

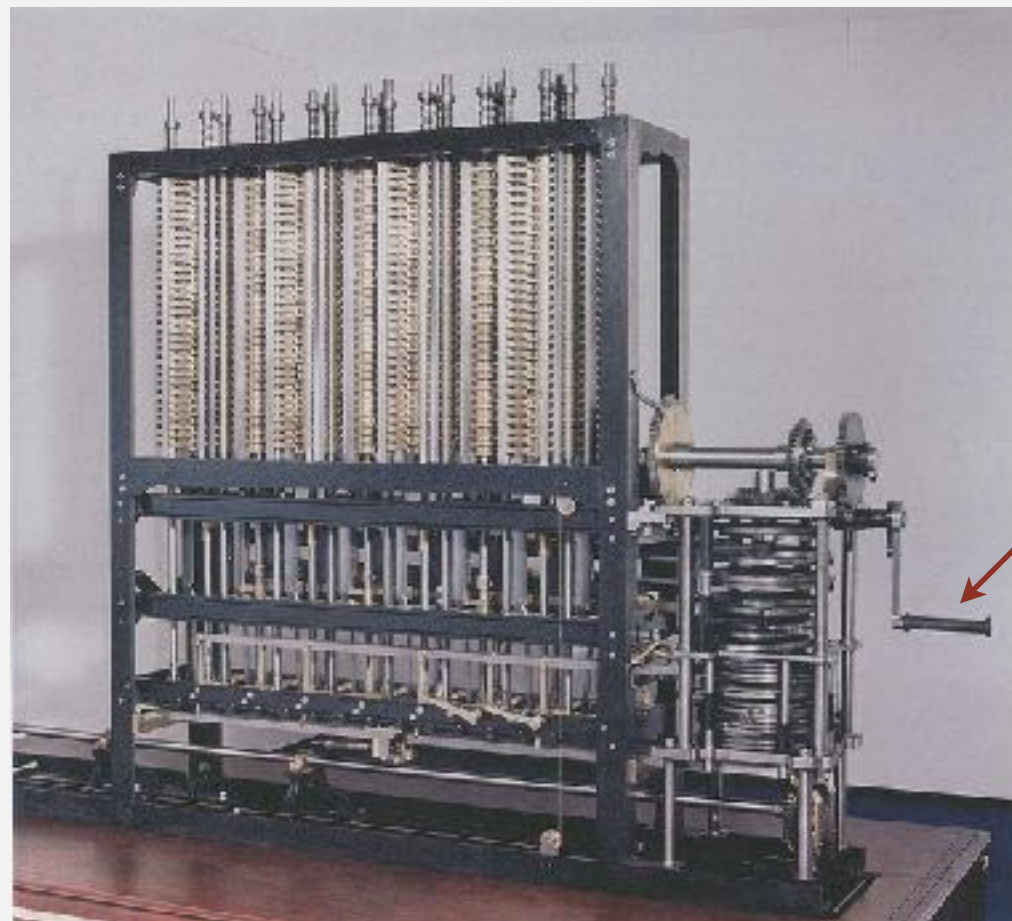
Analysis of Algorithms

Please note that these slides are based in part on material originally developed by Prof. Kevin Wayne of the CS Dept at Princeton University.

Introduction

Running time

“ As soon as an Analytic Engine exists, it will necessarily guide the future course of the science. Whenever any result is sought by its aid, the question will arise—By what course of calculation can these results be arrived at by the machine in the shortest time? ” — Charles Babbage (1864)



how many times do you
have to turn the crank?

Difference Engine

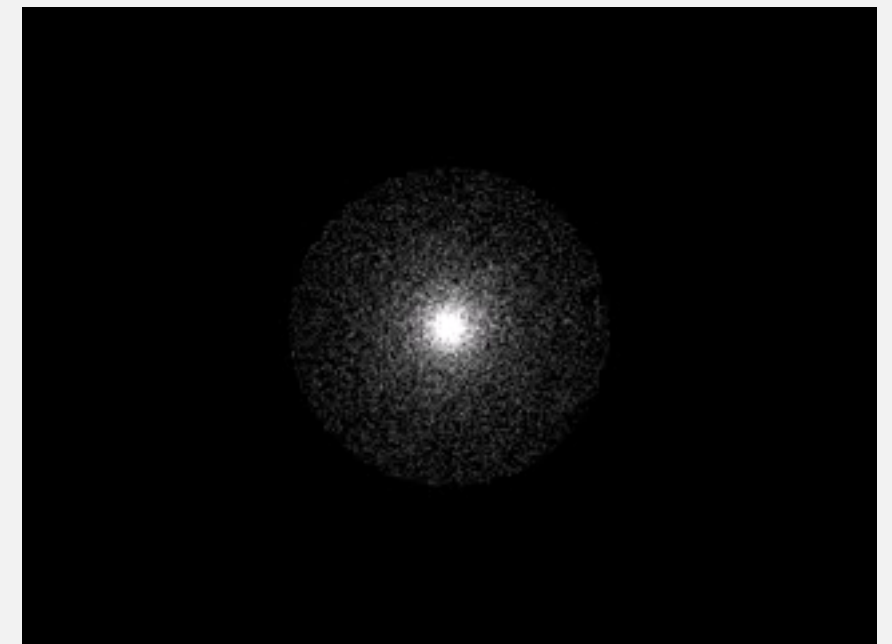
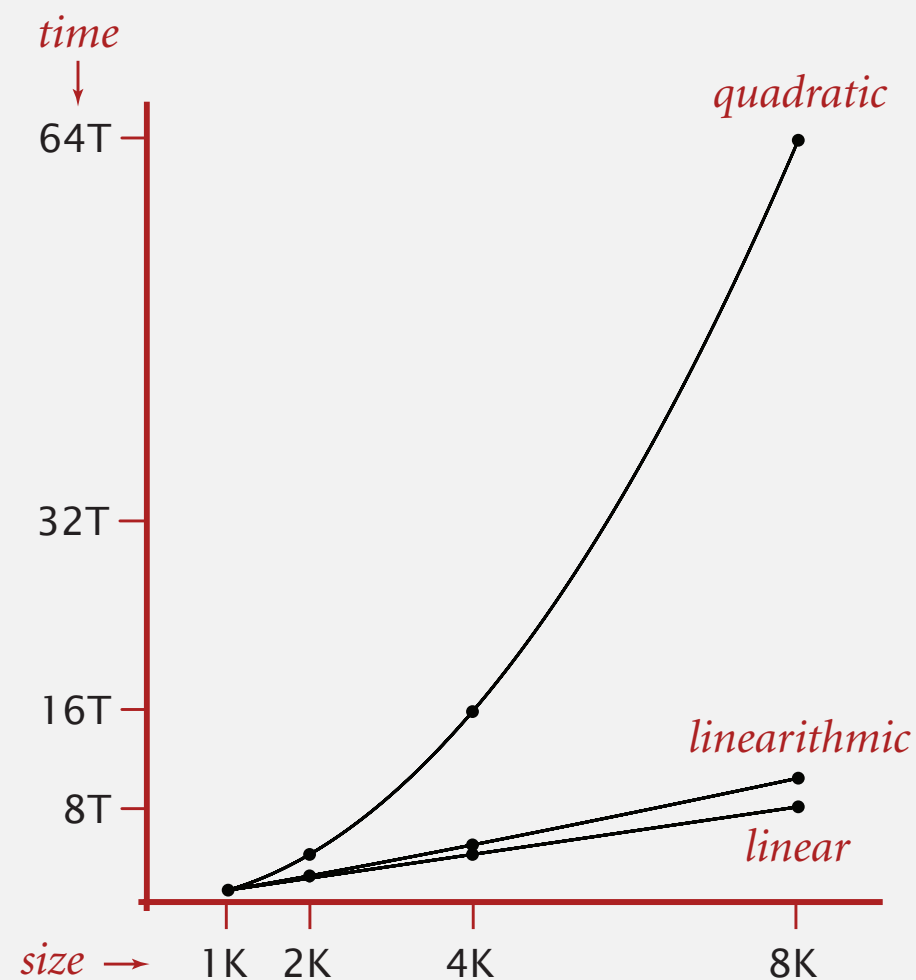
Some algorithmic successes

N-body simulation.

- Simulate gravitational interactions among N bodies.
- Brute force: N^2 steps.
- Barnes-Hut algorithm: $N \log N$ steps, **enables new research**.



Andrew Appel
PU '81



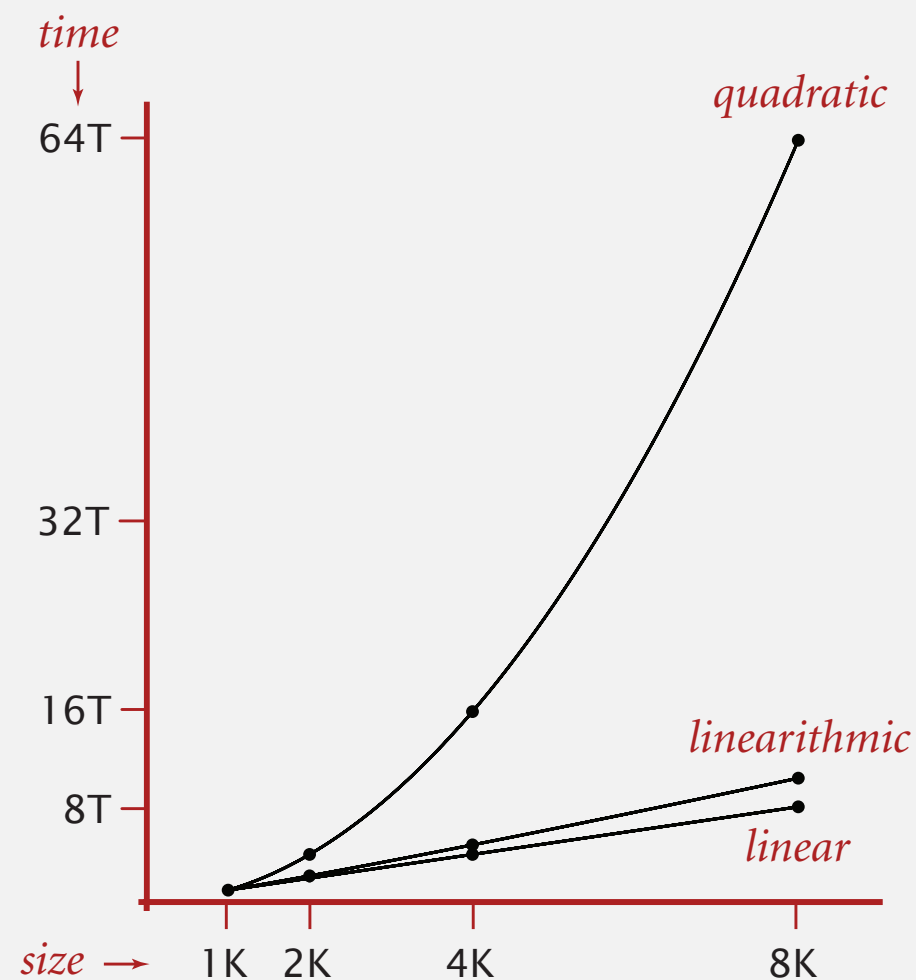
Some algorithmic successes

Discrete Fourier transform.

- Break down waveform of N samples into periodic components.
- Applications: DVD, JPEG, MRI, astrophysics,
- Brute force: N^2 steps.
- FFT algorithm: $N \log N$ steps, **enables new technology.**



Friedrich Gauss
1805



Scientific method applied to analysis of algorithms

A framework for predicting performance and comparing algorithms.

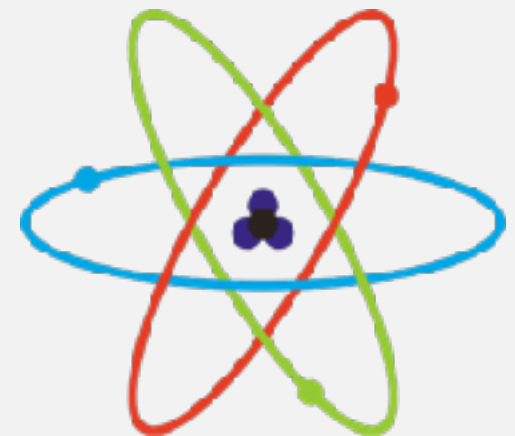
Scientific method.

- **Observe** some feature of the natural world.
- **Hypothesize** a model that is consistent with the observations.
- **Predict** events using the hypothesis.
- **Verify** the predictions by making further observations.
- **Validate** by repeating until the hypothesis and observations agree.

Principles.

- Experiments must be **reproducible**.
- Hypotheses must be **falsifiable**.

Feature of the natural world. Computer itself.



Falsifiability??

A distinguished naturalist proposes the following hypothesis to "model" his observations:

All swans are white.

Is this true? We don't know for sure but our DN certainly believes so.

Is it falsifiable? Yes, it is falsifiable because if anyone was able to find a black (or other color) swan, we would immediately know that the theory was false.

In fact, there are black swans (but, naturally, only in the Southern Hemisphere). So the hypothesis is false.

Observations

Example: 3-SUM

3-SUM. Given N distinct integers, how many triples sum to exactly zero?

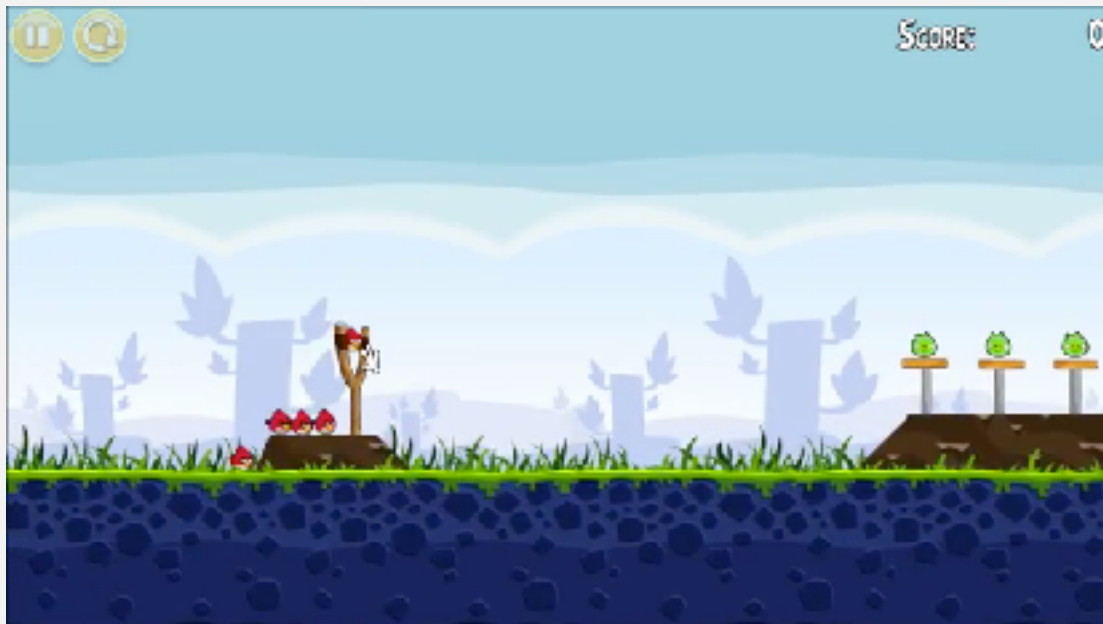
```
% more 8ints.txt
```

```
8
```

```
30 -40 -20 -10 40 0 10 5
```

```
% java ThreeSum 8ints.txt
```

```
4
```



	a[i]	a[j]	a[k]	sum
1	30	-40	10	0
2	30	-20	-10	0
3	-40	40	0	0
4	-10	0	10	0

Context. Deeply related to problems in computational geometry.

3-SUM: brute-force algorithm

```
public class ThreeSum
{
    public static int count(int[] a)
    {
        int N = a.length;
        int count = 0;
        for (int i = 0; i < N; i++)
            for (int j = i+1; j < N; j++)
                for (int k = j+1; k < N; k++)
                    if (a[i] + a[j] + a[k] == 0)
                        count++;
        return count;
    }

    public static void main(String[] args)
    {
        In in = new In(args[0]);
        int[] a = in.readAllInts();
        StdOut.println(count(a));
    }
}
```

← check each triple
← for simplicity, ignore integer overflow

Measuring the running time

Q. How to time a program?

A. Manual.



```
% java ThreeSum 1Kints.txt
```



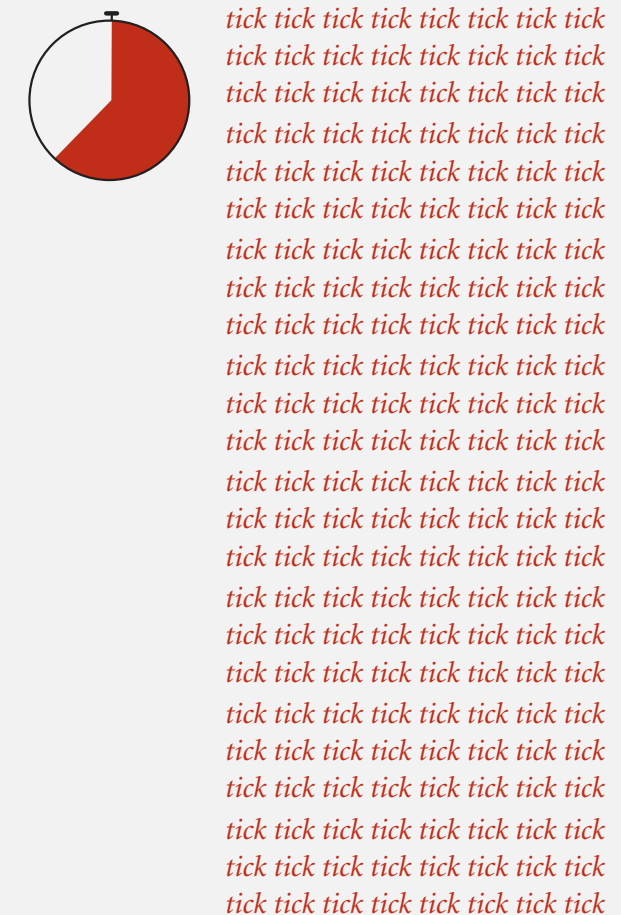
70

```
% java ThreeSum 2Kints.txt
```



528

```
% java ThreeSum 4Kints.txt
```



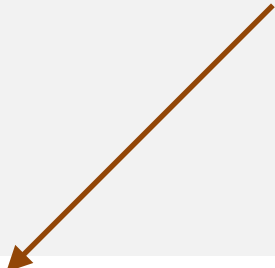
4039

Measuring the running time

Q. How to time a program?

A. Automatic.

But we will implement our own
“Benchmark” class to help with
measuring running time.



```
public class Stopwatch
```

(part of stdlib.jar)

```
    Stopwatch()
```

create a new stopwatch

```
    double   elapsedTime()
```

time since creation (in seconds)

```
public static void main(String[] args)
{
    In in = new In(args[0]);
    int[] a = in.readAllInts();
    Stopwatch stopwatch = new Stopwatch();
    StdOut.println(ThreeSum.count(a));
    double time = stopwatch.elapsedTime();
    StdOut.println("elapsed time " + time);
}
```

Empirical analysis

Run the program for various input sizes and measure running time.



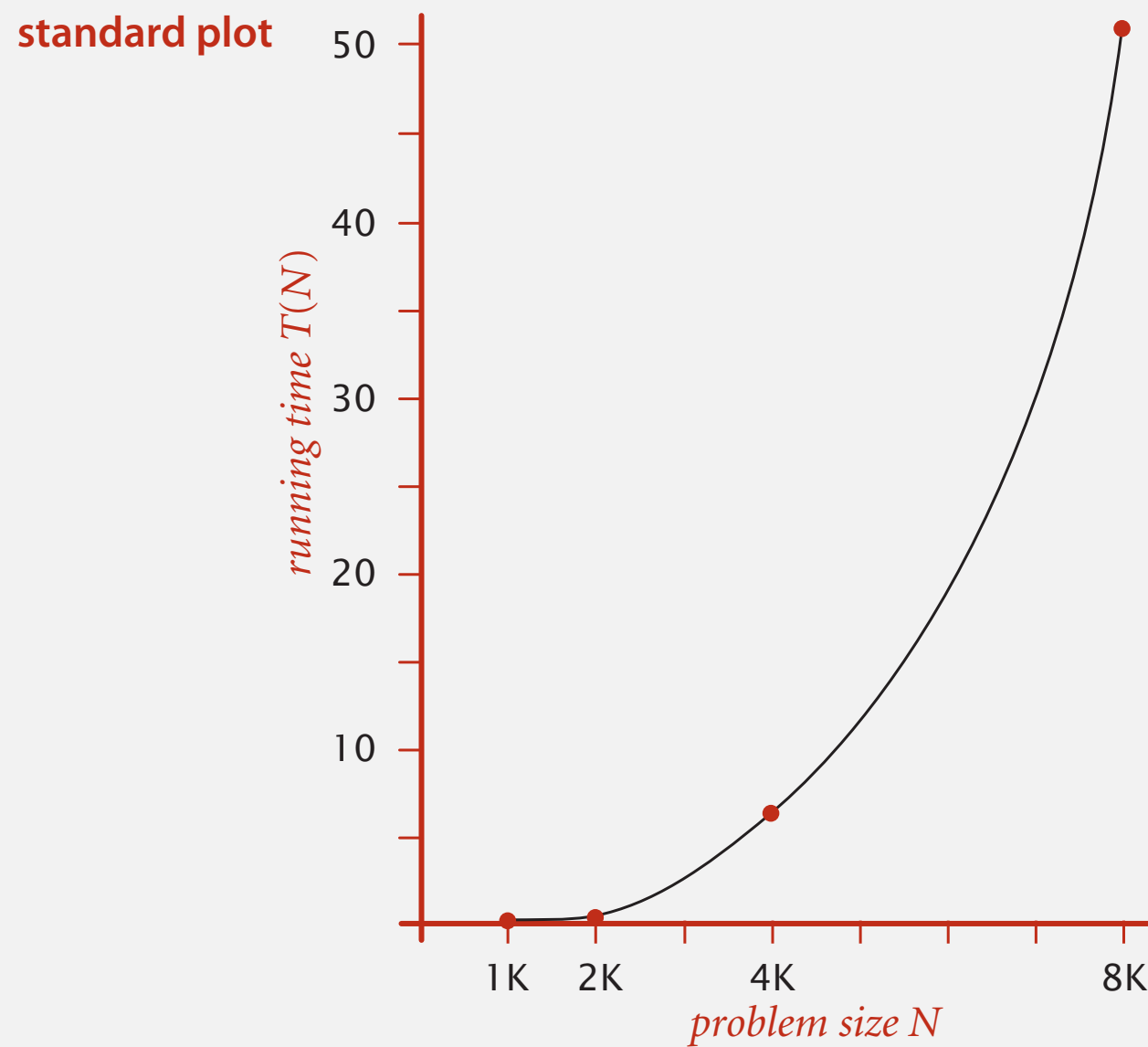
Empirical analysis

Run the program for various input sizes and measure running time.

N	time (seconds) †
250	0.003
500	0.015
1,000	0.1
2,000	0.8
4,000	6.4
8,000	51.1
16,000	?

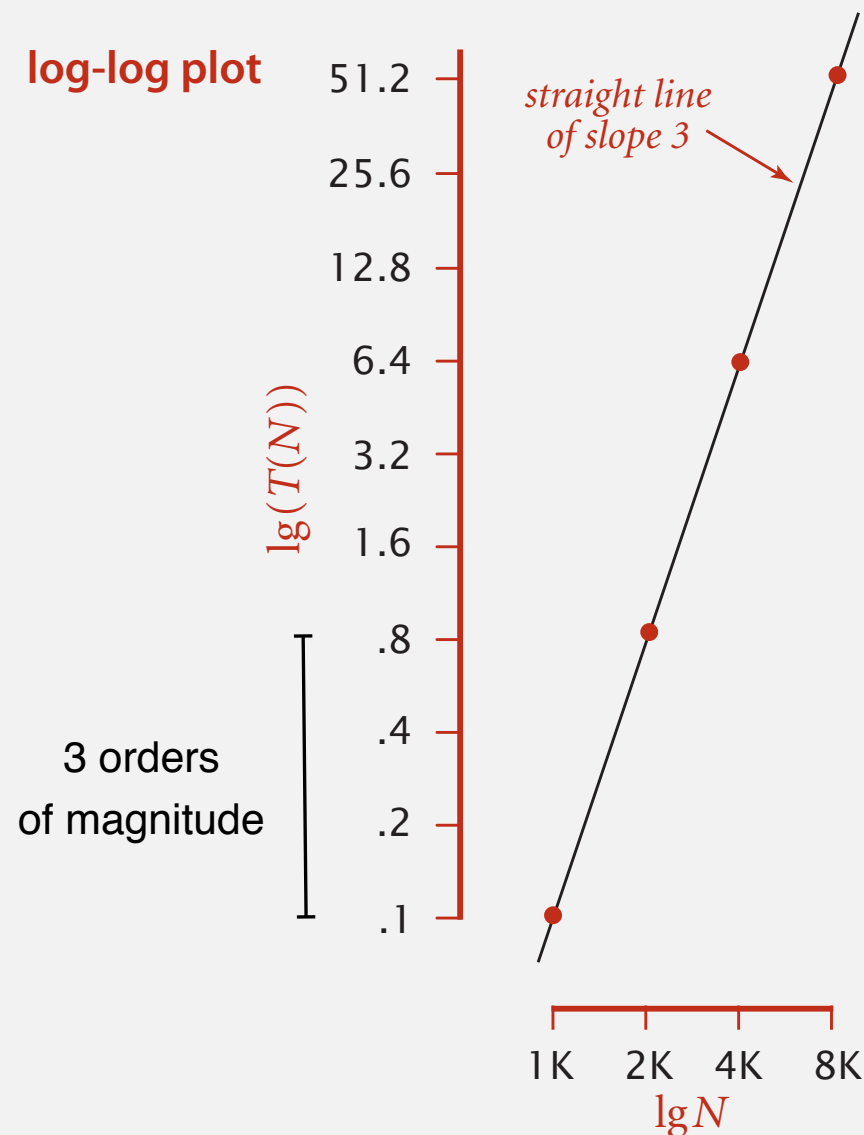
Data analysis

Standard plot. Plot running time $T(N)$ vs. input size N .



Data analysis

Log-log plot. Plot running time $T(N)$ vs. input size N using **log-log scale**.



$$\lg(T(N)) = b \lg N + c$$

$$b = 2.999$$

$$c = -33.2103$$

$$T(N) = a N^b, \text{ where } a = 2^c$$

Regression. Fit straight line through data points: $a N^b$.

Hypothesis. The running time is about $1.006 \times 10^{-10} \times N^{2.999}$ seconds.

power law
slope

Prediction and validation

Hypothesis. The running time is about $1.006 \times 10^{-10} \times N^{2.999}$ seconds.

"order of growth" of running
time is about N^3 [stay tuned]

Predictions.

- 51.0 seconds for $N = 8,000$.
- 408.1 seconds for $N = 16,000$.

Observations.

N	time (seconds) †
8,000	51.1
8,000	51
8,000	51.1
16,000	410.8

validates hypothesis!

Doubling hypothesis

Doubling hypothesis. Quick way to estimate b in a power-law relationship.

Run program, **doubling** the size of the input.

N	time (seconds) †	ratio	lg ratio
250	0.003	—	—
500	0.015	4.8	2.3
1,000	0.1	6.9	2.8
2,000	0.8	7.7	2.9
4,000	6.4	8	3
8,000	51.1	8	3

$$\begin{aligned}\frac{T(2N)}{T(N)} &= \frac{a(2N)^b}{aN^b} \\ &= 2^b\end{aligned}$$

← $\lg(6.4 / 0.8) = 3.0$

↑
seems to converge to a constant $b \approx 3$

Hypothesis. Running time is about $a N^b$ with $b = \lg \text{ratio}$.

Caveat. Cannot identify logarithmic factors with doubling hypothesis.

Doubling hypothesis

Doubling hypothesis. Quick way to estimate b in a power-law relationship.

Q. How to estimate a (assuming we know b) ?

A. Run the program (for a sufficient large value of N) and solve for a .

N	time (seconds) †
8,000	51.1
8,000	51
8,000	51.1

$$51.1 = a \times 8000^3$$

$$\Rightarrow a = 0.998 \times 10^{-10}$$

Hypothesis. Running time is about $0.998 \times 10^{-10} \times N^3$ seconds.



almost identical hypothesis
to one obtained via linear regression

Experimental algorithmics

System independent effects.

- Algorithm.
 - Input data.
- } determines exponent
in power law

System dependent effects.

- Hardware: CPU, memory, cache, ...
 - Software: compiler, interpreter, garbage collector, ...
 - System: operating system, network, other apps, ...
- } determines constant in
power law

Bad news. Difficult to get precise measurements.

Good news. Much easier and cheaper than other sciences.



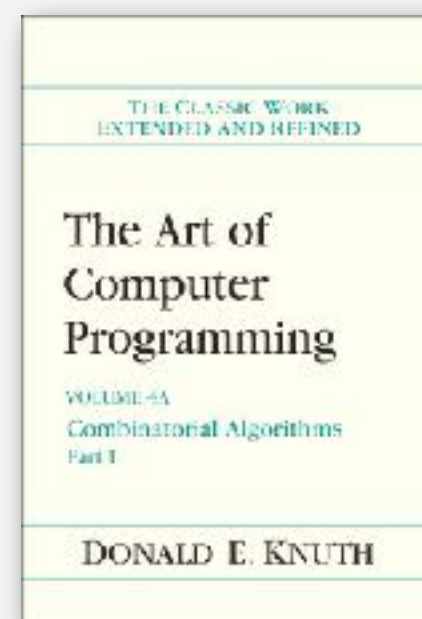
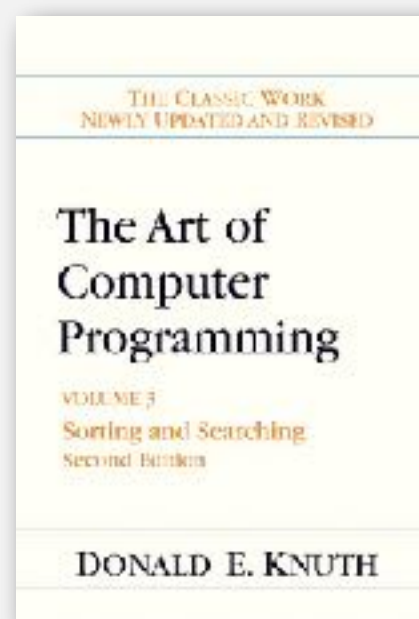
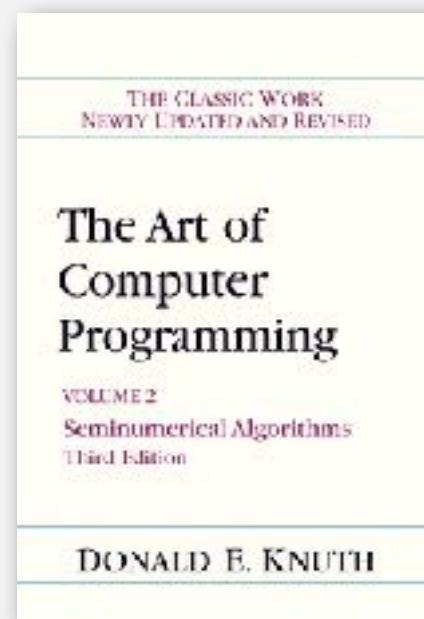
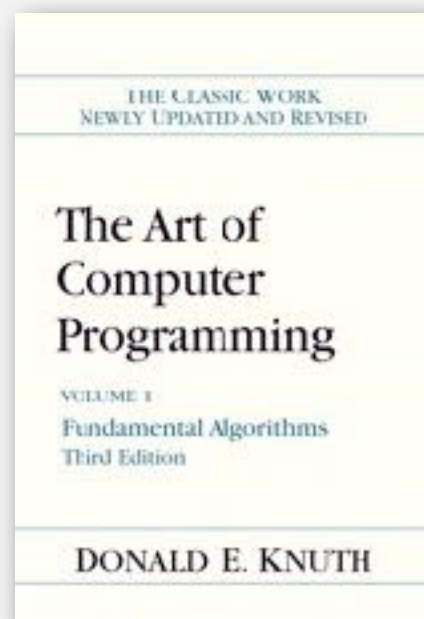
e.g., can run huge number of experiments

Analysis of Algorithms: Mathematical Models

Mathematical models for running time

Total running time: sum of cost \times frequency for all operations.

- Need to analyze program to determine set of operations.
- Cost depends on machine, compiler.
- Frequency depends on algorithm, input data.



Donald Knuth
1974 Turing Award

In principle, accurate mathematical models are available.

Cost of basic operations

Challenge. How to estimate constants.

operation	example	nanoseconds [†]
integer add	$a + b$	2.1
integer multiply	$a * b$	2.4
integer divide	a / b	5.4
floating-point add	$a + b$	4.6
floating-point multiply	$a * b$	4.2
floating-point divide	a / b	13.5
sine	<code>Math.sin(theta)</code>	91.3
arctangent	<code>Math.atan2(y, x)</code>	129
...

[†] Running OS X on Macbook Pro 2.2GHz with 2GB RAM

Cost of basic operations

Observation. Most primitive operations take constant time.

operation	example	nanoseconds [†]
variable declaration	<code>int a</code>	c_1
assignment statement	<code>a = b</code>	c_2
integer compare	<code>a < b</code>	c_3
array element access	<code>a[i]</code>	c_4
array length	<code>a.length</code>	c_5
1D array allocation	<code>new int[N]</code>	$c_6 N$
2D array allocation	<code>new int[N][N]</code>	$c_7 N^2$

Caveat. Non-primitive operations often take more than constant time.

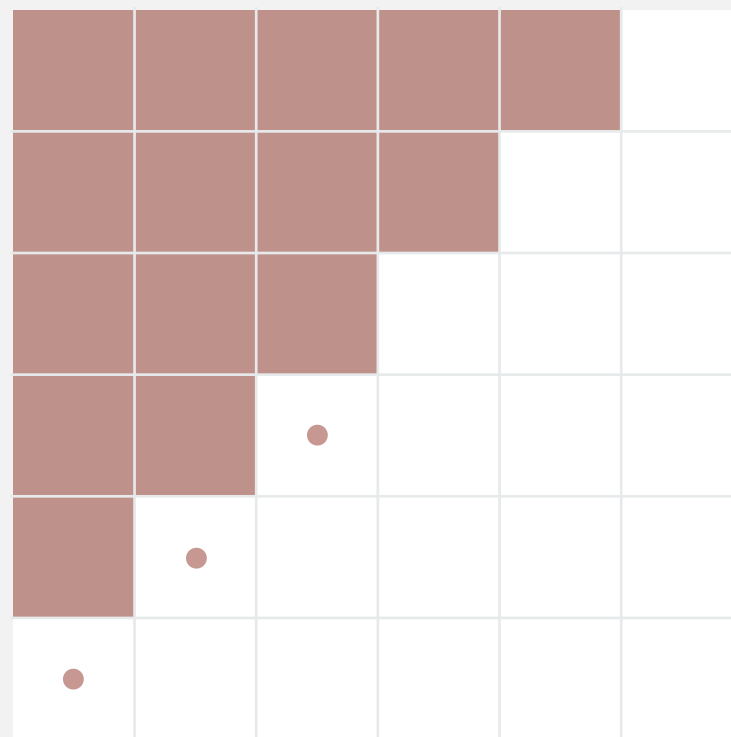
 novice mistake: abusive string concatenation

Example: 2-SUM

Q. How many instructions as a function of input size N ?

```
int count = 0;
for (int i = 0; i < N; i++)
  for (int j = i+1; j < N; j++)
    if (a[i] + a[j] == 0)
      count++;
```

Pf. [n even]



$$0 + 1 + 2 + \dots + (N - 1) = \frac{1}{2}N^2 - \frac{1}{2}N$$

half of square half of diagonal

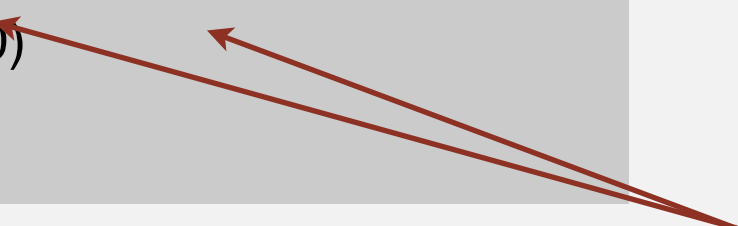
$$\begin{aligned} 0 + 1 + 2 + \dots + (N - 1) &= \frac{1}{2}N(N - 1) \\ &= \binom{N}{2} \end{aligned}$$

Note that because we skip self-comparisons, *and* redundant comparisons, we end up doing fewer than half of all possible comparisons. This diagram on the left is simply to illustrate that. The red dots illustrate by how much we would over-estimate the number of comparisons if we simply used $N^2/2$.

Example: 2-SUM

Q. How many instructions as a function of input size N ?

```
int count = 0;
for (int i = 0; i < N; i++)
    for (int j = i+1; j < N; j++)
        if (a[i] + a[j] == 0)
            count++;
```


$$0 + 1 + 2 + \dots + (N - 1) = \frac{1}{2} N (N - 1)$$
$$= \binom{N}{2}$$

operation	frequency
variable declaration	$N + 2$
assignment statement	$N + 2$
less than compare	$\frac{1}{2} (N + 1) (N + 2)$
equal to compare	$\frac{1}{2} N (N - 1)$
array access	$N (N - 1)$
increment	$\frac{1}{2} N (N - 1)$ to $N (N - 1)$

} tedious to count exactly

Simplifying the calculations

*“ It is convenient to have a **measure of the amount of work involved in a computing process**, even though it be a very **crude** one. We may count up the number of times that various elementary operations are applied in the whole process and then given them various weights. We might, for instance, count the number of additions, subtractions, multiplications, divisions, recording of numbers, and extractions of figures from tables. In the case of computing with matrices most of the work consists of multiplications and writing down numbers, and **we shall therefore only attempt to count the number of multiplications and recordings.** ” — Alan Turing*

ROUNDING-OFF ERRORS IN MATRIX PROCESSES

By A. M. TURING

(National Physical Laboratory, Teddington, Middlesex)

[Received 4 November 1947]

SUMMARY

A number of methods of solving sets of linear equations and inverting matrices are discussed. The theory of the rounding-off errors involved is investigated for some of the methods. In all cases examined, including the well-known ‘Gauss elimination process’, it is found that the errors are normally quite moderate: no exponential build-up need occur.



Some Computer/Information Science Pioneers you should know about

- [Charles Babbage](#) (1791–1871): Built Difference Engine, designed/began Analytical Engine; also world's first programmer: [Ada \(Byron\) Lovelace](#) (1815-1852)
- [John von Neumann](#) (1903-1957): Fundamental architecture; Merge Sort;
- [Alonzo Church](#) (1903-1995): Lambda Calculus;
- [Grace Hopper](#) (1906-1992): The “bug”; English-language compilers;
- [Alan Turing \(1912-1954\)](#): Turing Machine; Cryptanalysis; Bletchley Park;
- [Sir Maurice Wilkes](#) (1913-2010): 1st practical stored program computer (EDSAC); my head of dept., algorithms teacher, and Ph. D. Examiner;
- [Claude Shannon](#) (1916-2001): Father of Information Theory; Bell Labs;
- [Edsger Dijkstra](#) (1930-2002): Structured Programming, GOTO considered harmful;
- [Niklaus Wirth†](#) (1934-): Pascal, Modula-2;
- [Donald E. Knuth](#) (1938-): Algorithms, TeX, $O(N)$;
- [James Gosling](#) (Java), [Sir Timothy Berners-Lee](#) (WWW), etc.

Turing Award

q.v. [List of pioneers in computer science](#)

Simplification 1: cost model

Cost model. Use some basic operation as a proxy for running time.

```
int count = 0;
for (int i = 0; i < N; i++)
  for (int j = i+1; j < N; j++)
    if (a[i] + a[j] == 0)
      count++;
```

$$0 + 1 + 2 + \dots + (N - 1) = \frac{1}{2} N (N - 1) \\ = \binom{N}{2}$$

operation	frequency
variable declaration	$N + 2$
assignment statement	$N + 2$
less than compare	$\frac{1}{2} (N + 1) (N + 2)$
equal to compare	$\frac{1}{2} N (N - 1)$
array access	$N (N - 1)$
increment	$\frac{1}{2} N (N - 1)$ to $N (N - 1)$

cost model = array accesses

(we assume compiler/JVM do not optimize any array accesses away!)

Simplification 2: tilde notation

- Estimate running time (or memory) as a function of input size N .
- Ignore lower order terms.
- when N is large, terms are negligible
- when N is small, we don't care

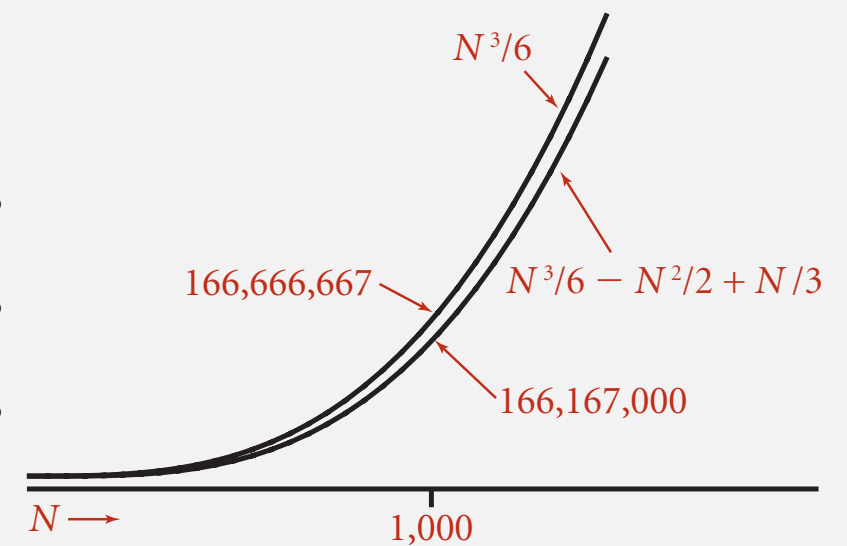
Ex 1. $\frac{1}{6} N^3 + 20 N + 16 \sim \frac{1}{6} N^3$

Ex 2. $\frac{1}{6} N^3 + 100 N^{4/3} + 56 \sim \frac{1}{6} N^3$

Ex 3. $\frac{1}{6} N^3 - \frac{1}{2} N^2 + \frac{1}{3} N \sim \frac{1}{6} N^3$

discard lower-order terms

(e.g., $N = 1000$: 166.67 million vs. 166.17 million)



Leading-term approximation

Technical definition. $f(N) \sim g(N)$ means: $\lim_{N \rightarrow \infty} \frac{f(N)}{g(N)} = 1$

Really
Important!

Simplification 2: tilde notation

- Estimate running time (or memory) as a function of input size N .
 - Always include the constant (coefficient).
 - Ignore lower order terms.
- when N is large, terms are negligible
 - when N is small, we don't care

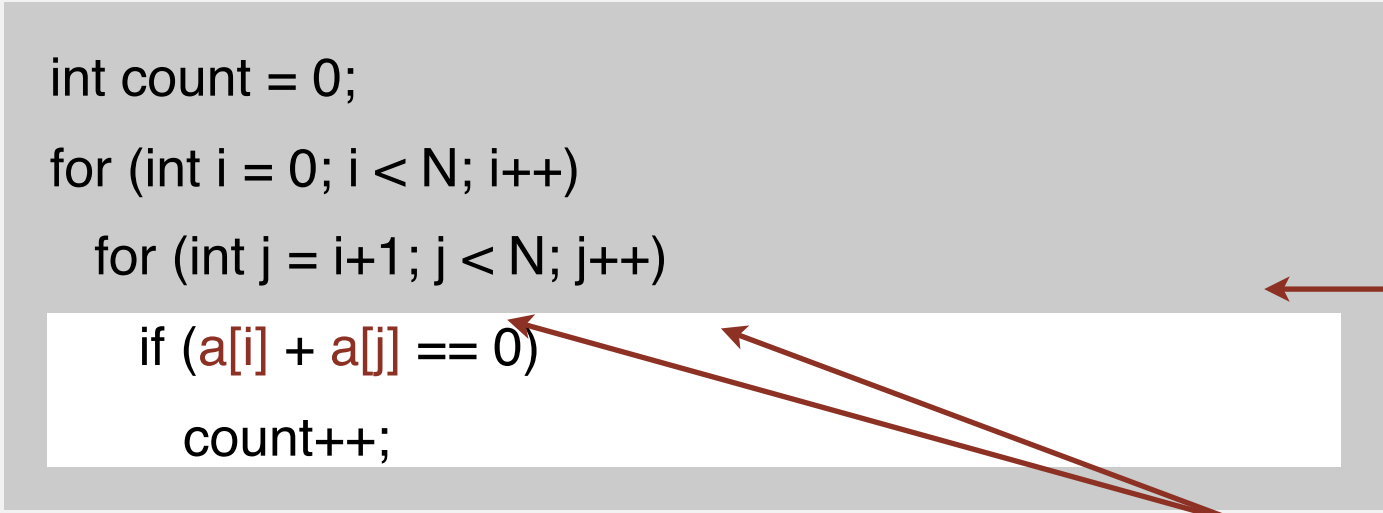
operation	frequency	tilde notation
variable declaration	$N + 2$	$\sim N$
assignment statement	$N + 2$	$\sim N$
less than compare	$\frac{1}{2} (N + 1) (N + 2)$	$\sim \frac{1}{2} N^2$
equal to compare	$\frac{1}{2} N (N - 1)$	$\sim \frac{1}{2} N^2$
array access	$N (N - 1)$	$\sim N^2$
increment	$\frac{1}{2} N (N - 1)$ to $N (N - 1)$	$\sim \frac{1}{2} N^2$ to $\sim N^2$

Example: 2-SUM

Q. Approximately how many array accesses as a function of input size N ?

```
int count = 0;
for (int i = 0; i < N; i++)
    for (int j = i+1; j < N; j++)
        if (a[i] + a[j] == 0)
            count++;
```

"inner loop"


$$0 + 1 + 2 + \dots + (N - 1) = \frac{1}{2} N (N - 1)$$
$$= \binom{N}{2}$$

A. $\sim N^2$ array accesses (double the number of comparisons, because each comparison involves two array accesses)

Bottom line. Use cost model and tilde notation to simplify counts.

Example: 3-SUM

Q. Approximately how many array accesses as a function of input size N ?

```
int count = 0;
for (int i = 0; i < N; i++)
  for (int j = i+1; j < N; j++)
    for (int k = j+1; k < N; k++)
      if (a[i] + a[j] + a[k] == 0)
        count++;
```

"inner loop"

A. $\sim \frac{1}{2} N^3$ array accesses (three times the number of comparisons).

$$\binom{N}{3} = \frac{N(N-1)(N-2)}{3!}$$
$$\sim \frac{1}{6} N^3$$

Diversion: estimating a discrete sum

Q. How to estimate a discrete sum?

A1. Take a discrete mathematics course.

A2. Replace the sum with an integral, and use calculus!

Ex 1. $1 + 2 + \dots + N$.

$$\sum_{i=1}^N i \sim \int_{x=1}^N x \, dx \sim \frac{1}{2} N^2$$

Ex 2. $1^k + 2^k + \dots + N^k$.

$$\sum_{i=1}^N i^k \sim \int_{x=1}^N x^k \, dx \sim \frac{1}{k+1} N^{k+1}$$

Ex 3. $1 + 1/2 + 1/3 + \dots + 1/N$.

$$\sum_{i=1}^N \frac{1}{i} \sim \int_{x=1}^N \frac{1}{x} \, dx = \ln N$$

Ex 4. 3-sum triple loop.

$$\sum_{i=1}^N \sum_{j=i}^N \sum_{k=j}^N 1 \sim \int_{x=1}^N \int_{y=x}^N \int_{z=y}^N dz \, dy \, dx \sim \frac{1}{6} N^3$$

Estimating a discrete sum

Q. How to estimate a discrete sum?

A1. Take a discrete mathematics course.

A2. Replace the sum with an integral, and use calculus!

Ex 4. $1 + \frac{1}{2} + \frac{1}{4} + \frac{1}{8} + \dots$

$$\sum_{i=0}^{\infty} \left(\frac{1}{2}\right)^i = 2$$

$$\int_{x=0}^{\infty} \left(\frac{1}{2}\right)^x dx = \frac{1}{\ln 2} \approx 1.4427$$

$$\begin{aligned}\ln 2 &= 0.69315 \\ \lg e &= 1.4427\end{aligned}$$

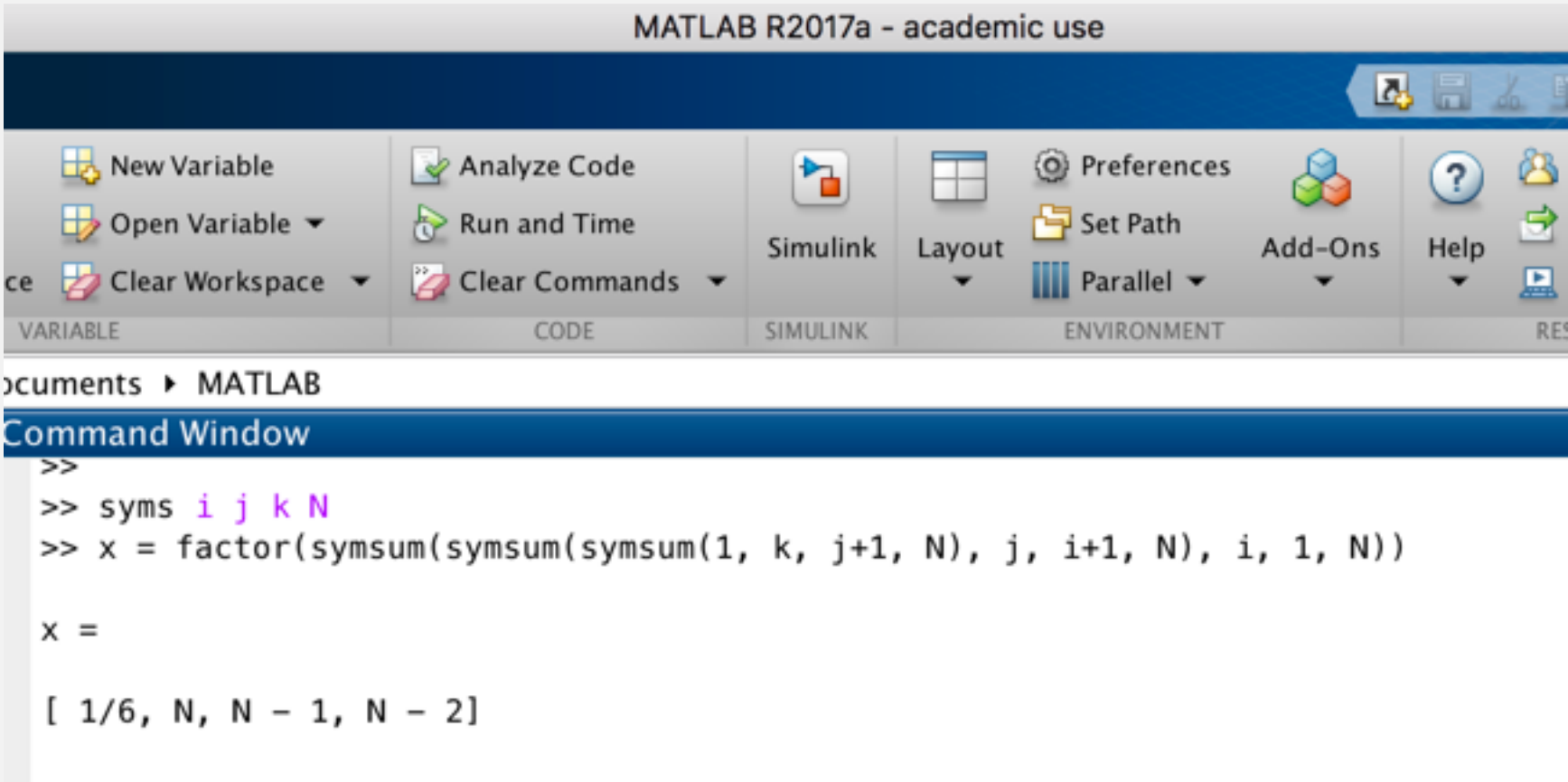
Oops!!!

Caveat. Integral trick doesn't always work!

Estimating a discrete sum

Q. How to estimate a discrete sum?

A3. Use MATLAB (or Wolfram or Maple)



The image shows the MATLAB R2017a - academic use interface. The Command Window displays the following code and output:

```
>>  
>> syms i j k N  
>> x = factor(symsum(symsum(symsum(1, k, j+1, N), j, i+1, N), i, 1, N))  
  
x =  
  
[ 1/6, N, N - 1, N - 2]
```

i.e.

$$\sum_{i=1}^N \sum_{j=i}^N \sum_{k=j}^N 1 \sim \int_{x=1}^N \int_{y=x}^N \int_{z=y}^N dz dy dx \sim \frac{1}{6} N^3$$

Mathematical models for running time

In principle, accurate mathematical models are available.

In practice,

- Formulas can be complicated.
- Advanced mathematics might be required.
- Exact models best left for experts.



costs (depend on machine, compiler)

$$T_N = c_1 A + c_2 B + c_3 C + c_4 D + c_5 E$$

A = array access
 B = integer add
 C = integer compare
 D = increment
 E = variable assignment

frequencies
(depend on algorithm, input)

Bottom line. We use **approximate** models in this course: $T(N) \sim c N^3$.

Order-Of-Growth Classification

Let's jump right in...

- Big O notation (Wikipedia)
- Big O cheat sheet (but I don't like their chart—too pessimistic)

Common order-of-growth classifications


Definition. If $f(N) \sim c g(N)$ for some constant $c > 0$, then the **order of growth** of $f(N)$ is $g(N)$.

- Ignores leading coefficient.
- Ignores lower-order terms.

Ex. The order of growth of the **running time** of this code is N^3 .

```
int count = 0;
for (int i = 0; i < N; i++)
    for (int j = i+1; j < N; j++)
        for (int k = j+1; k < N; k++)
            if (a[i] + a[j] + a[k] == 0)
                count++;
```

Typical usage. With running times.

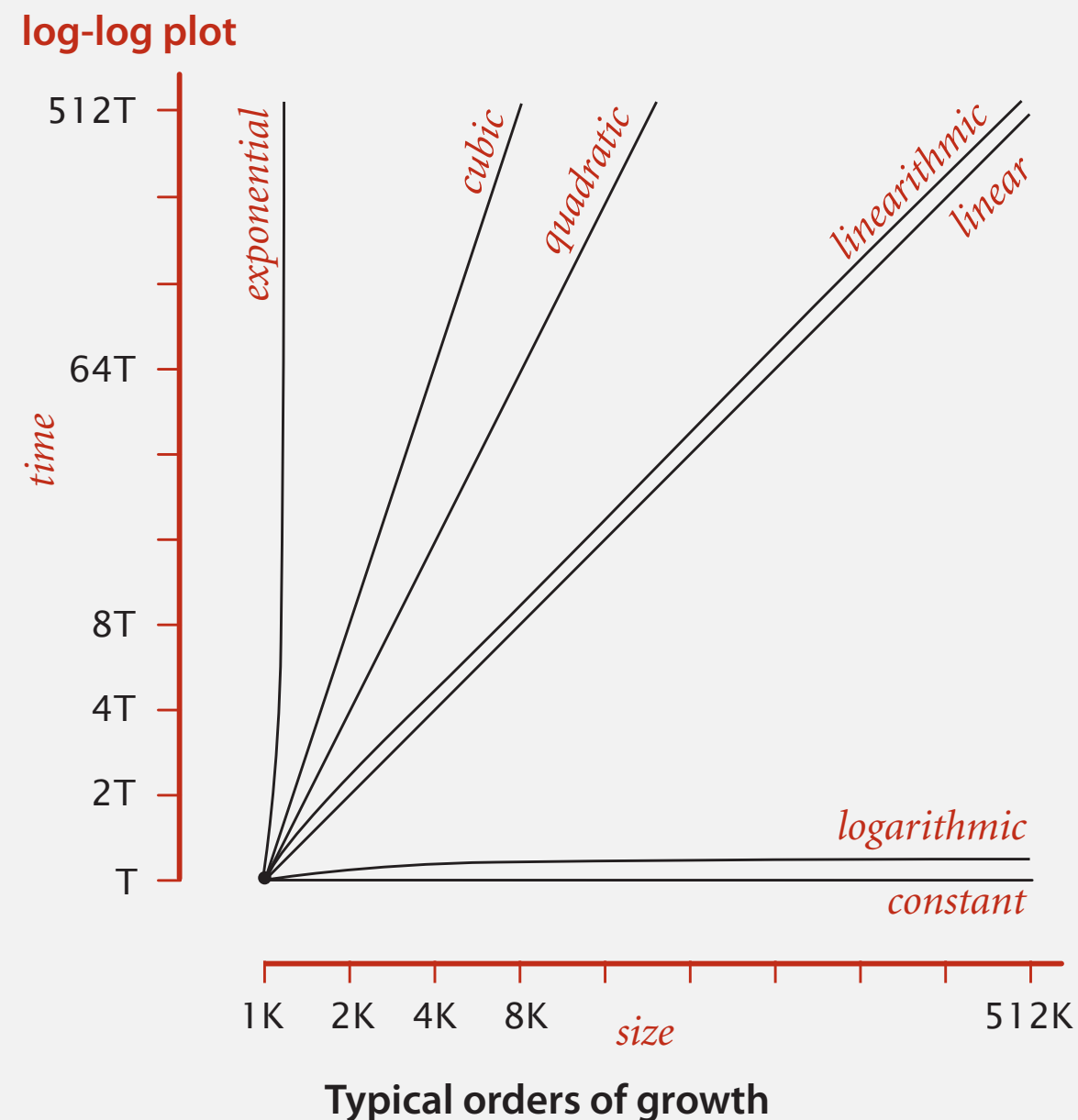
 where leading coefficient
depends on machine, compiler, JVM, ...

Common order-of-growth classifications

Good news. The set of functions

1 , $\log N$, N , $N \log N$, N^2 , N^3 , and 2^N

suffices to describe the order of growth of most common algorithms.



Common order-of-growth classifications

order of growth	name	typical code framework	description	example	$T(2N) / T(N)$
1	constant	<code>a = b + c;</code>	statement	add two numbers	1
$\log N$	logarithmic	<code>while (N > 1) { N = N / 2; ... }</code>	divide in half	binary search	~ 1
N	linear	<code>for (int i = 0; i < N; i++) { ... }</code>	loop	find the maximum	2
$N \log N$	linearithmic	[see mergesort lecture]	divide and conquer	mergesort	~ 2
N^2	quadratic	<code>for (int i = 0; i < N; i++) for (int j = 0; j < N; j++) { ... }</code>	double loop	check all pairs	4
N^3	cubic	<code>for (int i = 0; i < N; i++) for (int j = 0; j < N; j++) for (int k = 0; k < N; k++) { ... }</code>	triple loop	check all triples	8
2^N	exponential	[see combinatorial search lecture]	exhaustive search	check all subsets	$T(N)$

Practical implications of order-of-growth

growth rate	problem size solvable in minutes			
	1970s	1980s	1990s	2000s
1	any	any	any	any
$\log N$	any	any	any	any
N	millions	tens of millions	hundreds of millions	billions
$N \log N$	hundreds of thousands	millions	millions	hundreds of millions
N^2	hundreds	thousand	thousands	tens of thousands
N^3	hundred	hundreds	thousand	thousands
2^N	20	20s	20s	30

Bottom line. Need linear or linearithmic algorithm to keep pace with Moore's law (doubling every two years).

Practical implications of order-of-growth

growth rate	problem size solvable in minutes				time to process millions of inputs			
	1970s	1980s	1990s	2000s	1970s	1980s	1990s	2000s
1	any	any	any	any	instant	instant	instant	instant
log N	any	any	any	any	instant	instant	instant	instant
N	millions	tens of millions	hundreds of millions	billions	minutes	seconds	second	instant
N log N	hundreds of thousands	millions	millions	hundreds of millions	hour	minutes	tens of seconds	seconds
N ²	hundreds	thousand	thousands	tens of thousands	decades	years	months	weeks
N ³	hundred	hundreds	thousand	thousands	never	never	never	millennia

Practical implications of order-of-growth

growth rate	name	description	effect on a program that runs for a few seconds	
			time for 100x more data	size for 100x faster computer
1	constant	independent of input size	—	—
$\log N$	logarithmic	nearly independent of input size	—	—
N	linear	optimal for N inputs	a few minutes	100x
$N \log N$	linearithmic	nearly optimal for N inputs	a few minutes	100x
N^2	quadratic	not practical for large problems	several hours	10x
N^3	cubic	not practical for medium problems	several weeks	4–5x
2^N	exponential	useful only for tiny problems	forever	1x

Binary search demo

Goal. Given a sorted array and a key, find index of the key in the array?

Binary search. Compare key against middle entry.

- Too small, go left.
- Too big, go right.
- Equal, found.



successful search for 33

6	13	14	25	33	43	51	53	64	72	84	93	95	96	97
0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
↑														↑
lo														hi

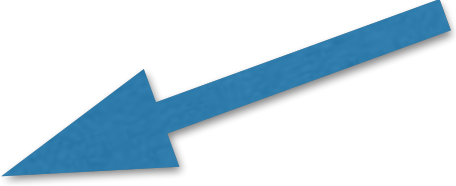
Binary search: Java implementation

Trivial to implement?

- First binary search published in 1946.
- First bug-free one in 1962.
- Bug in Java's `Arrays.binarySearch()` discovered in 2006.

```
public static int binarySearch(int[] a, int key)
{
    int lo = 0, hi = a.length-1;
    while (lo <= hi)
    {
        int mid = lo + (hi - lo) / 2;
        if (key < a[mid]) hi = mid - 1;
        else if (key > a[mid]) lo = mid + 1;
        else return mid;
    }
    return -1;
}
```

This used to read:
 $\text{mid} = (\text{low} + \text{high}) / 2$
but that could result in
integer overflow



one "3-way compare"



Invariant. If key appears in the array `a[]`, then $a[\text{lo}] \leq \text{key} \leq a[\text{hi}]$.

Binary search: mathematical analysis

Proposition. Binary search uses at most $1 + \lg N$ key compares to search in a sorted array of size N .

Def. $T(N)$ = # key compares to binary search a sorted subarray of size $\leq N$.

Binary search recurrence. $T(N) \leq T(N/2) + 1$ for $N > 1$, with $T(1) = 1$.

left or right half
(floored division)

possible to implement with one
2-way compare (instead of 3-way)

Pf sketch. [assume N is a power of 2]

$$\begin{aligned} T(N) &\leq T(N/2) + 1 && \text{[given]} \\ &\leq T(N/4) + 1 + 1 && \text{[apply recurrence to first term]} \\ &\leq T(N/8) + 1 + 1 + 1 && \text{[apply recurrence to first term]} \\ &\vdots \\ &\leq T(N/N) + 1 + 1 + \dots + 1 && \text{[stop applying, } T(1) = 1 \text{]} \\ &= 1 + \lg N \end{aligned}$$

Comparing programs

Hypothesis. The sorting-based $N^2 \log N$ algorithm for 3-SUM is significantly faster in practice than the brute-force N^3 algorithm.

N	time (seconds)
1,000	0.1
2,000	0.8
4,000	6.4
8,000	51.1

ThreeSum.java

N	time (seconds)
1,000	0.14
2,000	0.18
4,000	0.34
8,000	0.96
16,000	3.67
32,000	14.88
64,000	59.16

ThreeSumDeluxe.java

Guiding principle. Typically, better order of growth \Rightarrow faster in practice.

Theory of algorithms

Solving Problems: worst case

- If we have a problem $A(N)$, involving N elements:
 - Then, in general, we can rewrite this problem as \mathbf{B} and solve each sub-problem of $B_i(n_i)$, then “reduce” the results \mathbf{B}^* into a solution $A(N)^*$ which fits the original problem.
 - Of course, one way of solving $A(N)$ is simply to choose $\mathbf{B} = \{ A(N) \}$, i.e. we solve A directly.
 - So, if we can find any solution to $A(N)$ such that the worst case time (or space) required in its solution is $f(N)$ where f is some polynomial/log function, we can confidently state that the worst-case time/space to solve $A(N)$ is $f(N)$.

Solving Problems: best case

- If we have the same problem $A(N)$:
 - What about the best case?
 - If we can find any solution to $A(N)$ such that the best case time (or space) required in its solution is $g(N)$ where g is some polynomial/log function, can we confidently state that the best-case time/space to solve $A(N)$ is $g(N)$?
 - No! Because there might be some other as-yet-undiscovered solution to $A(N)$ which takes less time than $g(N)$.

Types of analyses

Best case. Lower bound on cost.

- Determined by “easiest” input.
- Provides a goal for all inputs.

Worst case. Upper bound on cost.

- Determined by “most difficult” input.
- Provides a guarantee for all inputs.

Average case. Expected cost for random input.

- Need a model for “random” input.
- Provides a way to predict performance.

this course

•

Ex 1. Array accesses for brute-force 3-SUM.

Best: $\sim \frac{1}{2} N^3$

Average: $\sim \frac{1}{2} N^3$

Worst: $\sim \frac{1}{2} N^3$

Ex 2. Compares for binary search.

Best: ~ 1

Average: $\sim \lg N$

Worst: $\sim \lg N$ $\longleftarrow (c = 1 + \lg N)$

Theory of algorithms

Goals.

- Establish “difficulty” of a problem.
- Develop “optimal” algorithms.

Approach.

- Suppress details in analysis: analyze “to within a constant factor.”
- Eliminate variability in input model: focus on the worst case.

Upper bound. Performance guarantee of algorithm for any input.

Lower bound. Proof that no algorithm can do better.

Optimal algorithm. Lower bound = upper bound (to within a constant factor).

Commonly-used notations in the theory of algorithms

notation	provides	example	shorthand for	used to
Big Theta	asymptotic order of growth	$\Theta(N^2)$	$\frac{1}{2} N^2$ $10 N^2$ $5 N^2 + 22 N \log N + 3N$ \vdots	classify algorithms
Big Oh	$\Theta(N^2)$ and smaller	$O(N^2)$	$10 N^2$ $100 N$ $22 N \log N + 3 N$ \vdots	develop upper bounds (guarantee)
Big Omega	$\Theta(N^2)$ and larger	$\Omega(N^2)$	$\frac{1}{2} N^2$ N^5 $N^3 + 22 N \log N + 3 N$ \vdots	develop lower bounds (best case)

Theory of algorithms: example 1

Goals.

- Establish “difficulty” of a problem and develop “optimal” algorithms.
- Ex. 1-SUM = “*Is there a 0 in the array?*”

Upper bound. A specific algorithm.

- Ex. Brute-force algorithm for 1-SUM: Look at every array entry.
- Running time of the optimal algorithm for 1-SUM is $O(N)$.

Lower bound. Proof that no algorithm can do better.

- Ex. Have to examine all N entries (any unexamined one might be 0).
- Running time of the optimal algorithm for 1-SUM is $\Omega(N)$.

Optimal algorithm.

- Lower bound equals upper bound (to within a constant factor).
- Ex. Brute-force algorithm for 1-SUM is optimal: its running time is $\Theta(N)$.

Theory of algorithms: example 2

Goals.

- Establish “difficulty” of a problem and develop “optimal” algorithms.
- Ex. 3-SUM.

Upper bound. A specific algorithm.

- Ex. Brute-force algorithm for 3-SUM.
- Running time of the optimal algorithm for 3-SUM is $O(N^3)$.

Theory of algorithms: example 2

Goals.

- Establish “difficulty” of a problem and develop “optimal” algorithms.
- Ex. 3-SUM.

Upper bound. A specific algorithm.

- Ex. **Improved** algorithm for 3-SUM.
- Running time of the optimal algorithm for 3-SUM is $O(N^2 \log N)$.

Lower bound. Proof that no algorithm can do better.

- Ex. Have to examine all N entries to solve 3-SUM.
- Running time of the optimal algorithm for solving 3-SUM is $\Omega(N)$.

Open problems.

- Optimal algorithm for 3-SUM?
- Subquadratic algorithm for 3-SUM?
- Quadratic lower bound for 3-SUM?

Algorithm design approach

Start.

- Develop an algorithm.
- Prove a lower bound.

Gap?

- Lower the upper bound (discover a new algorithm).
- Raise the lower bound (more difficult). *[And why would you want to?]*

Golden Age of Algorithm Design.

- 1970s-.
- Steadily decreasing upper bounds for many important problems.
- Many known optimal algorithms.

Caveats.

- Overly pessimistic to focus on worst case?
- Need better than “to within a constant factor” to predict performance.

Commonly-used notations in the theory of algorithms

notation	provides	example	shorthand for	used to
Tilde	leading term	$\sim 10 N^2$	$10 N^2$ $10 N^2 + 22 N \log N$ $10 N^2 + 2 N + 37$	provide approximate model
Big Theta	asymptotic order of growth	$\Theta(N^2)$	$\frac{1}{2} N^2$ $10 N^2$ $5 N^2 + 22 N \log N + 3N$	classify algorithms
Big Oh	$\Theta(N^2)$ and smaller	$O(N^2)$	$10 N^2$ $100 N$ $22 N \log N + 3 N$	develop upper bounds
Big Omega	$\Theta(N^2)$ and larger	$\Omega(N^2)$	$\frac{1}{2} N^2$ N^5 $N^3 + 22 N \log N + 3 N$	develop lower bounds

Common mistake. Interpreting big-Oh as an approximate model.

This course. Focus on approximate models: use Tilde-notation

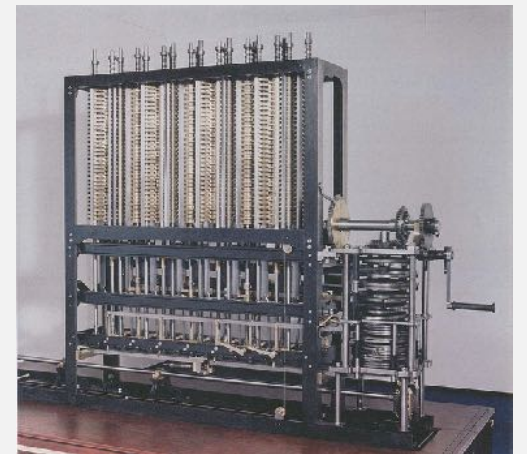
Turning the crank: summary

Empirical analysis.

- Execute program to perform experiments.
- Assume power law and formulate a hypothesis for running time.
- Model enables us to **make predictions**.

Mathematical analysis.

- Analyze algorithm to count frequency of operations.
- Use tilde notation to simplify analysis.
- Model enables us to **explain behavior**.



Scientific method.

- Mathematical model is independent of a particular system; applies to machines not yet built.
- Empirical analysis is necessary to validate mathematical models and to make predictions.