duplicate happens is about $\sqrt{\pi V/2}$

Example of a better experiment:

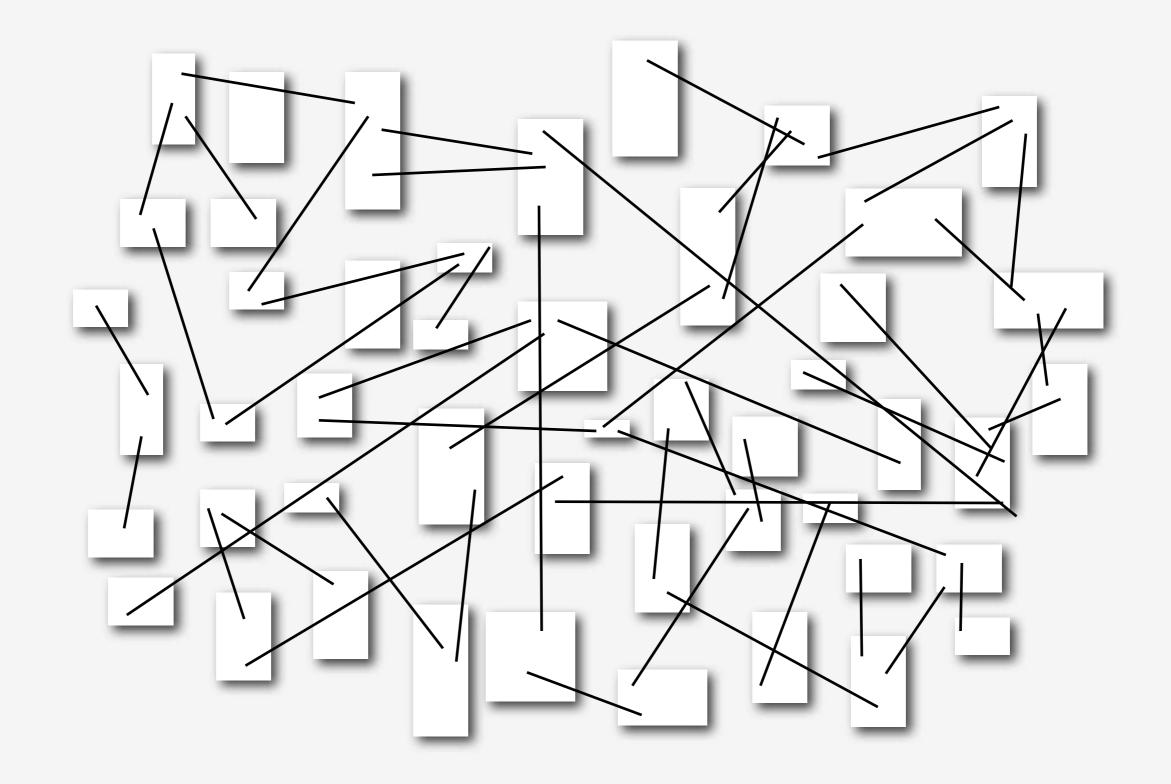
- generate numbers until duplicate
- check that count is close to $\sqrt{\pi V/2}$
- even better: repeat many times, check against distribution
- still better: run many similar tests for other properties

"Anyone who considers arithmetical methods of producing random digits is, of course, in a state of sin" — John von Neumann



Preliminary hypothesis (needs checking)

Modern software requires huge amounts of code

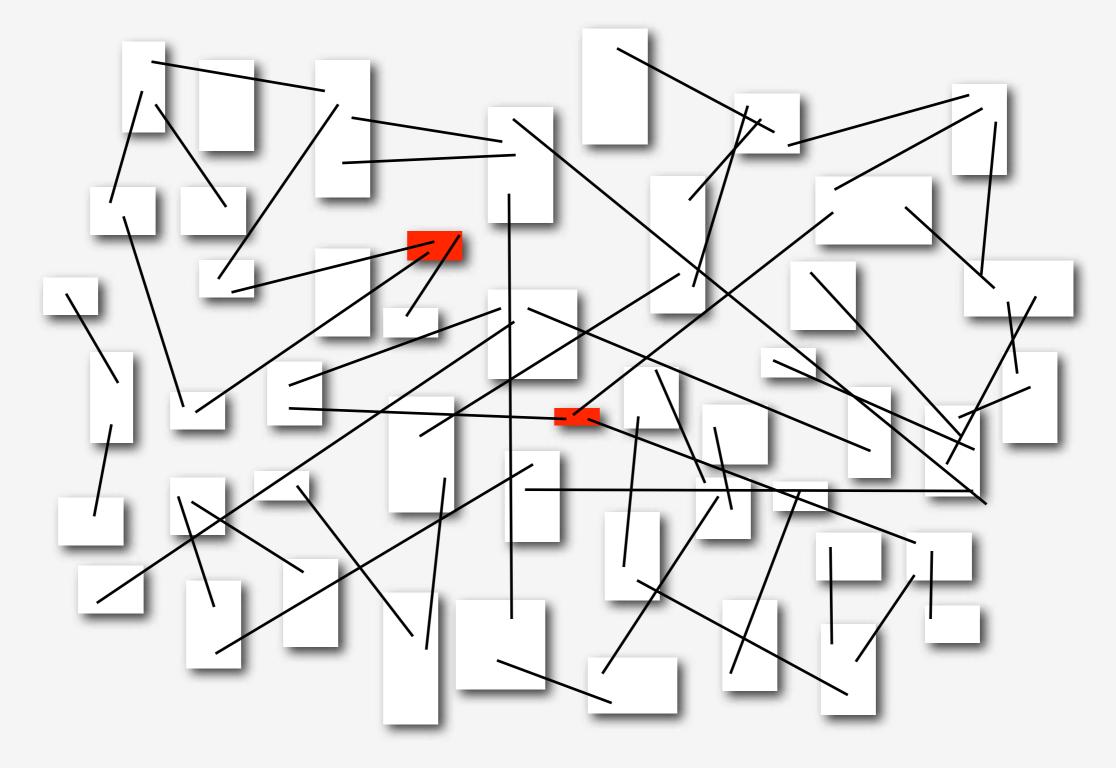


Preliminary hypothesis (needs checking)

Modern software development requires huge amounts of code

but

performance-critical code implements relatively few fundamental algorithms



How to predict performance (to compare algorithms)?

Not the scientific method: O-notation

Theorem: Running time is O(N^b)

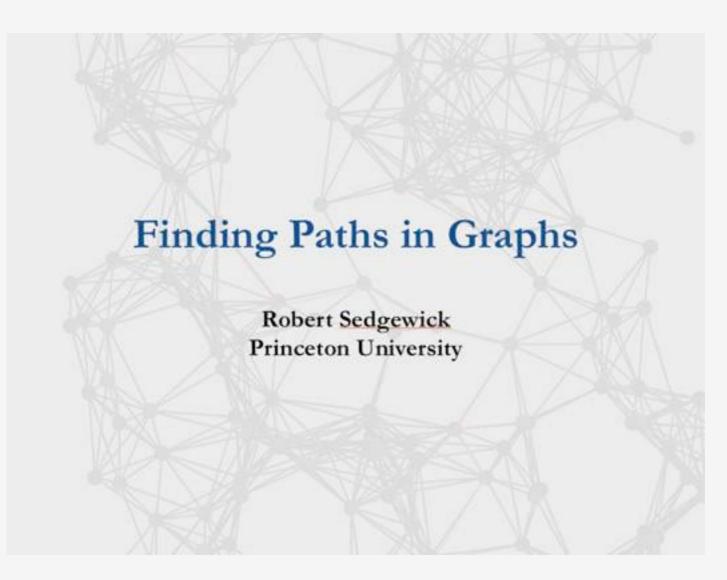
- hides details of implementation, properties of input
- useful for classifying algorithms and complexity classes
- not at all useful for predicting performance

Scientific method: Tilde-notation.

Hypothesis: Running time is ~aN^b

- doubling test: $T(2N)/T(N) \sim 2^{b}$
- an effective way to predict performance

A lecture within a lecture



Finding an st-path in a graph

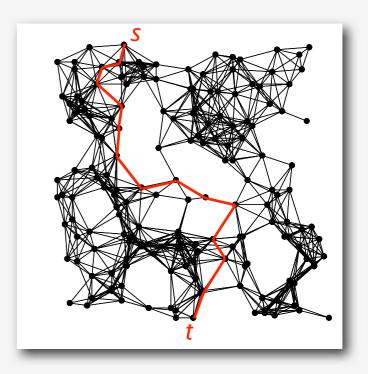
is a fundamental operation that demands understanding

Ground rules for this talk

- work in progress (more questions than answers)
- basic research
- save "deep dive" for the right problem

Applications

- graph-based optimization models
- networks
- percolation
- computer vision
- social networks
- (many more)

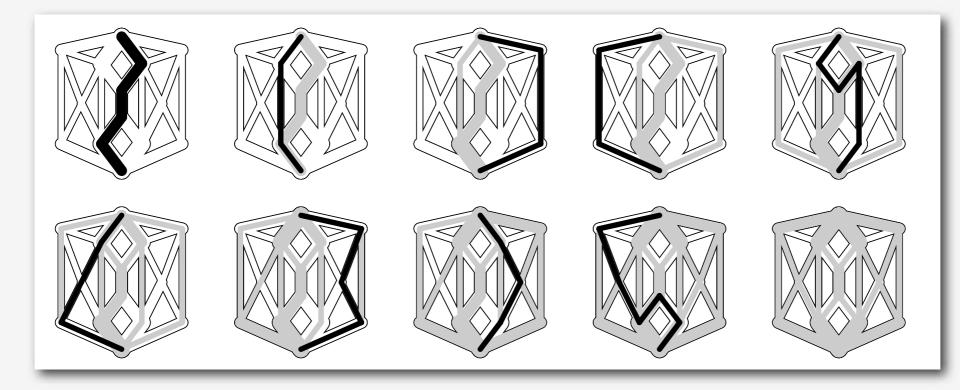


Basic research

- fundamental abstract operation with numerous applications
- worth doing even if no immediate application
- resist temptation to prematurely study impact

Ford-Fulkerson maxflow scheme

- find any s-t path in a (residual) graph
- augment flow along path (may create or delete edges)
- iterate until no path exists



Goal: compare performance of two basic implementations

- shortest augmenting path
- maximum capacity augmenting path

Key steps in analysis

research literature

this talk

- How many augmenting paths?
- What is the cost of finding each path?

Compare performance of Ford-Fulkerson implementations

- shortest augmenting path
- maximum-capacity augmenting path

Graph parameters

- number of vertices V
- number of edges E
- maximum capacity C

How many augmenting paths?

worst case upper boun			
shortest	VE/2 VC		
max capacity	2E lg C		

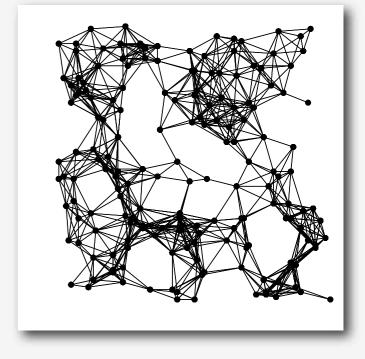
How many steps to find each path? E (worst-case upper bound)

Compare performance of Ford-Fulkerson implementations

- shortest augmenting path
- maximum-capacity augmenting path

Graph parameters for example graph

- number of vertices V = 177
- number of edges E = 2000
- maximum capacity C = 100



How many augmenting paths?

	worst case upper bound	for example
shortest	VE/2 VC	177,000 17,700
max capacity	2E lg C	26,575

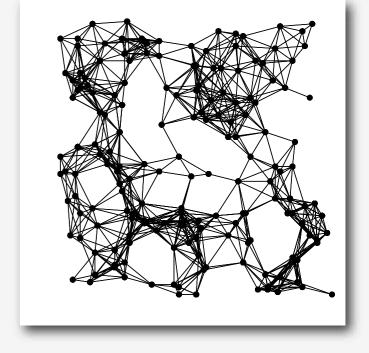
How many steps to find each path? 2000 (worst-case upper bound)

Compare performance of Ford-Fulkerson implementations

- shortest augmenting path
- maximum-capacity augmenting path

Graph parameters for example graph

- number of vertices V = 177
- number of edges E = 2000
- maximum capacity C = 100



How many augmenting paths?

	worst case upper bound	for example	actual
shortest	VE/2 VC	177,000 17,700	37
max capacity	2E lg C	26,575	7

How many steps to find each path? < 20, on average

total is a factor of 1 million high for thousand-node graphs!

Compare performance of Ford-Fulkerson implementations

- shortest augmenting path
- maximum-capacity augmenting path

Graph parameters

- number of vertices V
- number of edges E
- maximum capacity C

Total number of steps?

	worst case upper bound	
shortest	VE ² /2 VEC	WARNING: The Algorithm General has determined that using such results
max capacity	2E ² lg C	to predict performance or to compare algorithms may be hazardous.

Goals of algorithm analysis

- predict performance (running time)
- guarantee that cost is below specified bounds

Common wisdom

- random graph models are unrealistic
- average-case analysis of algorithms is too difficult
- worst-case performance bounds are the standard

Unfortunate truth about worst-case bounds

- often useless for prediction (fictional)
- often useless for guarantee (too high)
- often misused to compare algorithms

Bounds are useful in some applications:

Open problem: Do better!



which ones??

worst-case bounds

An actual exchange with a theoretical computer scientist:

TCS (in a talk):Algorithm A is bad.Google should be interested in my new Algorithm B.

- RS: What's the matter with Algorithm A?
- TCS: It is not optimal. It has an extra O(log log N) factor.
 - RS: But Algorithm B is very complicated, Ig Ig N is less than 6 in this universe, and that is just an upper bound. Algorithm A is certainly going to run 10 to 100 times faster in any conceivable real-world situation. Why should Google care about Algorithm B?

TCS: Well, I like it. I don't care about Google.

- is a basic operation in a great many applications
- Q. What is the **best** way to find an *st*-path in a graph?

A. Several well-studied textbook algorithms are known

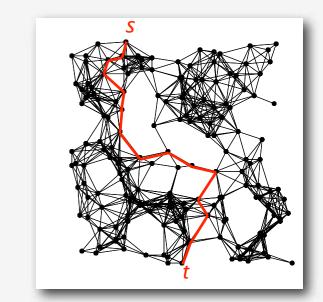
- Breadth-first search (BFS) finds the shortest path
- Depth-first search (DFS) is easy to implement
- Union-Find (UF) needs two passes



- all three process all E edges in the worst case
- diverse kinds of graphs are encountered in practice

Worst-case analysis is useless for predicting performance

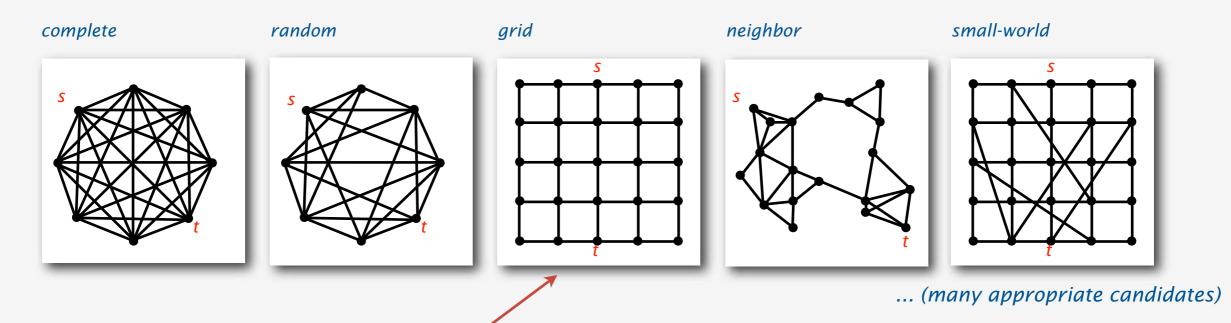
Which basic algorithm should a practitioner use?





Grid graphs

Algorithm performance depends on the graph model



Initial choice: grid graphs

- sufficiently challenging to be interesting
- found in practice (or similar to graphs found in practice)
- scalable
- potential for analysis

```
Ex: easy to find short paths quickly with A* in geometric graphs (stay tuned)
```

Ground rules

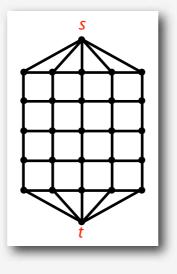
- algorithms should work for all graphs
- algorithms should not use any special properties of the model

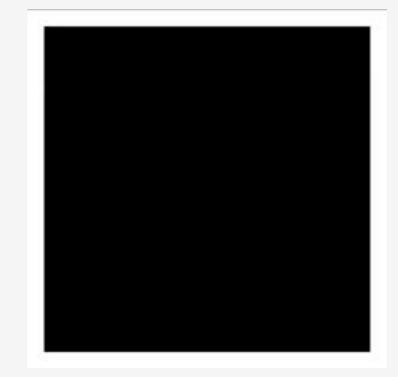
Applications of grid graphs

conductivity concrete granular materials porous media polymers forest fires epidemics Internet resistor networks evolution social influence Fermi paradox fractal geometry stereo vision image restoration *object segmentation* scene reconstruction

Example 1: Percolation

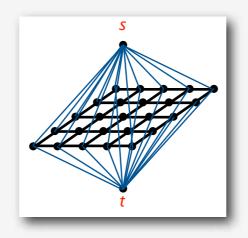
- widely-studied model
- few answers from analysis
- arbitrarily huge graphs





Example 2: Image processing

- model pixels in images
- DFS, maxflow/mincut, and other algs
- huge graphs

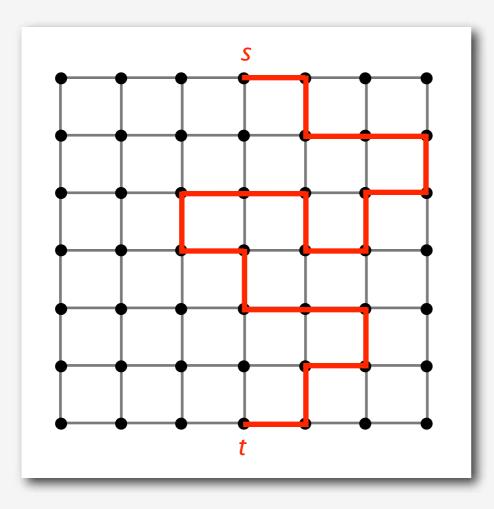






M by M grid of vertices undirected edges connecting each vertex to its HV neighbors source vertex s at center of top boundary destination vertex t at center of bottom boundary

Find any path connecting s to t



M² vertices about 2M² edges

vertices	edges
49	84
225	420
961	1860
3969	7812
16129	32004
65025	129540
261121	521220
	49 225 961 3969 16129 65025

Cost measure: number of graph edges examined

Finding an st-path in a grid graph

Similar problems are covered extensively in the literature

- Percolation
- Random walk
- Nonselfintersecting paths in grids
- Graph covering
- . . .

Elementary algorithms are found in textbooks

- Depth-first search (DFS)
- Breadth-first search (BFS)
- Union-find
- . .

Which basic algorithm should a practitioner use to find a path in a grid-like graph?

Literature is no help, so

- Implement elementary algorithms
- Use scientific method to study performance

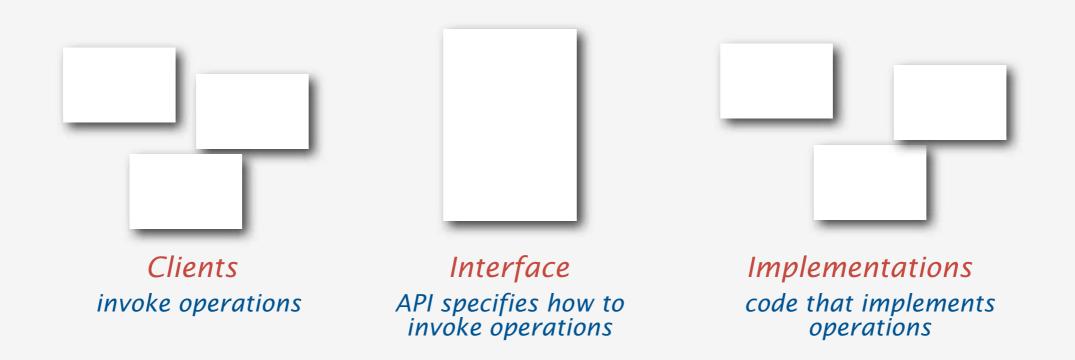




Data abstraction

a modern tool to separate clients from implementations

A data type is a set of values and the operations performed on them An abstract data type (ADT) is a data type whose representation is hidden An applications programming interface (API) is a specification



Implementation should not be tailored to particular client

Develop implementations that work properly for all clients Study their performance for the client at hand

Implementing a GRAPH data type

is an exercise in software engineering

```
Sample "design pattern" (for this talk)
```

GRAPH API

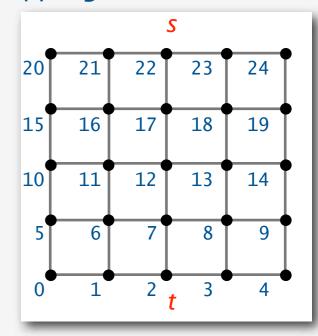
Vertices are integers in [0, V) Edges are vertex pairs

public class GRAPH	
GRAPH(Edge[] a)	construct a GRAPH from an array of edges
<pre>void findPath(int s, int t)</pre>	conduct a search from s to t
int st(int v)	return predecessor of v on path found

Client code for grid graphs

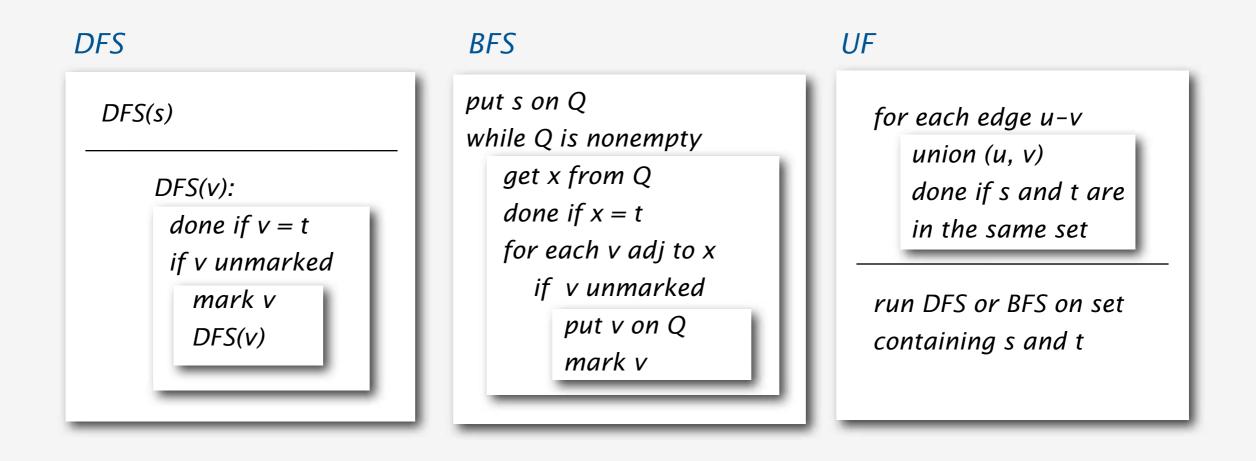
```
int e = 0;
Edge[] a = new Edge[E];
for (int i = 0; i < V; i++)
{ if (i < V-M) a[e++] = new Edge(i, i+M);
    if (i >= M) a[e++] = new Edge(i, i-M);
    if ((i+1) % M != 0) a[e++] = new Edge(i, i+1);
    if (i % M != 0) a[e++] = new Edge(i, i-1);
}
GRAPH G = new GRAPH(a);
G.findPath(V-1-M/2, M/2);
for (int k = t; k != s; k = G.st(k))
    System.out.println(s + "-" + t);
```

M = 5



Three standard ways to find a path

Depth-first search (DFS): recursive (stack-based) search Breadth-first search (BFS): queue-based shortest-path search Union-find (UF): use classic set-equivalence algorithms



First step: Implement GRAPH using each algorithm

GRAPH constructor code

```
for (int k = 0; k < E; k++)
{ int v = a[k].v, w = a[k].w;
    adj[v] = new Node(w, adj[v]);
    adj[w] = new Node(v, adj[w]);
}</pre>
```

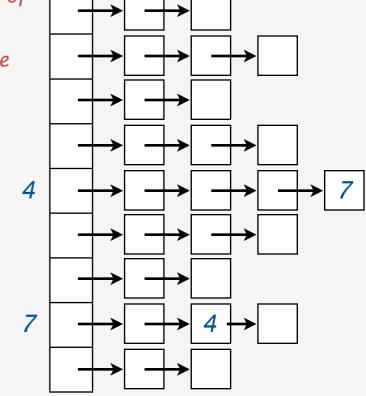
graph representation

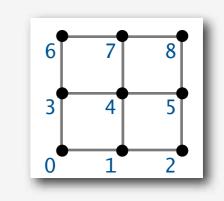


two nodes per edge

DFS implementation (code to save path omitted)

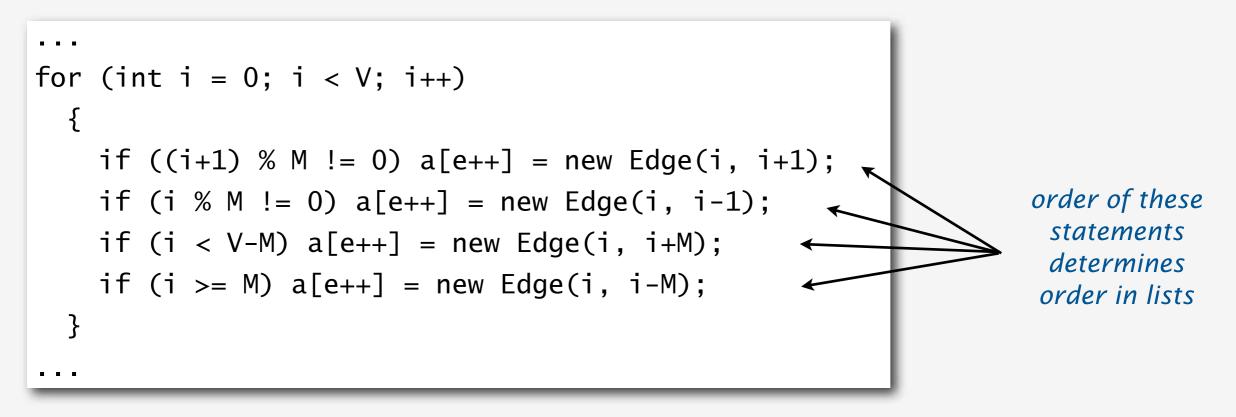
```
void findPathR(int s, int t)
{ if (s == t) return;
    visited(s) = true;
    for(Node x = adj[s]; x != null; x = x.next)
        if (!visited[x.v]) findPathR(x.v, t);
    }
void findPath(int s, int t)
    { visited = new boolean[V];
        searchR(s, t);
    }
```



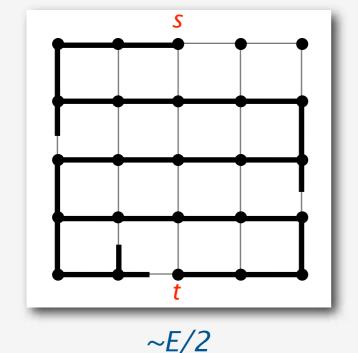


Basic flaw in standard DFS scheme

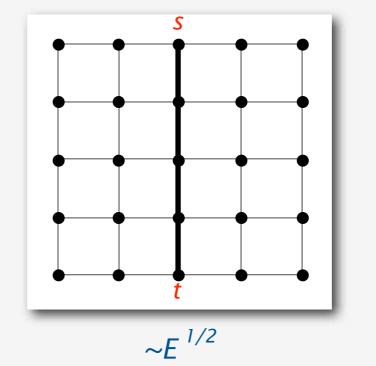
cost strongly depends on arbitrary decision in client (!!)



west, east, north, south



south, north, east, west



order in lists has drastic effect on running time



Advise the client to randomize the edges?

- no, very poor software engineering
- leads to nonrandom edge lists (!)

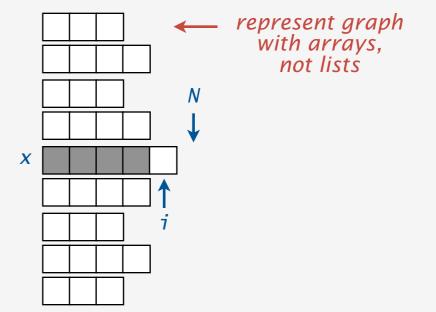
Randomize each edge list before use?

• no, may not need the whole list

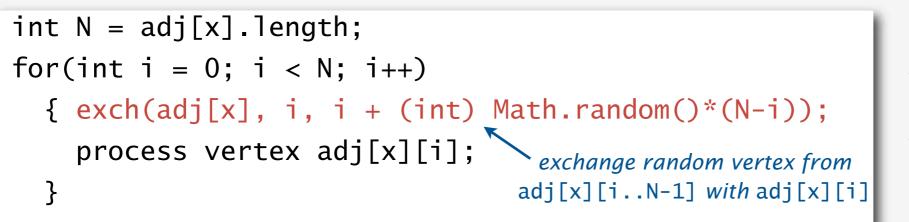
Solution: Use a randomized iterator

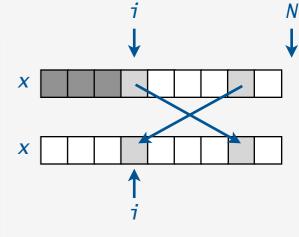
standard iterator

int N = adj[x].length;
for(int i = 0; i < N; i++)
 { process vertex adj[x][i]; }</pre>



randomized iterator

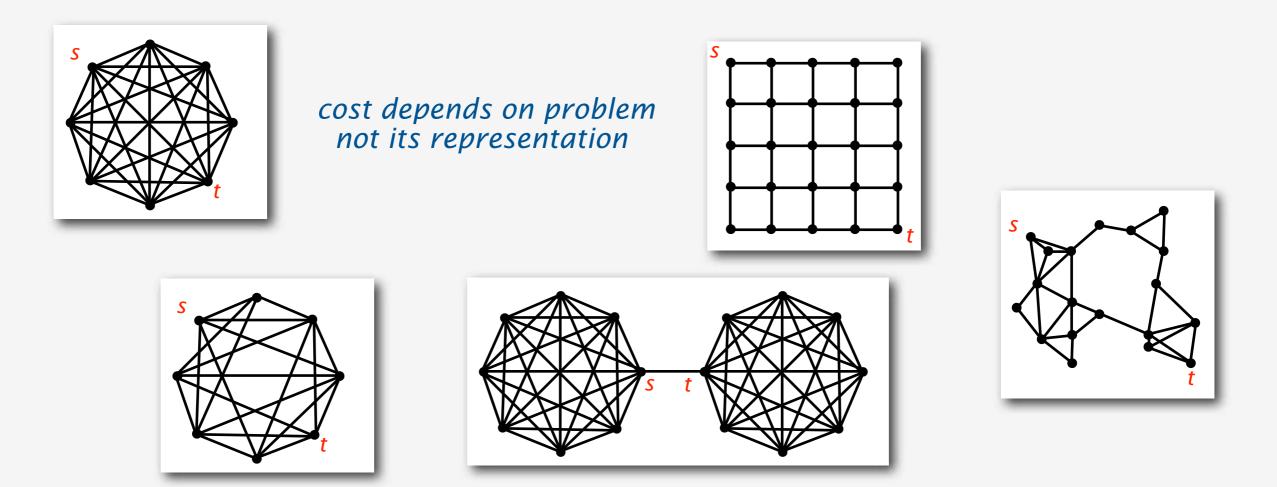




Use of randomized iterators

turns every graph algorithm into a randomized algorithm

Important practical effect: stabilizes algorithm performance



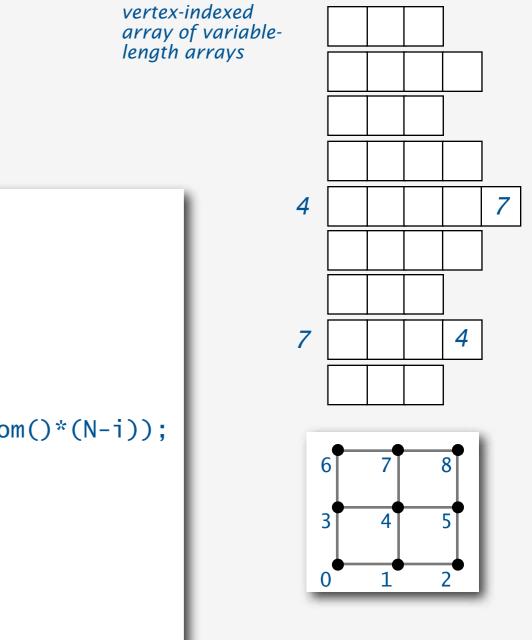
Yields well-defined and fundamental analytic problems

- Average-case analysis of algorithm X for graph family Y(N)?
- Distributions?
- Full employment for algorithm analysts

graph ADT constructor code

```
for (int k = 0; k < E; k++)
{
    int v = a[k].v, w = a[k].w;
    adj[v][deg[v]++] = w;
    adj[w][deg[w]++] = v;
}</pre>
```

graph representation

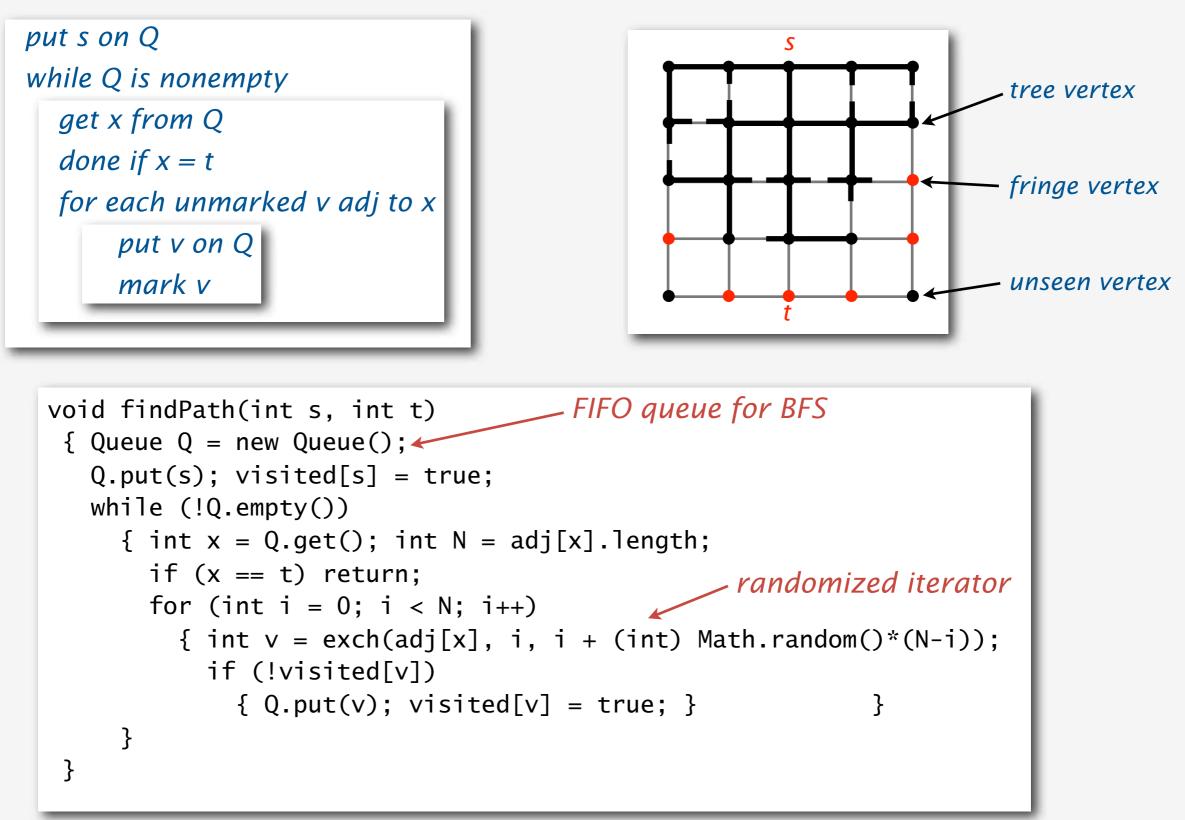


DFS implementation (code to save path omitted)

```
void findPathR(int s, int t)
{
    int N = adj[s].length;
    if (s == t) return;
    visited(s) = true;
    for(int i = 0; i < N; i++)
    {
        int v = exch(adj[s], i, i+(int) Math.random()*(N-i));
        if (!visited[v]) searchR(v, t);
    }
    void findPath(int s, int t)
    {
        visited = new boolean[V];
        findpathR(s, t);
    }
}</pre>
```

BFS: standard implementation

Use a queue to hold fringe vertices



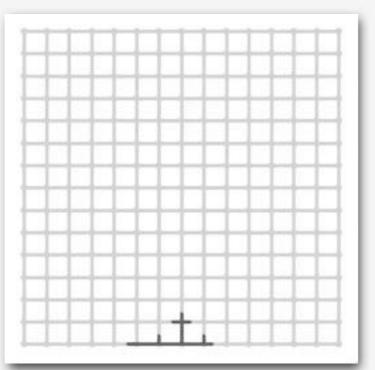
Generalized graph search: other queues yield DFS, A* and other algorithms

Animations

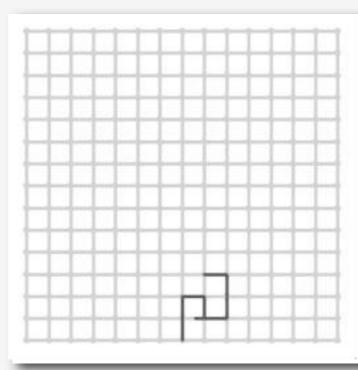
give intuition on performance and suggest hypotheses to verify with experimentation

Aside: Are you using animations like this regularly? Why not?

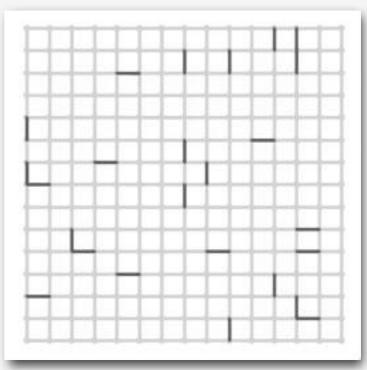
BFS



DFS



UF (code omitted)



Experimental results

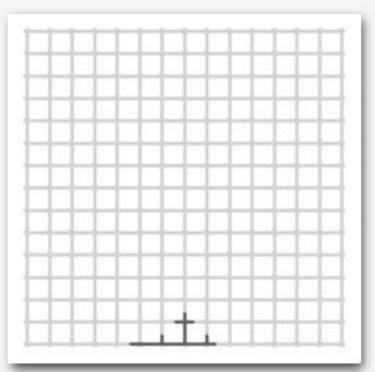
show that DFS is faster than BFS and UF on the average

M	V	Ε	BFS	DFS	UF
7	49	168	0.75	0.32	1.05
15	225	840	0.75	0.45	1.02
31	961	3720	0.75	0.36	1.14
63	3969	15624	0.75	0.32	1.05
127	16129	64008	0.75	0.40	0.99
255	65025	259080	0.75	0.42	1.08
·					

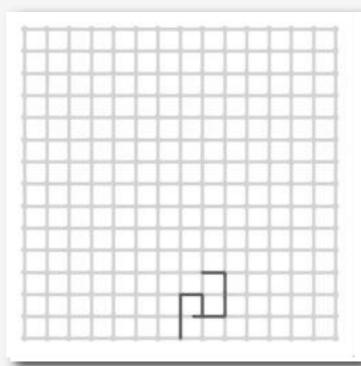
Analytic proof?

Faster algorithms available?

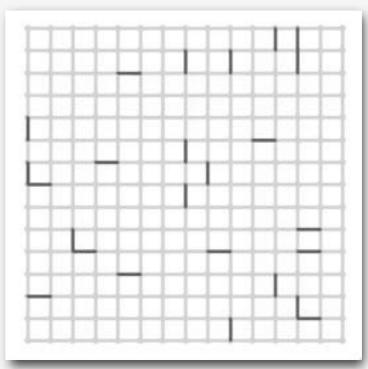
BFS



DFS



UF



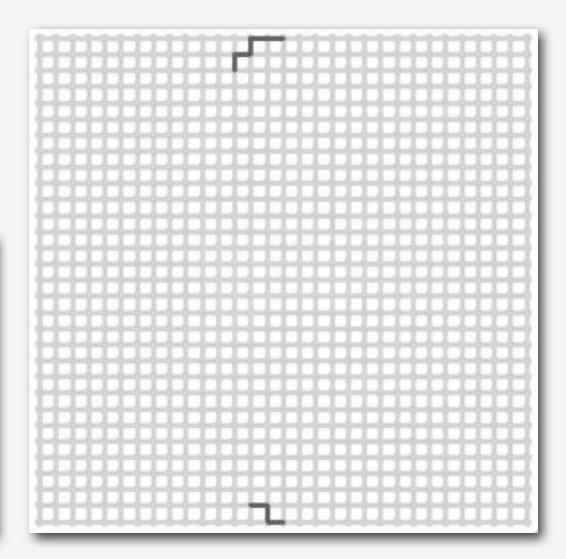
A standard search paradigm

gives a faster algorithm or finding an *st*-path in a graph

Use two depth-first searches

- one from the source
- one from the destination
- interleave the two

V	E	BFS	DFS	UF	two
49	168	0.75	0.32	1.05	0.18
225	840	0.75	0.45	1.02	0.13
961	3720	0.75	0.36	1.14	0.15
3969	15624	0.75	0.32	1.05	0.14
16129	64008	0.75	0.40	0.99	0.13
65025	259080	0.75	0.42	1.08	0.12
	49 225 961 3969 16129	49 168 225 840 961 3720 3969 15624 16129 64008	491680.752258400.7596137200.753969156240.7516129640080.75	491680.750.322258400.750.4596137200.750.363969156240.750.3216129640080.750.40	491680.750.321.052258400.750.451.0296137200.750.361.143969156240.750.321.0516129640080.750.400.99



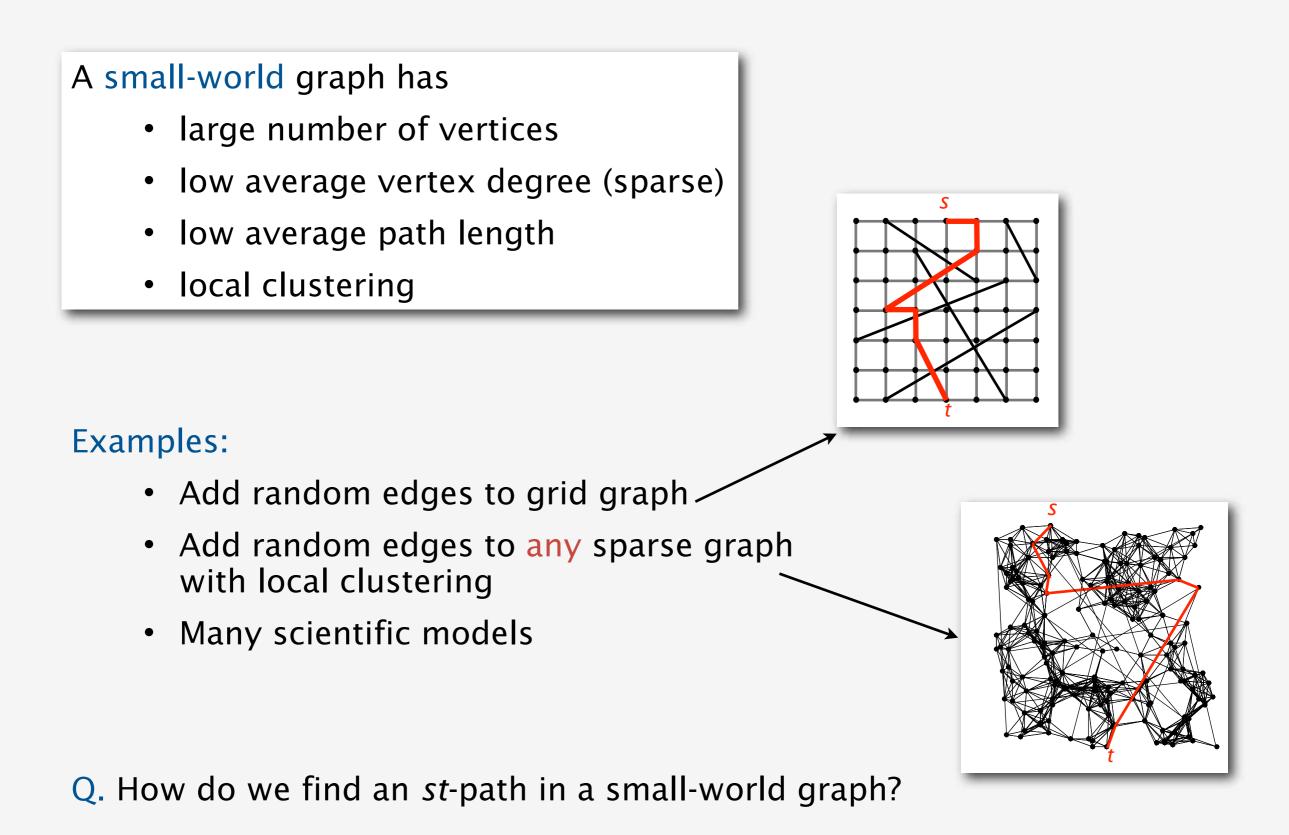
Examines 13% of the edges

3-8 times faster than standard implementations

Faster approach? Other models? Not log log N, but not bad!

Small-world graphs

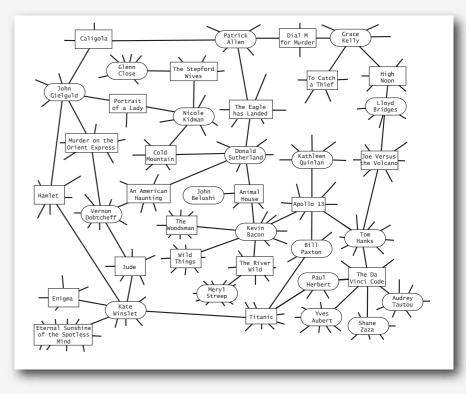
are a widely studied graph model with many applications



social networks airlines roads neurobiology evolution social influence protein interaction percolation internet electric power grids political trends

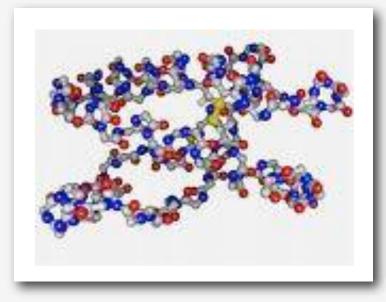
Example 1: Social networks

- infectious diseases
- extensive simulations
- some analytic results
- huge graphs

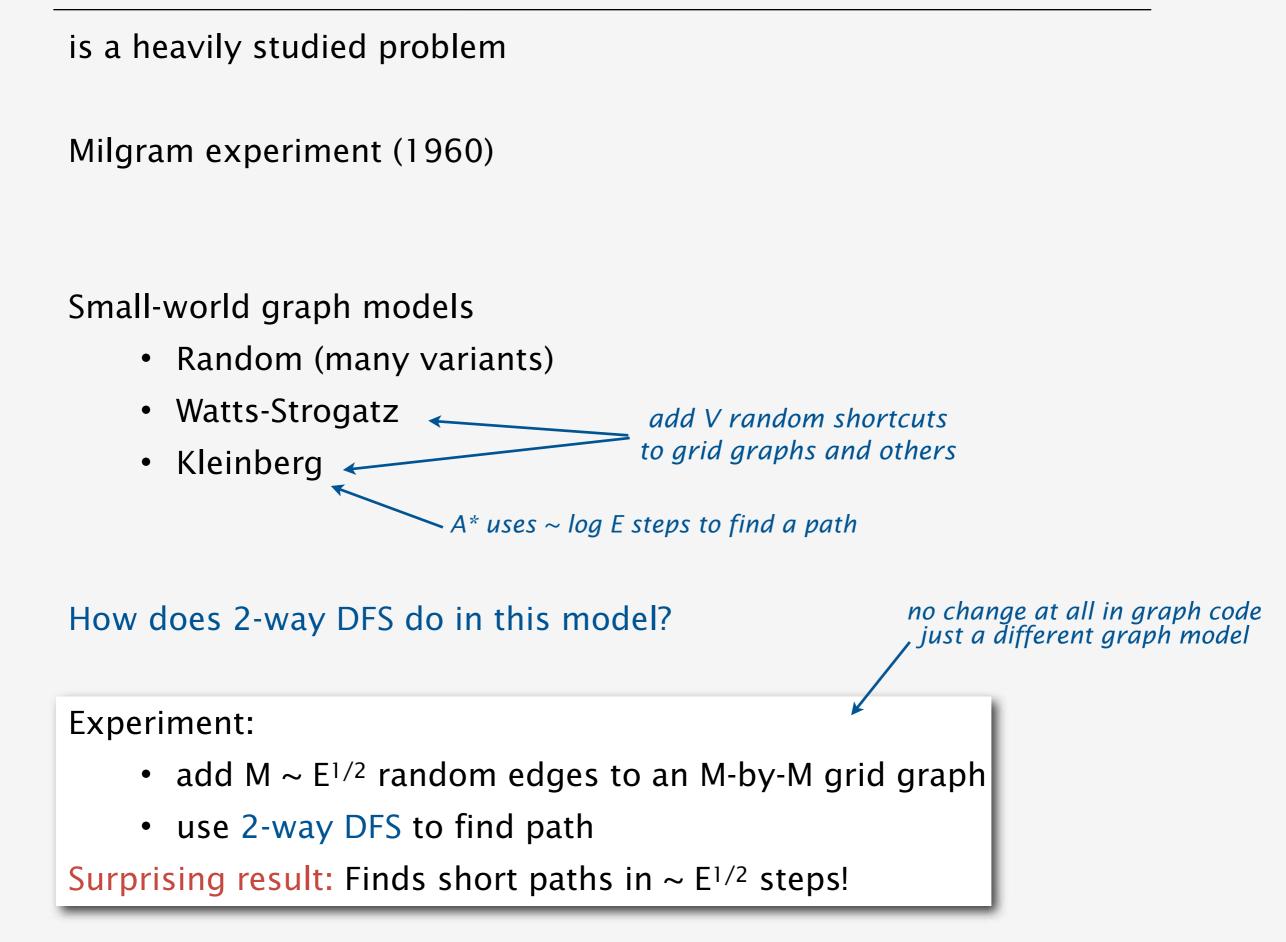


Example 2: Protein interaction

- small-world model
- natural process
- experimental validation



Finding a path in a small-world graph



Finding a path in a small-world graph

is much easier than finding a path in a grid graph

Conjecture: Two-way DFS finds a short *st*-path in sublinear time in any small-world graph

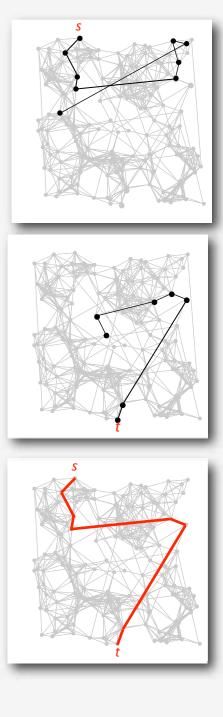
Evidence in favor

- 1. Experiments on many graphs
- 2. Proof sketch for grid graphs with V shortcuts
 - step 1: 2 $E^{1/2}$ steps ~ 2 $V^{1/2}$ random vertices
 - step 2: like birthday paradox

two sets of 2V ^{1/2} randomly chosen vertices are highly unlikely to be disjoint

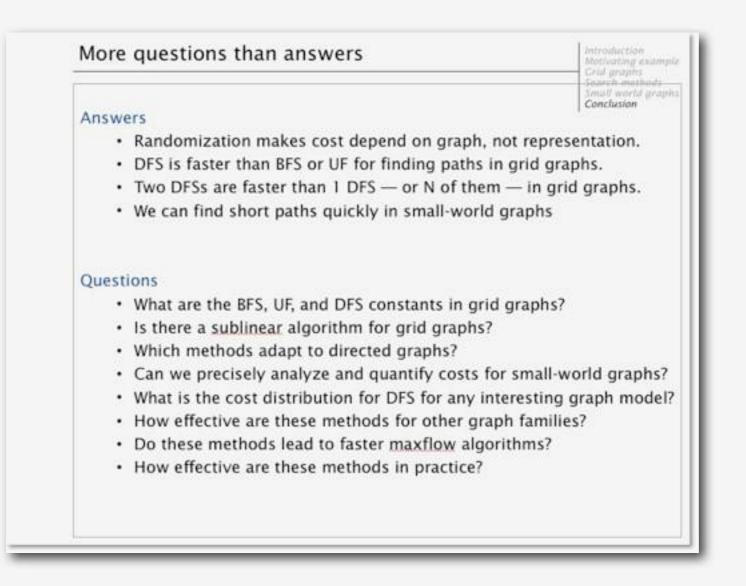
Path length? Multiple searchers revisited?

Next steps: refine model, more experiments, detailed proofs



Detailed example: paths in graphs

End of "lecture-within-a-lecture"



Lessons

- Data abstraction is for everyone
- We know much less about graph algorithms than you might think
- The scientific method is essential in understanding performance

in understanding performance

Worrisome point

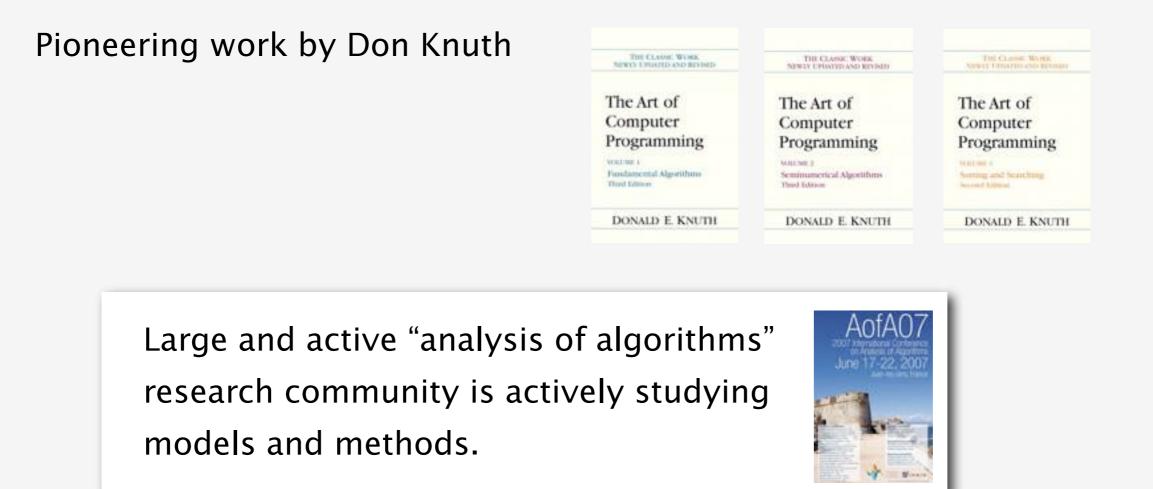
- Complicated mathematics seems to be needed for models
- Do all programmers need to know the math?

Good news

- Many people are working on the problem
- Simple universal underlying models are emerging

Appropriate mathematical models

are essential for scientific studies of program behavior



Caution: Not all mathematical models are appropriate!

Analytic Combinatorics

is a modern basis for studying discrete structures

Developed by Philippe Flajolet and many coauthors (including RS) based on classical combinatorics and analysis

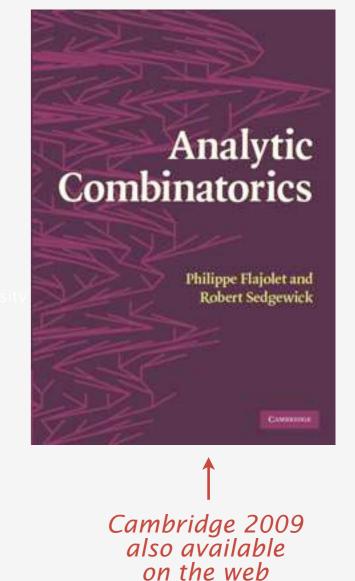
Generating functions (GFs) encapsulate sequences

Symbolic methods treat GFs as formal objects

- formal definition of combinatorial constructions
- direct association with generating functions

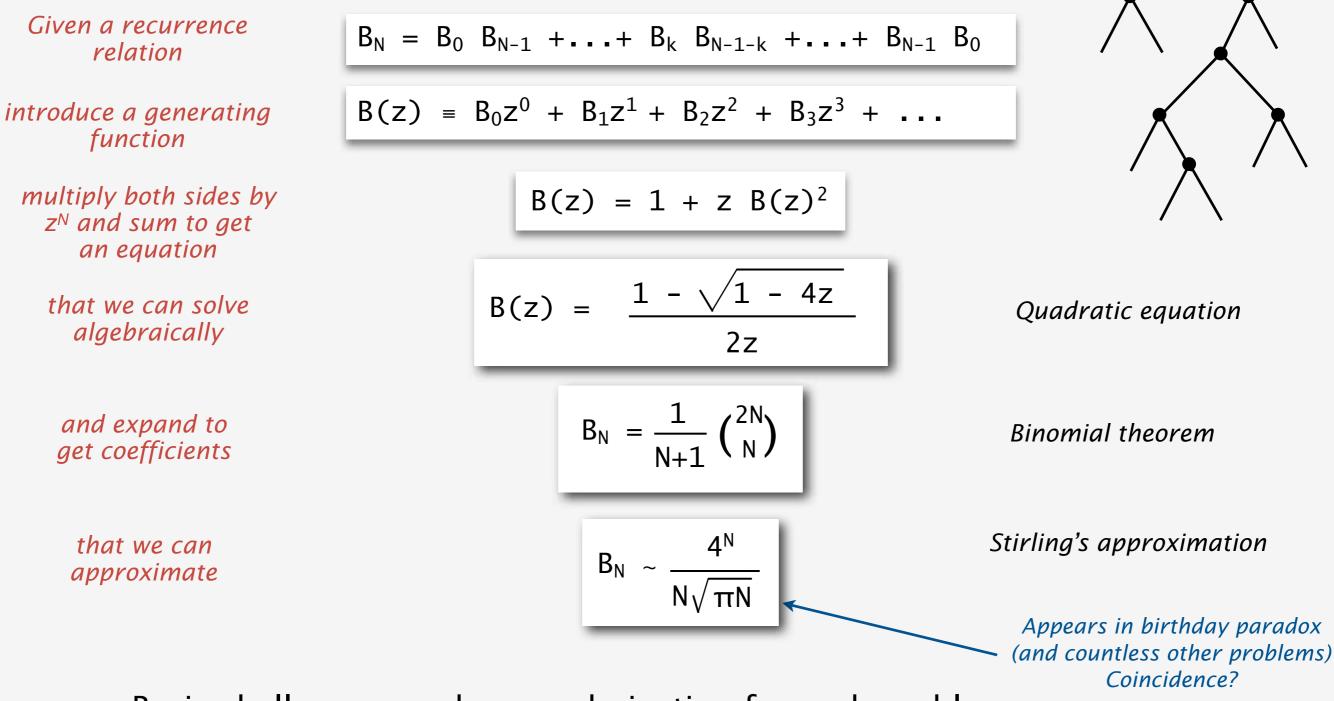
Complex asymptotics treat GFs as functions in the complex plane

- Study them with singularity analysis and other techniques
- Accurately approximate original sequence



Analysis of algorithms: classic example

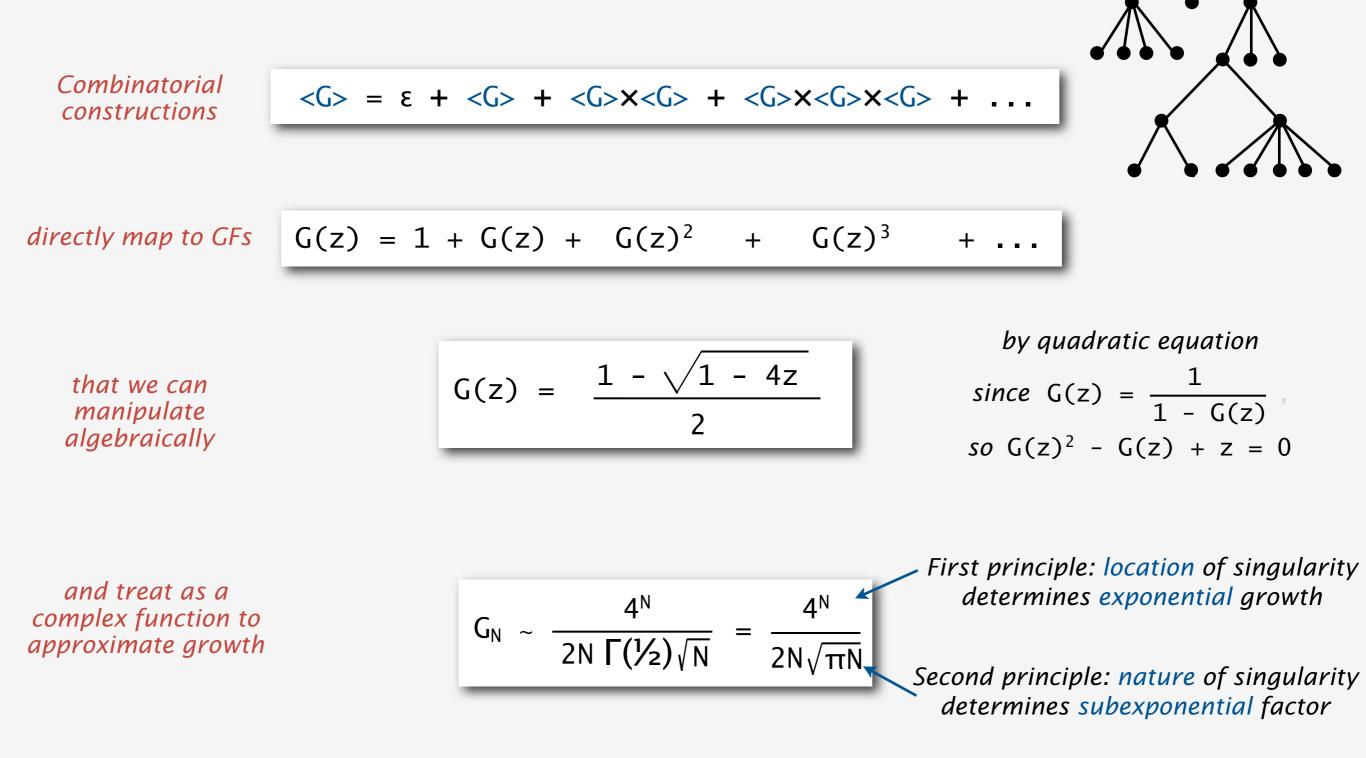
A binary tree is a node connected to two binary trees. How many binary trees with N nodes?



Basic challenge: need a new derivation for each problem

Analytic combinatorics: classic example

A tree is a node connected to a sequence of trees How many trees with N nodes?



Analytic combinatorics: singularity analysis

is a key to extracting coefficient asymptotics

Exponential growth factor

- depends on location of dominant singularity
- is easily extracted

$$[z^{N}](1 - bz)^{c} = b^{N} [z^{N}](1 - z)^{c}$$

Polynomial growth factor

- depends on nature of dominant singularity
- can often be computed via contour integration

Ex:

$$\begin{bmatrix} z^{N} \end{bmatrix} (1 - z)^{c} = \frac{1}{2\pi i} \int_{C} \frac{(1 - z)^{c}}{z^{N+1}} dz$$

$$\sim \frac{1}{2\pi i} \int_{H} \frac{(1 - z)^{c} dz}{z^{N+1}} dz$$

$$\sim \frac{1}{\Gamma(c)N^{c+1}}$$
Cauchy coefficient formula
Hankel contour
many details
omitted!

Analytic combinatorics: universal laws

of sweeping generality derive from the same technology

Ex. Context free constructions

Combinatorial constructions		like context-free language (or Java data type)
directly map to a system of GFs	$\begin{array}{l} G_{0}(z) \ = \ F_{0}(\ G_{0}(z),\ G_{1}(z)\ \ldots,\ G_{t}(z)) \\ G_{1}(z) \ = \ F_{1}(\ G_{0}(z),\ G_{1}(z)\ \ldots,\ G_{t}(z)) \\ \ldots \\ G_{t}(z) \ = \ F_{t}(\ G_{0}(z),\ G_{1}(z)\ \ldots,\ G_{t}(z)) \end{array}$	Groebner-basis elimination
that we can manipula algebraically to get a single complex functio	$(1 - 1)^{-C}$	Drmota-Lalley-Woods
that is amenable to singularity analysi	$G_N \sim a b^N N^C$ for any contexts	xt-free construction !

Good news: Several such laws have been discovered

Better news: Distributions also available (typically normal, small sigma)

A general hypothesis from analytic combinatorics

The running time of your program is $\sim a b^{N} N^{C} (\lg N)^{d}$

- the constant a depends on both complex functions and properties of machine and implementation
- the exponential growth factor b should be 1
- the exponent **c** depends on singularities
- the log factor d is reconciled in detailed studies

Why?

- data structures evolve from combinatorial constructions
- universal laws from analytic combinatorics have this form

To compute values:

• $Ig(T(2N)/T(N) \rightarrow c$

• $T(N)/b^N N^c \rightarrow a$

the doubling test that is the basis for predicting performance!

Plenty of caveats, but provides, in conjunction with the scientific method,

a basis for studying program performance

Performance matters in software engineering

Writing a program without understanding performance is like

not knowing where a rocket will go



not knowing the dosage of a drug



not knowing the strength of a bridge



The scientific method is an integral part of software development

Unfortunate facts

Many scientists lack basic knowledge of computer science Many computer scientists lack back knowledge of science

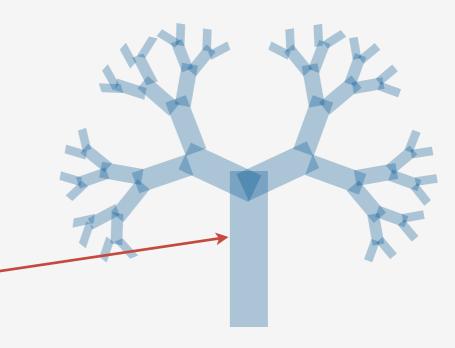
1970s: Want to use the computer? Take intro CS.

2000s: Intro CS course relevant only to future cubicle-dwellers

One way to address the situation

- identify fundamentals
- teach them to all students who need to know them
- as early as possible -





Central Thesis (1992)

First-year college students need a computer science course

Computer science embraces a significant body of knowledge that is

- intellectually challenging
- pervasive in modern life
- critical to modern science and engineering

Traditional barriers

- obsolescence
- high equipment costs
- no room in curriculum
- incorrect perceptions about CS
- programming courses bludgeon students with tedium
- one course fits all?
- no textbook

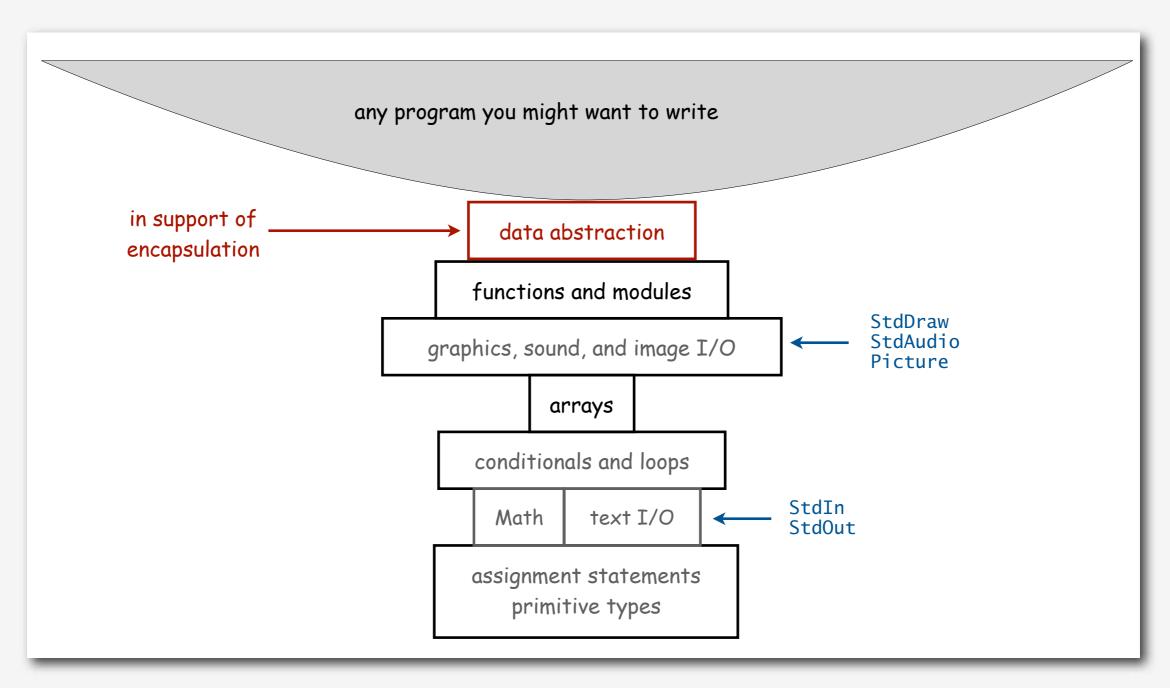
Reading, writing, and computing

Programming is for everyone

- it's easier than most challenges you're facing
- you cannot be successful in any field without it

Computer science is intellectually challenging, worth knowing

Key ingredient: a modern programming model



Basic requirements

- full support of essential components
- freely available, widely used

1990: C/C++, 2010: Java, 2020: ??

functions	<pre>sin() cos(), log()</pre>
libraries	I/O, data analysis
ID arrays	sound
2D arrays	images
strings	genomes
object-oriented I/O	streaming from the web
OOP	Brownian motion
data structures	small-world phenomenon

Progress report (2010)

Stable intro CS course for all students

modern programming model

- Basic control structures
- Standard input and output streams
- Drawings, images and sound
- Data abstraction
- Use any computer, and the web

relevant CS concepts

- Understanding of the costs
- Fundamental data types
- Computer architecture
- Computability and Intractability

Goals

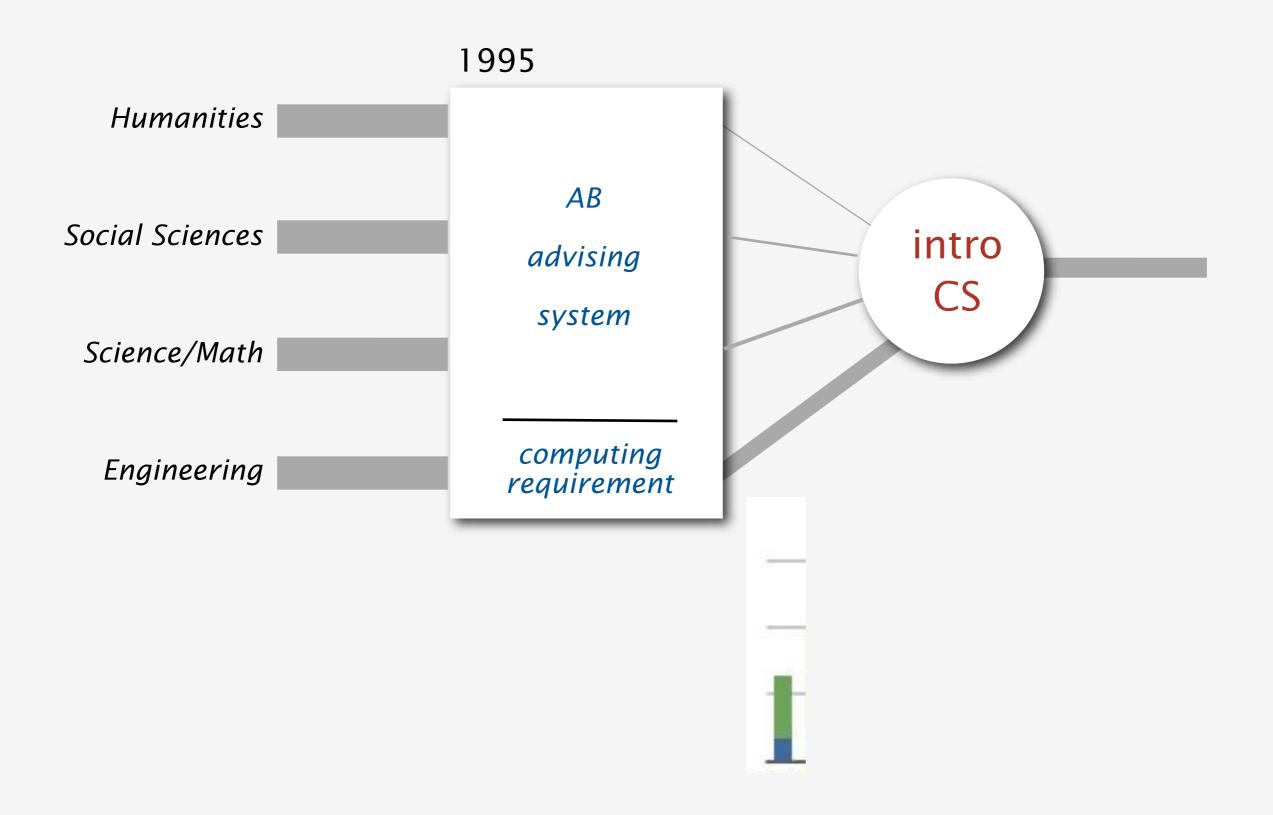
- demystify computer systems
- empower students to exploit computation
- build awareness of intellectual underpinnings of CS

	Course Catalog
	All Courses Unsersature Decen Extent Decen
	The is the last of clusters that the department may offer. The (c) is (c) in (c) many pipe late the current's estimated courses.
	Note: Undergred ocurve numbers gar to 4H4, ginal courses are \$100 and above. Not at audiprite can faits at courses.
	COS109 - Computers in Our World (Fel)
	Computers are all around us. How does this affect the world we live in? This course is a broa- introduction to computing technology for humanities and social science students. Topics will be drawn from current issues and events, and will include discussion of how computers work, wh programming is and why & is hard, how the Internet and the Web work, security and privacy Two 50 minute lettures, one three-how faboratory.
	COS116 - The Computational Universe (Spring)
	Computers have brought the world bo our fingertips. We will try to understand, at a high leve the science roll and new understring the new Computational Universe. Our quest bases us to thread sweep of scientific involvedge (and technologies they enable); propositional logic of the ancient Greeks (microprocessors); quantum methanics (slicon chos); network and system phenomena (internet and search engines);computational intractability (becurs empryption); efficient algorithm algoromic sequencing). Utimately, this study makes us look anew at ourselves-our genome; language; music; "knowledge", and above all;the mystery of our interlinence.
-	C05126 - General Computer Science (Fall, Spring)
	An introduction to computer science in the context of scientific, engineering, and commercial applications. The goal of the course is to teach besic principles and practical means, while at 0 arms three properties dividents to use computative effectively for applications in computer science, physics, biology, chemistry, engineering, and other disciplines. Topics include hardware and software systems, programming in Java, apporthma and data structures, fundamental principles of computation; and scientific computing, including simulation, optimization, and data analysis. No prior programming experience required. Two loctures, two classes.
	COS217 - Introduction to Programming Systems (Fell, Spring)
	An introduction to computer organization and system software. The former includes topics as as processor and memory organization, input/output devices, and interrupt structures. The latter includes assemblers, loaders, Bharries, and tompilers. Programming assignments are implemented in assembly language and C using the UNIX operating system. Three Antures. Prerequisite(s) : 126 or instructor's permission.
	COS226 - Algorithms and Data Structures (Vall, Spring)
	The study of fundamental data structures such as lists, cursues, stacks, trees, hearn, hash tables, and their variations. The implementation and analysis of important algorithms for sorting, searching, strong processing, geometric applications, and graph manipulation. Introduction to advanced algorithms and techniques. Two lectures, one precipitorial. Prevegulate(s) : 125 or instructor's permission.
	C05231/C05232 - An Integrated, Quantitative Introduction to the Natural Sciences

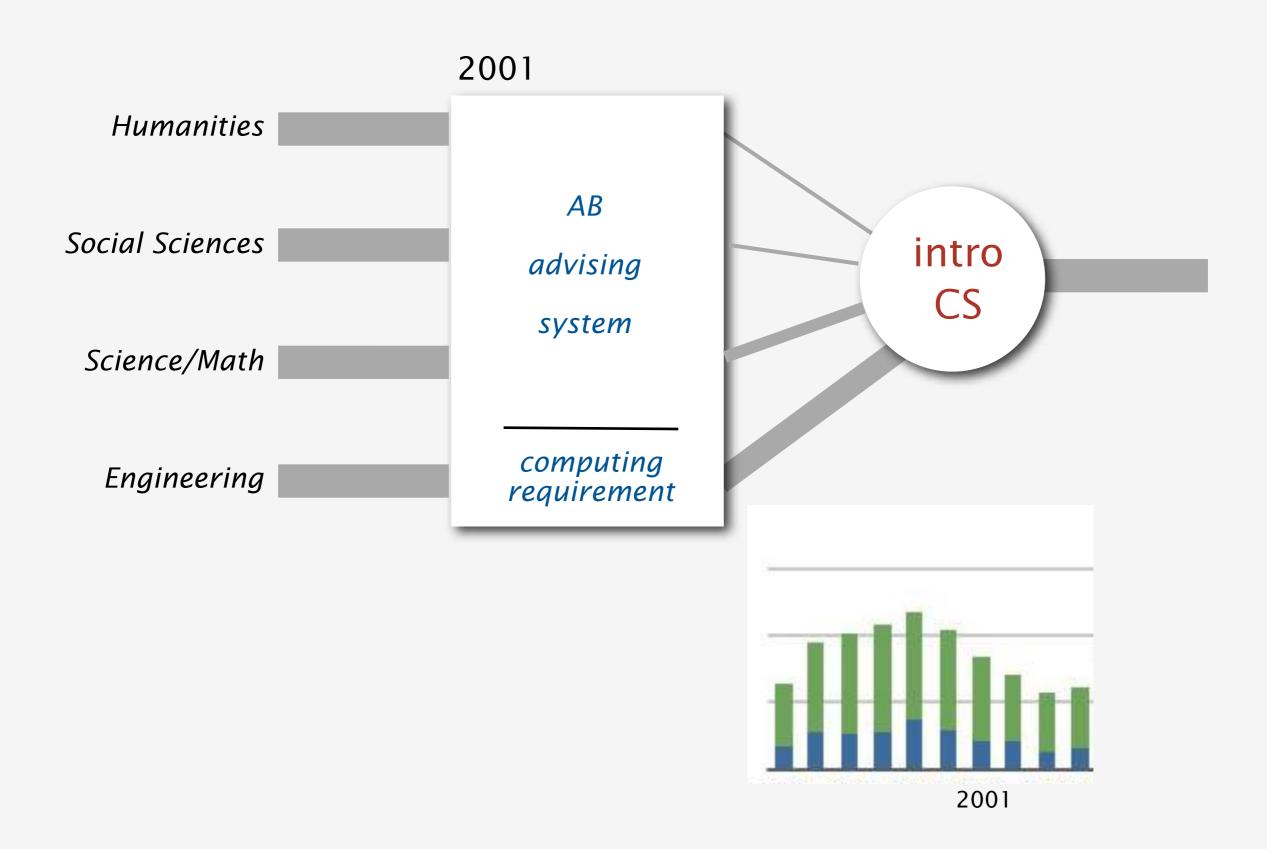
scientific content

- Scientific method
- Data analysis
- Simulation
- Applications

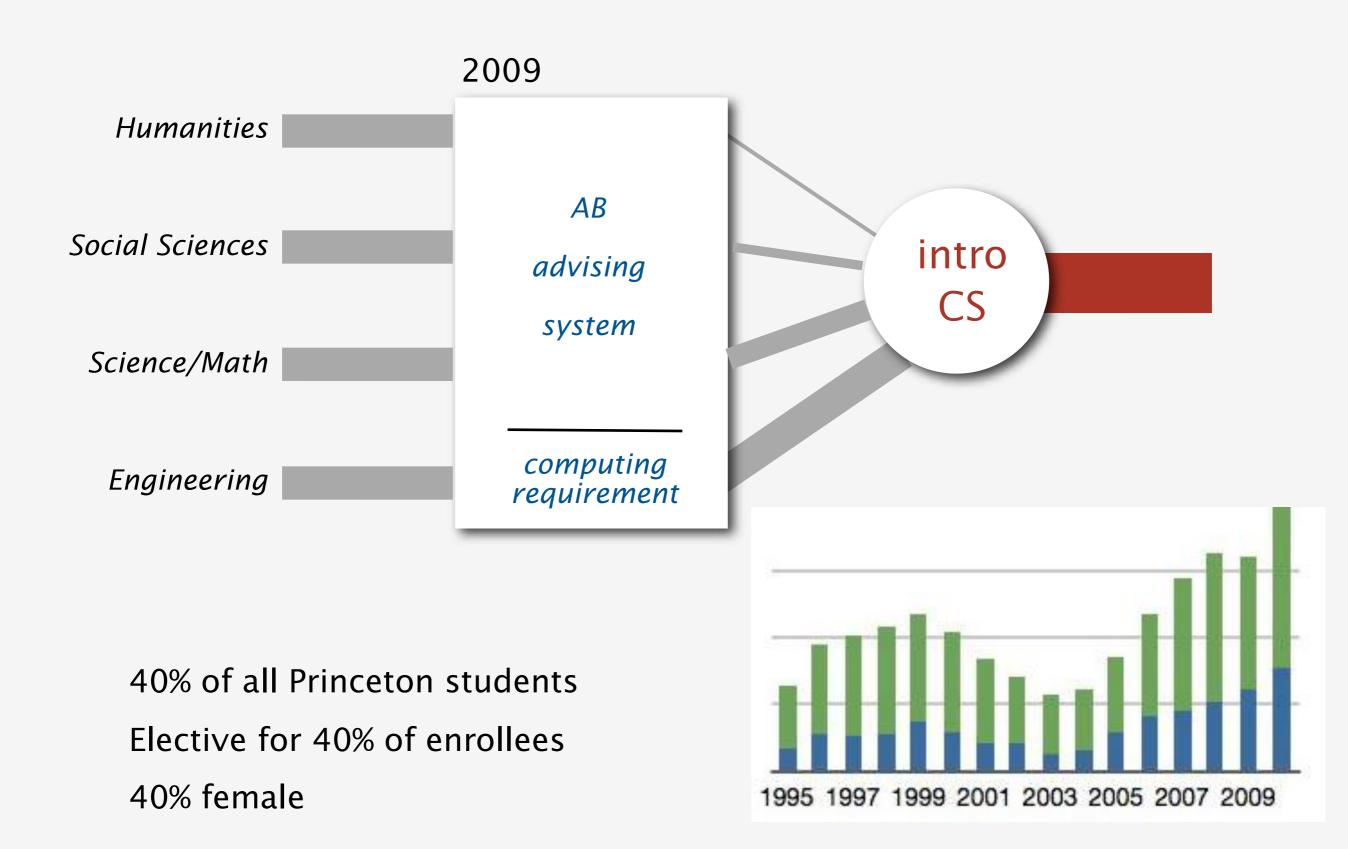
Standard enrollment pattern



Standard enrollment pattern (up and down)

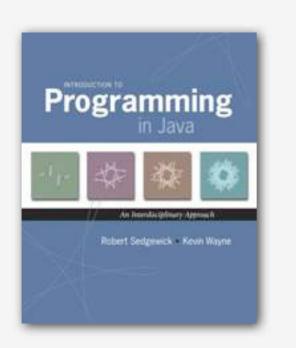


Standard enrollment pattern (up and down), but now is skyrocketing

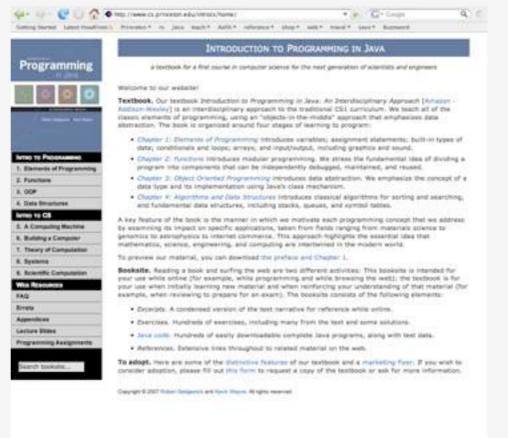


Progress report continued (2009)

Textbook and booksite available and widely used



www.cs.princeton.edu/introcs



Anyone can learn the importance of

- modern programming models
- the scientific method in understanding program behavior
- fundamental precepts of computer science
- computation in a broad variety of applications
- preparing for a lifetime of engaging with computation

Textbook

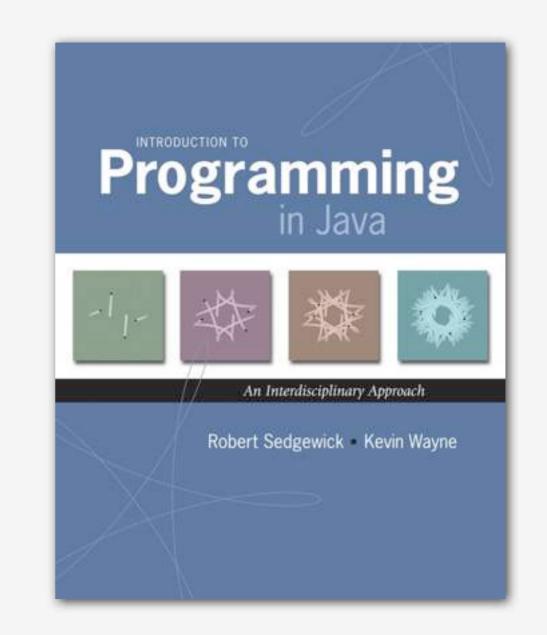
Introduction to Programming in Java: An interdisciplinary approach

R. Sedgewick and K. Wayne

Elements of Programming

Your First Program Built-in types of Data Conditionals and Loops Arrays Input and Output Case Study: Random WebSurfer **Functions and Modules** Static Methods Libraries and Clients Recursion Case Study: Percolation **Object-Oriented Programming** Data Types Creating DataTypes **Designing Data Types** Case Study: Percolation **Algorithms and Data Structures** Performance

Sorting and Searching Stacks and Queues Symbol Tables Case Study: Small World



Stay tuned

Introduction to Computer Science

R. Sedgewick and K. Wayne

Prologue

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Your First Program Built-in types of Data Conditionals and Loops Arrays Input and Output Case Study: Random WebSurfer

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Algorithms and Data Structures

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A Computing Machine

Data representations TOY machine Instruction Set Machine-Language Programming Simulator

Building a Computer

Boolean Logic and Gates Combinational Circuits Sequential Cricuits TOY machine architecture

Theory of Computation

Formal Languages and Machines Turing Machines Universality Computability Intractability

Systems

Library Programming Compilers, Interpreters, and Emulators Operating Systems Networks Applications Systems

Scientific Computation

Precision and Accuracy Differential Equations Linear Algebra Optimization Data Analysis Simulation

Booksite

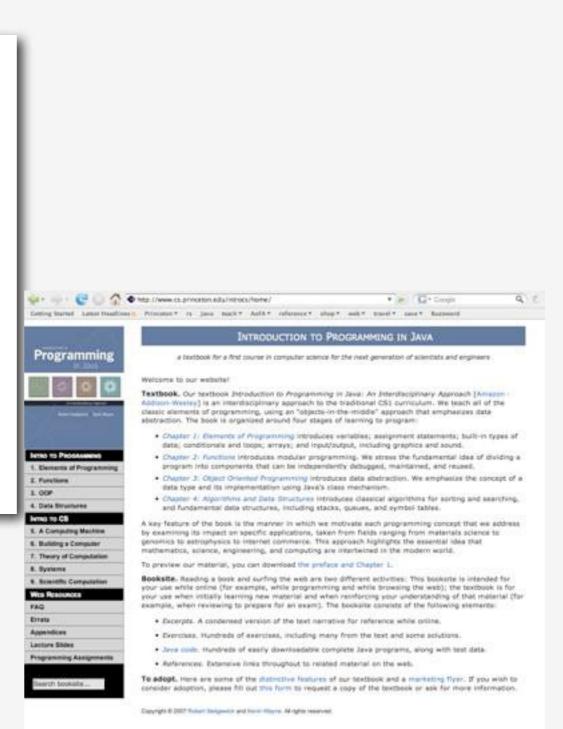
extends text with supplementary material on the web

www.cs.princeton.edu/IntroCS

- Text digests
- Supplementary exercises/answers
- Links to references and sources
- Modularized lecture slides
- Programming assignments
- Demos for lecture and precept
- Simulators for self-study
- Scientific applications

Also: Book development laboratory

- 10000+ files
- 2000+ Java programs
- 50+ animated demos
- 20,000+ files transferred per week



Obsolescence?

- focus on concepts reduces language dependencies
- basic features of modern languages are converging

High equipment costs?

- students use their own computers
- basic features of modern OSs are converging

No room in curriculum?

- extensive AP placement makes room
- replace legacy programming courses

Incorrect perceptions about CS?

- yesterday's predictions are today's reality
- young scientists/engineers appreciate importance of CS

also address some traditional barriers

No room in curriculum?

- appeal to familiar concepts from HS science and math saves room
- broad coverage provides real choice for students choosing major
- modular organization gives flexibility to adapt to legacy courses
- detailed examples useful throughout curriculum

Incorrect perceptions about CS?

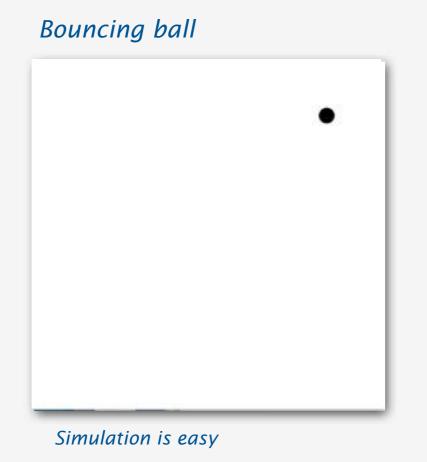
- scientific basis gives students the big picture
- students are enthusiastic about addressing real applications

Excessive focus on programming?

- careful introduction of essential constructs
- nonessential constructs left for later CS courses
- library programming restricted to key abstractions
- taught in context with plenty of other material

Ideal programming example/assignment

- teaches a basic CS concept
- solves an important problem
- appeals to students' intellectual interest
- illustrates modular programming
- is open-ended



```
public class BouncingBall
   public static void main(String[] args)
   { // Simulate the movement of a bouncing ball.
      StdDraw.setXscale(-1.0, 1.0);
      StdDraw.setYscale(-1.0, 1.0);
      double rx = .480, ry = .860;
      double vx = .015, vy = .023;
      double radius = .05:
      int dt = 20:
      while(true)
      { // Update ball position and draw it there.
         if (Math.abs(rx + vx) + radius > 1.0) vx = -vx;
         if (Math.abs(ry + vy) + radius > 1.0) vy = -vy;
         rx = rx + vx;
         ry = ry + vy;
         StdDraw.clear();
         StdDraw.filledCircle(rx, ry, radius);
         StdDraw.show(dt);
     ł
  }
7
```

Familiar and easy-to-motivate applications

Ideal programming example/assignment

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Bouncing balls



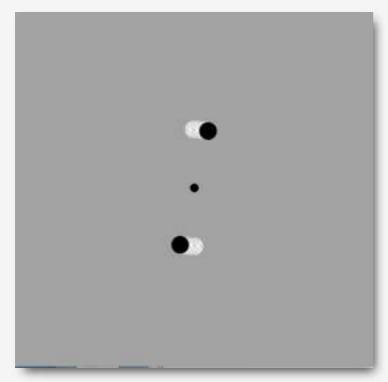
OOP is helpful

Familiar and easy-to-motivate applications

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N-body



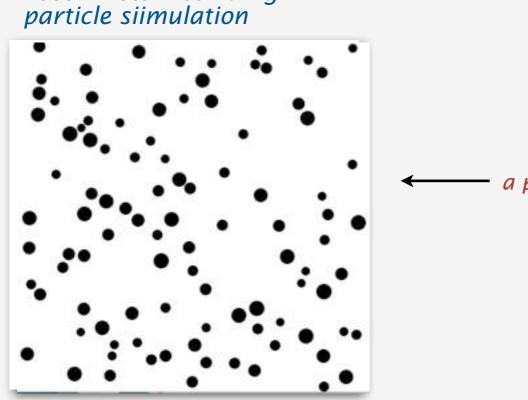
data-driven programs are useful

Familiar and easy-to-motivate applications

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Bose-Einstein colliding



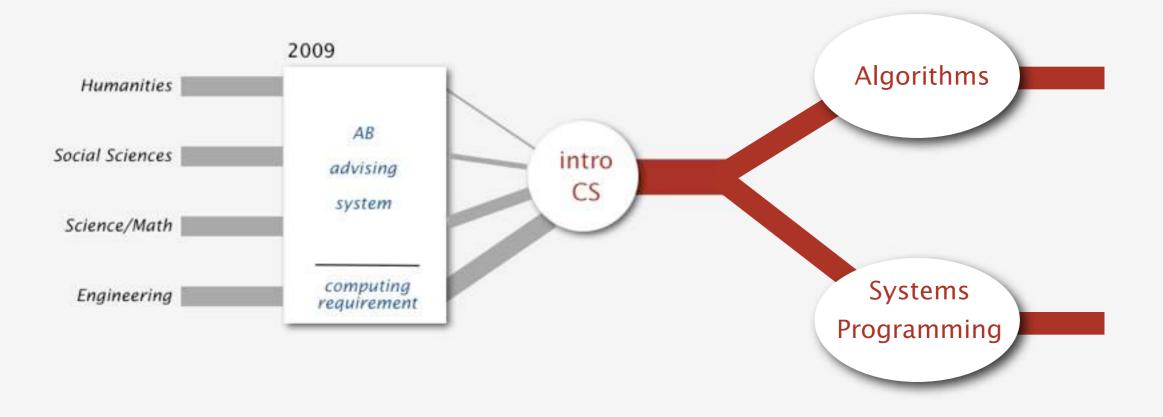
a poster child for priority queue abstraction

efficient algorithms are necessary

"Algorithms" and "Systems Programming" benefit from the approach.

About half of the IntroCS students take both!

Half of those pursue a certificate program in Applications in Computing



Summary

Computer science embraces a significant body of knowledge that is pervasive in modern life and critical to every students' education

Embracing, supporting, and leveraging science in a single intro CS course can serve large numbers of students.

Proof of concept: Intro CS at Princeton

- 40% of Princeton students in a single intro course
- Stable content for a decade

Next goal: 40% of US college students

- Classical textbook model
- New media
- Evangelization
- Viral spread of content

Q. Why Java?

A. Widely available, easily installed on any machine.

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Q. Why not Matlab?

A. Not free.

- A. Poor data abstraction ("i = 0").
- A. Not so relevant to students who do not know linear algebra.

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Q. How do I use the booksite?

A. 17-year olds have absolutely no trouble doing it!