



Fakultät für Informatik

Algorithms and data structures VU

4 hours / 6 ECTS points

Lecture part

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Content overview

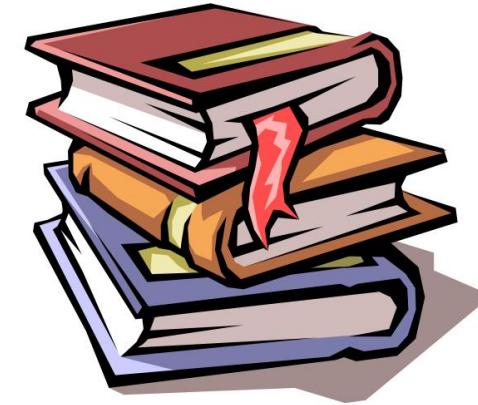
1. Algorithms
paradigms, analysis
2. Data structures
Motivation, overview
3. Vector
hashing, sorting
4. Lists
Linear memory structures, stack, queue
5. Trees
Search structures
6. Graph
traversal and optimization algorithms



literature

R. Sedgewick, *Algorithms in C++* (Parts 1-4), Addison Wesley,
3rd revised edition, 2002

Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest and
Clifford Stein, *Introduction to Algorithms*, published by MIT
Press, 2009



thanksgiving

My special goes to collaboration and reviewing the slides

Thanks to Helmut Wanek and Martin Polaschek

My further thanks go to numerous students from recent years
who provided the basis for some of the dynamic examples of
the VO as part of their exercises.



Chapter 1

Algorithms

1.1 Motivation

Algorithms

Procedural regulations, instruction sequences, process modeling,
described solutions

Two goals

1. Find algorithms for problems!

Find and “construct” solutions 2.

Find “good” algorithms!

“better” algorithms

faster, more complete, more correct, ...

“more powerful” data structures, more

compact, more efficient, more flexible, ...

In general: savings in computing time and/or storage space

Find algorithms for problems!

Task: “Sum of the integers up to n”

Straight-forward solution: “Summing up the individual values between 1 and n”

$$\sum_{i=1}^n i$$

Realization (C/C++ program) **int**

```
sum(int n) {  
    int i, summe = 0; for(i=1;  
    i<=n; i++) summe += i;  
    return summe;  
}
```

Compare with other programming approaches, e.g. while instead of for loop! ÿ alternative programming style

Alternative implementation (1)

Two alternatives

1. Alternative programming style

Maintain problem-solving approach, but implement it in programming terms
revise

Example:

Loop shape (see above)

Recursion instead of iteration

```
int sum(int n) { if(n <= 0) return 0; if(n == 1) return 1; else return n+sum(n-1); }
```

Alternative implementation (2)

2. Alternative solution

Choosing a different way to solve the problem, e.g.
 Gaussian molecular formula

$$\bar{y} = \frac{\sum_{i=1}^n i}{2}$$

implementation

```
int sum(int n) {
    return (n*(n+1))/2;
}
```

Derivation of Gauss' molecular formula

1	... n	
n ... 1		
n+1 ... n+1		

= 2 * Sum from 1 to n

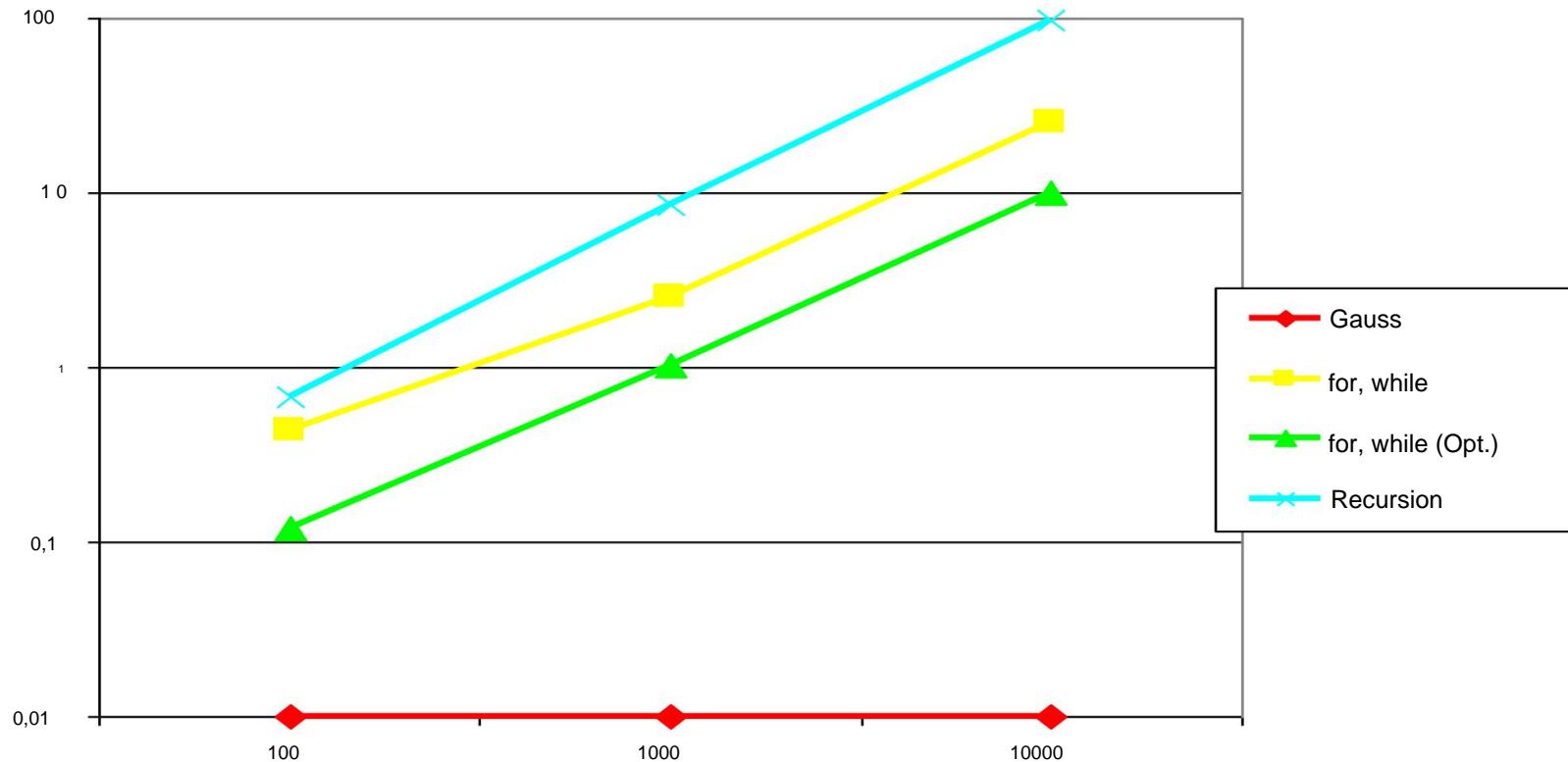
From this it follows that
 Sum formula

$$n * (n+1) / 2$$

Find “good” algorithms!

Comparison of running times

Sum calculation, 100000 repetitions, CPU: 200 MHz Pentium



What is good? Or maybe better?

Problem: Comparing running times only leads to selective quality determination

Runtime, storage space consumption

Depending on

Computer

operating system

Compiler, ...

Goal: Methodology for general quality comparison between Algorithms

Independent of external influences

1.2 Algorithm paradigms

General techniques for solving large classes of Problems

Greedy algorithms

“gluttonous, greedy” approach, choosing the local optimum

Divide-and-conquer algorithms

step-by-step decomposition of the problem of size n into smaller ones

Partial problems

Dynamic programming

Dynamic, successive construction of the solution from already calculated ones

Partial solutions

1.2.1 Greedy (1)

In each step of a *greedy* algorithm, the *option* that is *immediately* (locally) *optimal* is chosen (smallest or largest) *value* with respect to the *objective function*. The global view of the end goal is neglected.

Advantage:

Efficient problem solving, often very quickly, can in many cases find a relatively good solution

Disadvantage:

Often does not find an optimal solution

Greedy (2)

Example: coin changing machine

“Change the amount of 18.- into as small a number as possible

Coins in size 10, 5 and 1”

Greedy approach:

choose largest coin

less than amount

spend the coin

subtract hers

Value of the amount

repeat until difference

equals 0

dh:

$$18.- - \mathbf{10.-} = 8.- \text{ ü}$$

$$8.- - \mathbf{5.-} = 3.- \text{ ü}$$

$$3.- - \mathbf{1.-} = 2.- \text{ ü}$$

$$2.- - \mathbf{1.-} = 1.- \text{ ü}$$

$$1.- - \mathbf{1.-} = 0 \text{ ü}$$



The solution to this problem is not just “good” but even optimal!

Greedy (3)

BUT

Problem with small change in the problem statement:

5.- ÿ 6.-

Coin values 10.-, **6.-**

1.-



greedy approach delivers

$$18.- - \mathbf{10.-} = 8.-$$

ÿ

$$8.- - \mathbf{6.-} = 2.-$$

ÿ

$$2.- - \mathbf{1.-} = 1.-$$

ÿ

$$1.- - \mathbf{1.-} = 0$$

ÿ

ÿ 4 coins

But optimal would be 3 x 6.-

$$18.- - \mathbf{6.-} = 12.-$$

ÿ

$$12.- - \mathbf{6.-} = 6.-$$

ÿ

$$6.- - \mathbf{6.-} = 0$$

ÿ

ÿ 3 coins

1.2.2 Divide-and-conquer (1)

In *divide-and-conquer* algorithms

Starting from a general abstraction, the problem is iteratively refined until solutions for simplified sub-problems have been found, from which an overall solution can be constructed.



This approach is often referred to as “stepwise refinement” or “top-down approach”.

Divide-and-conquer (2)

Different approaches

Problem size division

Decomposition of a problem of size n into a finite number of
Subproblems smaller than n

Step division

Splitting a task into a sequence (sequence) of individual ones
Subtasks

Case division

Identification of special cases for a general problem from a certain
level of abstraction

...

Problem size division

By decomposition reducing the problem size, ie

$$P(n) \in k^*P(m), \\ \text{where } k, m < n$$

Binary search

Find a number x in the (ascending) sorted sequence z_1, z_2, \dots, z_n (generally: z_l, z_{l+1}, \dots, z_r with $l=1, r=n$) and determine its

position i . Decomposition: $k =$

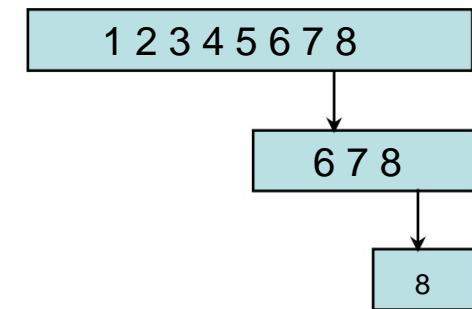
1 and $m \in n/2$ Trivial: find middle index

$m = (l+r)/2$ If $z_m=x$ result m ,

otherwise If $x < z_m$ find x in the range

z_l, z_2, \dots, z_{m-1} else search x in the range z_m+1, z_m+2, \dots, z_r

Find number 8



Step division

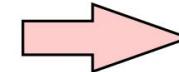
Idea: street sweeper philosophy:

“Breath - broom stroke - step”

Example

Salary increase

Designate employees
Find unique identification
Search the database
Determine current salary
Change to new salary
Store information
Notes change process



Store information

Delete old record

Insert new record

Case division

Approach: Identification of case differences in
Problem data area

Example

Calculating the solutions to a quadratic equation

$$\begin{aligned} az^2 + bz + c &= 0 \\ &= \frac{2b \pm \sqrt{b^2 - 4ac}}{2a}, \quad b^2 - 4ac \text{ and} \end{aligned}$$

if $b^2 - 4ac < 0$, no real roots

$b^2 - 4ac = 0$, real double solution $x = -\frac{b}{2a}$

$b^2 - 4ac > 0$, pair of complex roots

1.2.3 Dynamic Programming (1)

Problem

Often a division of the original problem into a 'small' number of Partial problems are not possible, but leads to an exponential algorithm.

But we know that there is only a polynomial number of subproblems.

Idea Dynamic Programming

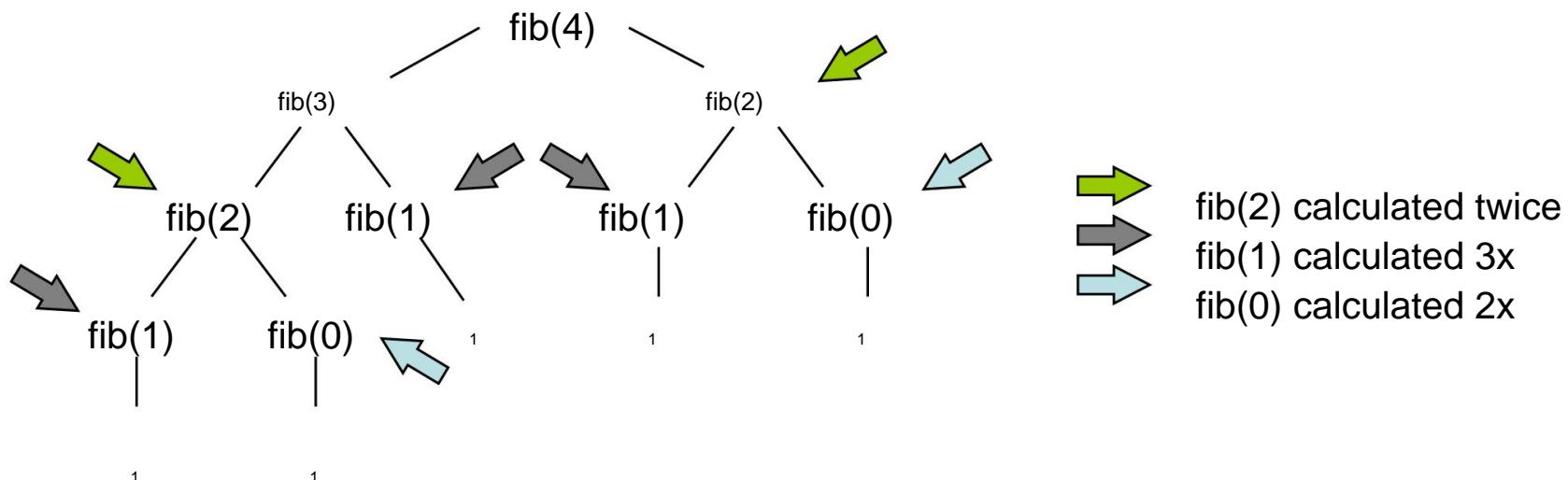
not start from problem size n and split up to size 1,
RATHER

Start with solution for problem size 1, combination of the calculated partial solutions until a solution for problem size n was reached.

Dynamic Programming (2)

Example: Calculating the Fibonacci numbers

```
int fib(int n) {
    if(n <= 1) return 1;
    return fib(n-1) + fib(n-2)
}
```



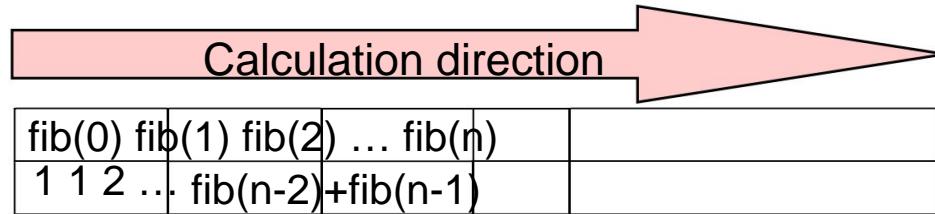
Problem: Repeated solution of a sub-problem



Dynamic Programming (3)

solution

Start with calculation for **fib(0)**, create a table of all calculated values and construction of the new values from the calculated table entries.



```
int fib(int n) {
    int F[MAXSIZE];
    F[0] = 1; F[1] = 1;
    for(i = 2; i <= n; i++) {
        F[i] = F[i-1] + F[i-2];
    }
    return F[n];
}
```

Values come from the
taken from table

Note: Improvement in runtime BUT additional storage space required

1.3 Analysis and evaluation of algorithms



The aim is to objectively evaluate algorithms
criteria
effectiveness

Is the problem solvable, can the approach be implemented in a program?

correctness

Does the algorithm do what it's supposed to do?

Termination

Does the algorithm stop, does it have a finite execution time?

Complexity

How fast is the algorithm $\ddot{\vee}$ Runtime complexity?

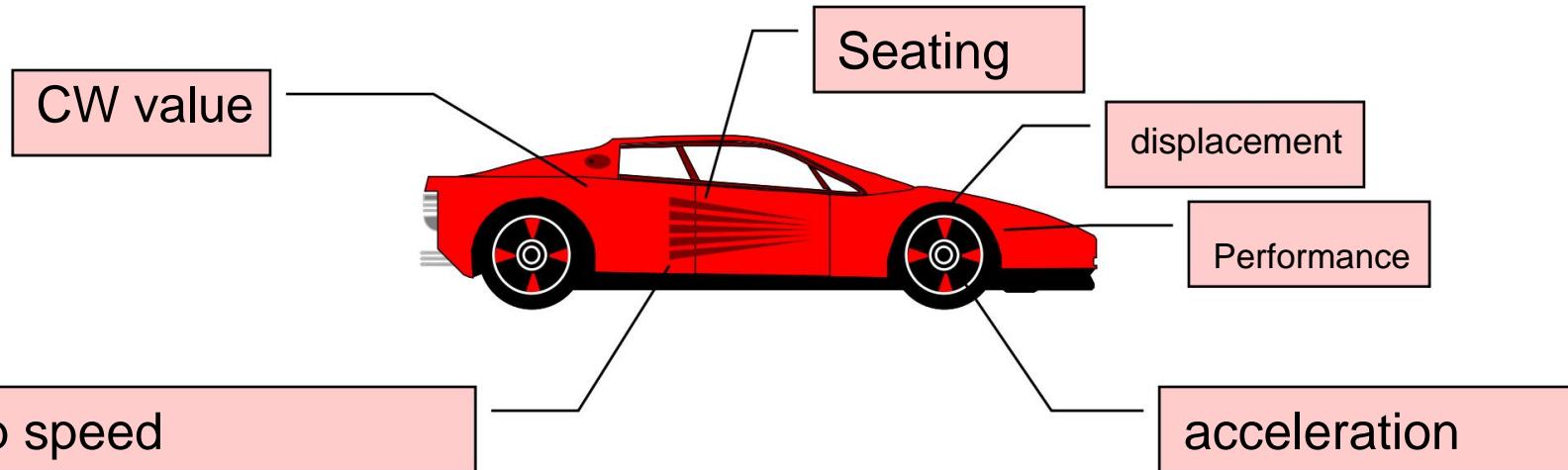
How structured is the algorithm $\ddot{\vee}$ structural complexity?

How much storage space does the algorithm need $\ddot{\vee}$
Space complexity?

Analogy: Car

Specific criteria

Selection



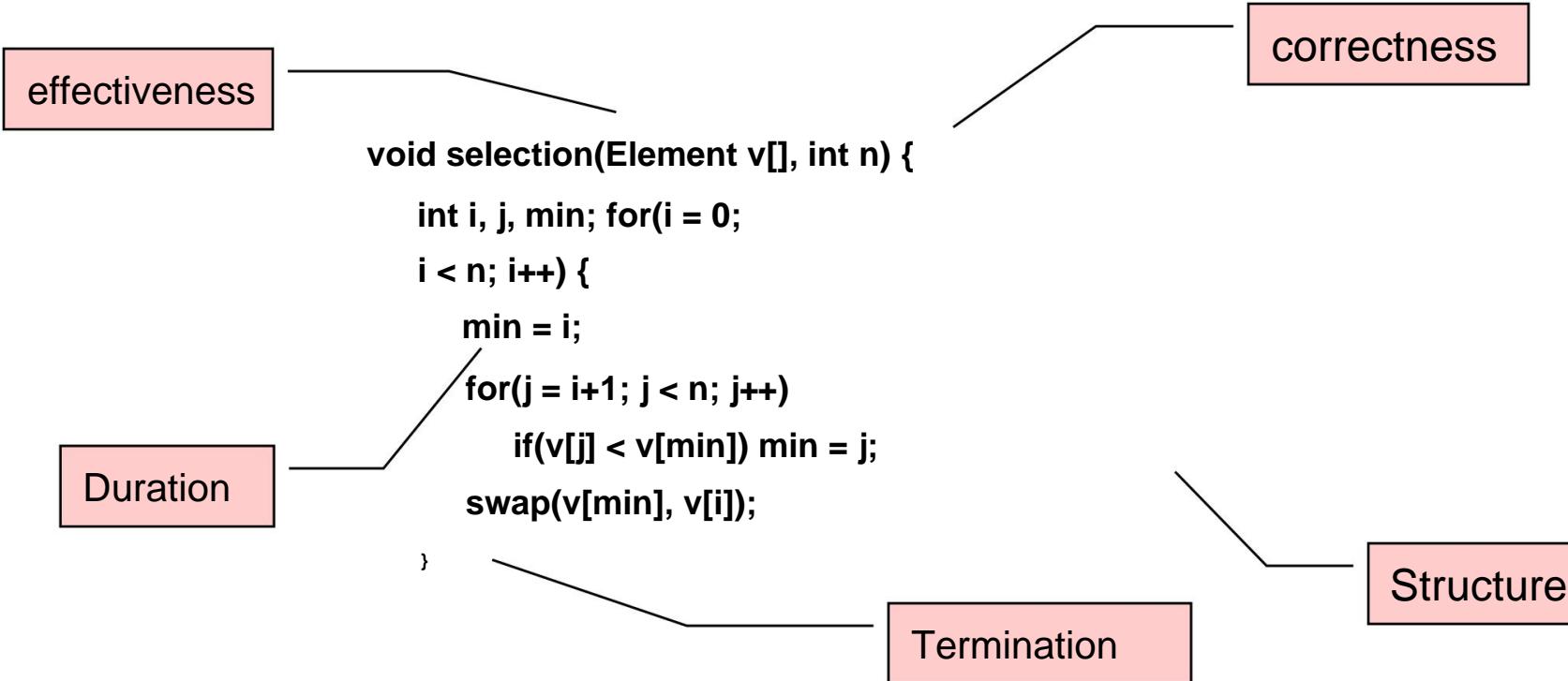
Statistical key figures

Assessment option, classification option sports
cars, trucks, family sedans, ...



Evaluation of programs

Example sorting program



Classification

fast, correct, maintainable, problem-covering, finally, ...



1.3.1 Effectiveness

Principle

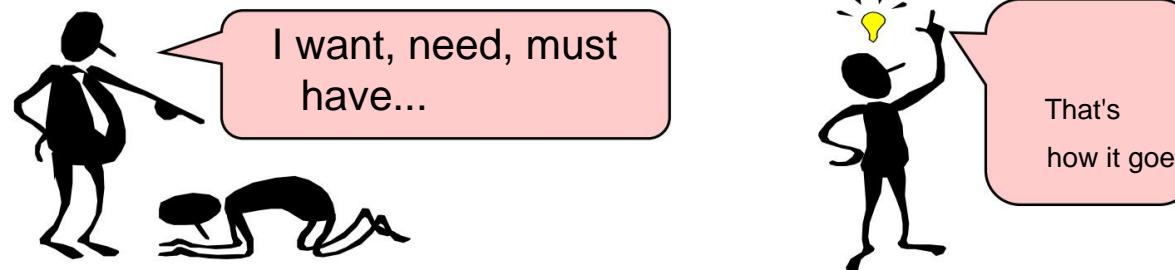
Algorithm can be formulated as an executable computer program.
effective → it does work

Problem

formulation

Transformation of the problem description into an executable one
algorithm

Question: Is there even an executable solution to this problem?
Problem?



1.3.2 Correctness

Does the algorithm produce the desired result?

Two procedures possible

To test

Verification

To test

Complete testing is usually not possible

Statistical approach is usually followed, e.g. path coverage (structural Complexity)

At best “falsification” is achievable

Only errors can be found, but correctness cannot be found
be proven

Verification

Mathematically oriented verification techniques allow
Correctness of program pieces depending on
To prove conditions on the input data (premises).

forces the developer to revisit design decisions and helps find
logical errors

Algorithm needs to be understood
the larger a program system, the more difficult it is
Verification (hardly important in practice)

Proof approach depends on the problem

Mathematical proof

Complete induction

Example: Gaussian molecular formula

$$\sum_{i=1}^n i = \frac{n(n+1)}{2}$$

Ind. start for

$$n = 1 \quad \sum_{i=1}^1 i = 1 \quad \text{true}$$

Ind. prerequisite

$$\sum_{i=1}^{n-1} i = (n-1)n/2$$

Ind.

$$\begin{aligned} \text{conclusion } & \sum_{i=1}^n i = \sum_{i=1}^{n-1} i + n = (n-1)n/2 + n = ((n-1)n + 2n)/2 = (n^2 - n + 2n)/2 = n(n+1)/2 \quad \text{true} \end{aligned}$$

Program verification

different approaches

McCarthy, Naur, Floyd, Hoare, Knuth, Dijkstra, etc.

“Backward proof”:

Structured approach, based on *predicate transformation*

Checking whether the *weakest preconditions* (*wp*) on the input data guarantee that the program terminates in a state that meets the desired program goal.

This program goal, which describes the task of the program, is called *the correctness condition, KB*

For this purpose, the program may only consist of simple assignments, comparisons, while-form loops and sequences of statements. All other constructs must be translated.

Verification - example

Example

Backward proof

```
int sum(int n) {  
    int s = 0;  
    int i = 1;  
    while(i <= n) {  
        s = s + i;  
        i = i + 1;  
    }  
    return s;  
}
```

Correctness condition KB s

$$= \ddot{\bar{y}}_j$$

(I) Loop invariant Sets

$$SI: s_i = \bar{y}_i f_{e(i)} \bar{y}_{i+1}$$

(1) *S / Bed KE*

```
s = s + i;  
i = i + 1;
```

}

return s;

}

(2) *SI Bed wp loop block S*

$$((\bar{w} \bar{p} s s i w p i - i = + - 1) (s = \bar{\bar{y}} -) (1))) ((j i n \bar{y} \bar{y} + \bar{y} = + w p s s i s = \bar{\bar{y}} j) \bar{y})$$

(II) Rest of the program

s (α | α[†]) wp s wp and SI wp

$$s = \sum_{j=1}^{11} j (\ddot{Y} \ddot{Y})^j$$

$$\ddot{y} = (0 \quad \ddot{\bar{y}}_j) (\ddot{y}_j \ddot{y}_{j+1} \dots \ddot{y}_{n-1})$$

1.3.3 Termination (1)

If the algorithm stops, that is, it has a finite Execution time?

If not clear, the following technique can sometimes be used:

Find the determining quantity or property of the Algorithm that satisfies the following 3 characteristics:

A 1-1 mapping of this size to the integers can be constructed become.

This quantity is positive.

The size increases continuously during the execution of the algorithm from (decremented).



Termination (2)

Idea:

At the start of the algorithm, the size found has a predetermined positive starting value that continuously decreases. Since the size can never become negative, it follows that the algorithm must terminate before the size is less than 0.

Example:

```
Size n
int sum(int n) {
    if(n <= 0) return 0;
    if(n == 1) return 1;
    else
        return n+sum(n-1);
}
```

Termination
before $n < 0$

Decrement

1.3.4 Runtime complexity

The *runtime complexity* provides information about this
Runtime behavior of algorithms depending on the
Problem size

Goal

Compare algorithms

Approach

Measuring the execution time of each instruction

Determine how often each statement is executed during program execution

becomes

Calculate total

Problem

Execution times depend on machine or system architecture, translation
quality of the compiler, etc.



Sum example: simple approach

```

int sum(int n) int s
  = 0; int i = 1;
  while(i <= n) { s = s +
    i; i = i + 1;}
  return s;
}
  
```

Time in msec

T1 ≈ 0.1

T2 ≈ 0.1

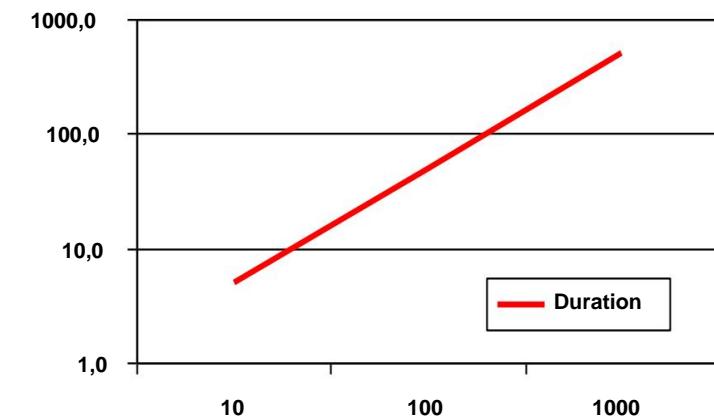
T3 ≈ 0.3

T4 ≈ 0.1

T5 ≈ 0.1

T6 ≈ 0.1

Measured times in
program



Calculation of the term

$$fsum(n) = T1 + T2 + n * (T3 + T4 + T5) + T3 + T6$$

$$fsum(10) = 0.1 + 0.1 + 10 * (0.3 + 0.1 + 0.1) + 0.3 + 0.1 = 5.6$$

$$fsum(100) = 0.1 + 0.1 + 100 * (0.3 + 0.1 + 0.1) + 0.3 + 0.1 = 50.6$$

$$fsum(1000) = 0.1 + 0.1 + 1000 * (0.3 + 0.1 + 0.1) + 0.3 + 0.1 = 500.6$$

$$fsum(n) = 0.6 + n * (0.5)$$

Problems of the simple approach

Corresponds to a “try it out” approach Only
possible in certain

 areas Specific problem size, data
 distribution Special cases
 problematic

 System-dependent Hardware, processor, ...

 Operating systems, compilers, libraries, ...

Load-
dependent question difficult to answer as to whether
“gradual” or “fundamental” improvement can be achieved

Order notation

Basic principle

The exact values of the execution times are uninteresting!

Using the *order notation*, one would like to make statements (see goal) that algorithm A is roughly the same speed as algorithm B.

By describing the running times of A and B using functions $f(n)$ and $g(n)$, this question is reduced to a comparison of these functions.

One considers the *asymptotic growth* of the execution times of the algorithms as the problem size n increases.

that is, when the problem size approaches infinity



Big - O / W / \tilde{O} - Notation

Big-O notation: A function $f(n)$ is said to be of order $O(g(n))$ if two constants $c_0 > 0$ and n_0 exist such that $f(n) \leq c_0 g(n)$ for all $n > n_0$.

provides an upper bound for the growth rate of functions $f \in O(g)$ if f grows at most as fast as g .

zB: $17n^2 \in O(n^2)$, $17n^2 \in O(2n)$

Big- Ω Notation: A function $f(n)$ is said to be of order $W(g(n))$ if there exist two constants $c_0 > 0$ and n_0 such that $f(n) \geq c_0 g(n)$ for all $n > n_0$.

provides a lower bound for the growth rate of functions $f \in \Omega(g)$ if f grows at least as fast as g .

zB: $17n^2 \in \Omega(n^2)$, $2n \in \Omega(n^{\frac{1}{2}})$, $n^{37} \in \Omega(n^2)$

\tilde{O} -Notation: The runtime behavior is $\tilde{O}(g(n))$ if the following applies: $f(n) \in O(g(n))$ and $f(n) \in W(g(n))$ (exactly describes the runtime behavior)

More notations

Little-o notation: A function $f(n)$ is called of order $o(g(n))$, if for every $c > 0$ there exists an n_0 such that $f(n) \ll cg(n)$ for all $n > n_0$.

f is asymptotically negligible compared to g .

Little \ddot{o} notation: A function $f(n)$ is said to be of order $\ddot{o}(g(n))$, if for every $c > 0$ there exists an n_0 such that $f(n) \ll cg(n)$ for all $n > n_0$.

f dominates g asymptotically

\ddot{o} -Notation: $f(n)g(n)$, if $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 1$

f and g are asymptotically equal.

Remarks

Instead of \ddot{y} , the use of $=$ is (unfortunately) also widespread,
e.g.: $f(x)=O(g(x))$. Avoid confusion!

The notations presented are often referred to as Landau notation,
Bachmann-Landau notation, or also as Landau symbols,
Bachmann-Landau symbols.

In mathematics the definitions are generally formulated somewhat more strictly. The absolute values of the functions $f(x)$ and $g(x)$ are considered. This is not necessary in our context because the functions used for runtime analysis always only return positive values.

There is also another ⁱⁿ definition for the symbol in mathematics (especially in number theory) that is incompatible with the one used here.

Sum example

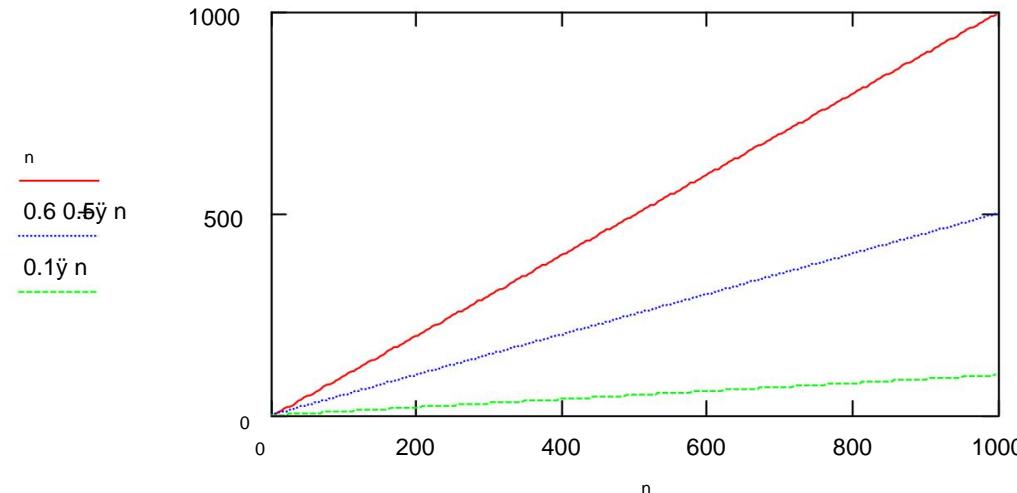
Note: $fsum(n) = T1 + T2 + n * (T3 + T4 + T5) + T3 + T6$ Message: $T1=0.1$,
 $T2=0.1$, $T3=0.3$, $T4=0.1$, $T5=0.1$, $T6=0.1$

gives $fsum(n) = 0.6 + n * (0.5)$

$g(n)=n$ Lower limit: $0.1 \cdot g(n)$ Upper limit: $h(n)=1 \cdot g(n)$

real values, in which
Implementation
measured

one of many
possible
Boundaries



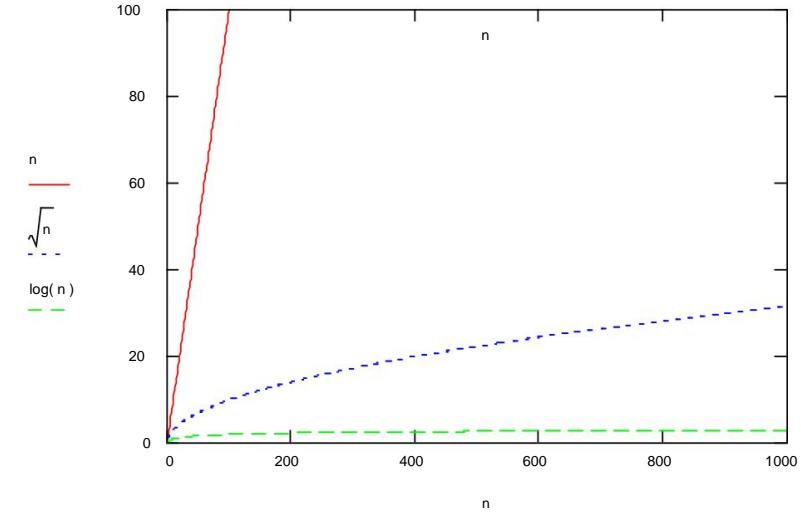
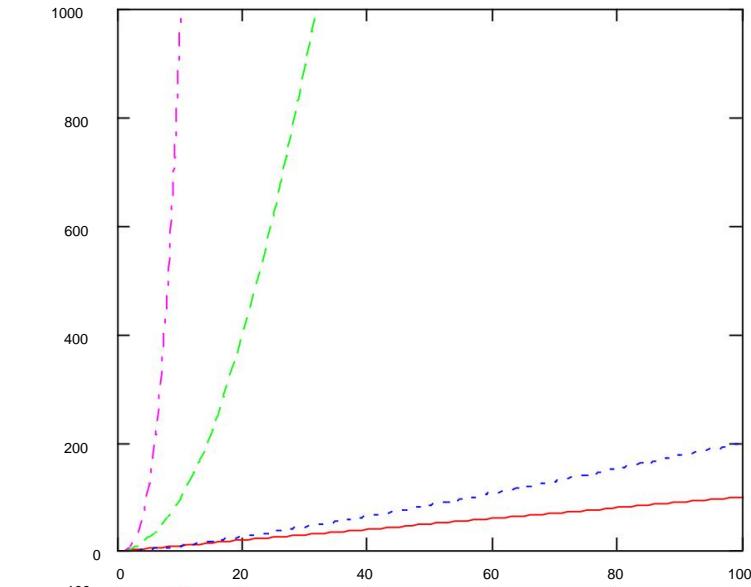
From this it follows regarding the order of the
algorithm $fsum(n) \in O(n)$ and further $fsum(n) \in W(n)$, ie $fsum(n) \in \tilde{\Theta}(n)$.

The statement that can be derived from this for our example is that the running time
of the algorithm is directly proportional to the problem size n

Runtime comparison (1)

Running time comparison
 assumption given
 problem size and
 various
 Runtime behavior

Order	Duration
$\log n$	1.2×10^{-5} sec
\sqrt{n}	3.2×10^{-4} sec
n	0.1 sec
$n \log n$	1.2 sec
$n \sqrt{n}$	6.5 sec
n^2	2.8 h
n^3	31.7 a
2^n	over 1 century



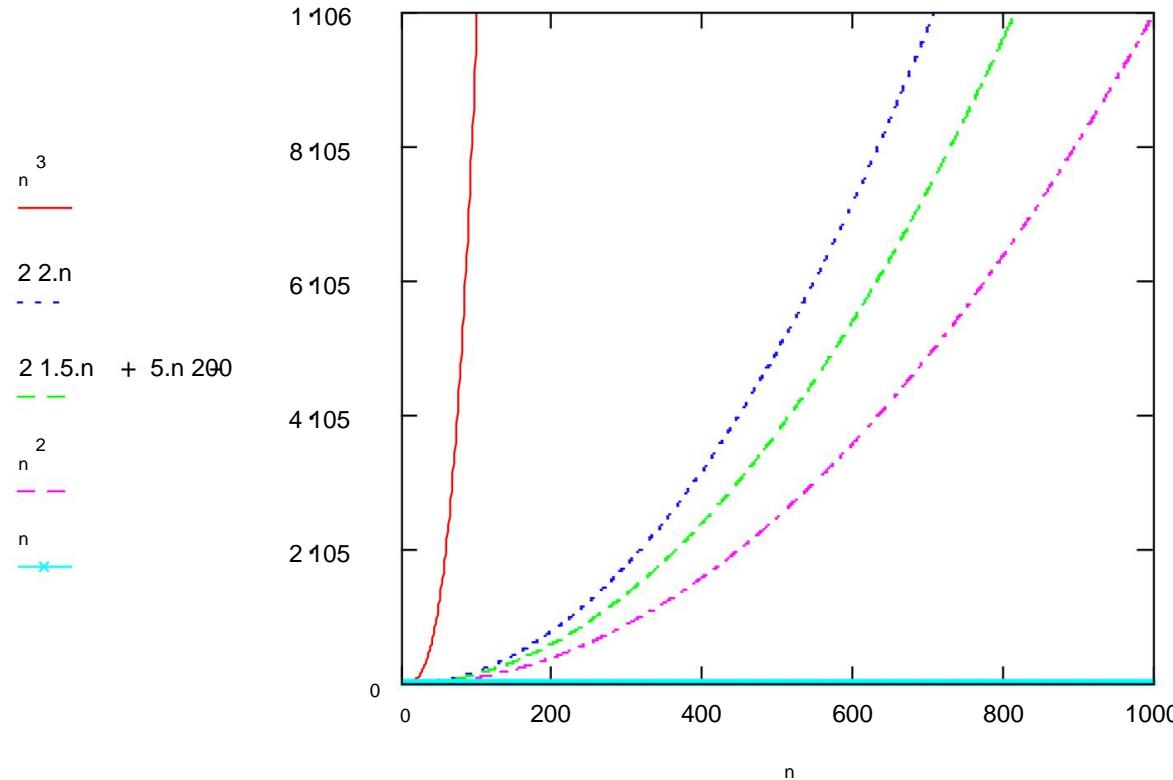


Runtime comparison (2)

Description of the runtime behavior

through upper $O(n)$ and lower bound $W(n)$

e.g.: $T(n) = 1.5n^2 + 5n - 200 \in O(n^2)$, since $n^2 \in T(n) \in 2n^2$



Analysis approach

Principles of mathematical analysis

Definition of the problem size n

Finding a suitable problem parameter that describes the problem size. This characterizes the load ($= f(n)$)

worst-case versus average-case

worst-case: behavior in the worst case, maximum expected Expense

average-case: typical behavior, expected value of the effort

Runtime analysis via $O(n)$ and $W(n)$

Ignore constant factors

Note only highest powers

often difficult to determine



Practical runtime analysis

Ignore constant factors Constant values are reduced to a factor of 1, ie

$$T(n) = 13 * n \in O(n)$$

$$T(n) = \log_2(n) \in O(\log(n)), \text{ da } \log_x(n) = \log_a(n) / \log_a(x)$$

Note only highest potency

Ignore all other powers except the highest

$$T(n) = n^2 - n + 1 \in O(n^2)$$

Therefore in combination:

$$T(n) = 13*n^2 + 47*n - 11*\log_2(n) + 50000 \in O(n^2)$$

Example: Runtime analysis 'Bubblesort'

```
void bubble(Element v[], int n) {
    int i, j; for(i = n-1; i >= 1; i--)
        for(j = 1; j <= i; j++) if(v[j-1] > v[j])
            swap(v[j-1], v[j]);
}
```

Problem size n

T1

T2

T3

T4

T5

Assumption

$T_1 = \dots T_5 = 1$

Informal approach:

$$T(n) = T_1 + (n-1)(T_2 + (n-1)(T_3 + T_4 + T_5))$$

Find equation

$$T(n) = 1 + (n-1)(1 + (n-1)(1+1+1)) = 3n^2 - 5n + 3$$

Ignore constant factors

$$T(n) = n^2 - n + 1$$

Note highest potency

$$T(n) = O(n^2) = W(n^2) = \tilde{O}(n^2)$$

worst-case =
best-case =
average case



Recurrences

Simple recursion

```
int sum(int n) { if(n <=
    0) return 0; if(n == 1) return
    1; return n + sum(n-1);
}
```

T₁
T₂
T_{3+T(n-1)}

Recurrence equation approach:

$$T(n) = T_1 + T_2 + T_3 + T(n-1)$$

$$T(n) = T(n-1) + 1 \quad T(0)=T(1)=1$$

$$T(n) = T(n-2) + 1 + 1$$

...

$$T(n) = \underbrace{1 + \dots + 1}_{n} + 1$$

$$T(n) = O(n)$$

Some important recurrences

$$T(n) = T(n-1) + n \quad \dots$$

$$T(n) = n^*(n+1)/2 = O(n^2)$$

$$T(n) = T(n/2) + 1 \quad \dots \quad T(n) = \log_2 n = O(\log n)$$

$$T(n) = T(n/2) + n \quad \dots \quad T(n) = 2^n = O(n)$$

$$T(n) = 2*T(n/2) + n \quad \dots$$

$$T(n) = n^*\log_2 n = O(n^*\log n)$$

$$T(n) = 2*T(n/2) + 1 \quad \dots \quad T(n) = 2^{n-1} = O(n)$$



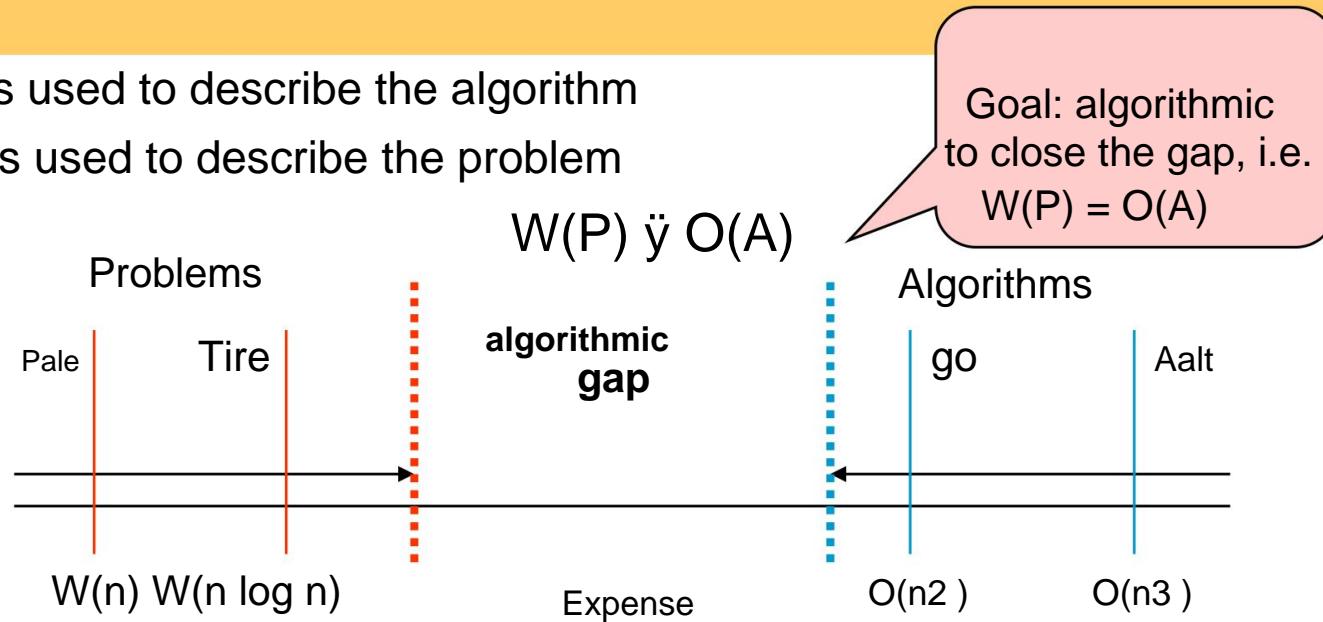
Algorithmic gap

An *algorithmic gap* for a problem exists if the effort required by the known problem-solving algorithms A is greater than the derivable effort required to solve the problem P.

$O(A)$ is used to describe the algorithm

$W(P)$ is used to describe the problem

Goal: algorithmic
to close the gap, i.e.
 $W(P) = O(A)$



Closed gap

Search in sorted sequence, $T(A) = O(\log(n)) = W(\log(n))$

Sort, $T(A) = O(n^2 \log(n)) = W(n^2 \log(n))$

Open gap

Graph isomorphism, $T(\text{Anaiv})$ from $O(|V|!)$

1.3.5 Runtime analysis of recursive programs

The runtime analysis of recursive programs is usually non-trivial

The runtime behavior of a recursive program can be described by a recurrence

Example: merge sort

$$T(n) = \begin{cases} 1 & \text{if } n = 1 \\ 2T(m) + 1 & \text{if } n > 1 \end{cases}$$

where the following solution was given

$$T(n) = \Theta(\log n)$$

Solutions

There are different approaches to solving the problem, such as:

Substitutionsmethode

Guessing an asymptotic limit and proving that limit by
Induction

Iterationsmethode

Converting the recurrence into a sum and applying
Techniques for calculating limit values of sums

Mastermethode

Provides bounds for recurrences of the form

$T(n) = aT(n/b) + f(n)$, where $a \geq 1$, $b > 1$ and $f(n)$ is a given function

Master Theorem

The *Master Theorem* provides a “recipe” for determining the runtime behavior

Simplified form (general version Cormen et al.)

Let $a \geq 1$, $b > 1$ and $c \geq 0$ be constants

If $T(n)$ is defined by $aT(n/b) + \Theta(nc)$, where
 n/b is either $\lceil n/b \rceil$ or $\lfloor n/b \rfloor$,

Then $T(n)$ has the following asymptotic limit

Case 1: if $c < \log_b a$ (ie $bc < a$) then $T(n) = \Theta(n \log_b a)$

Case 2: if $c = \log_b a$ (ie $bc = a$) then $T(n) = \Theta(n c \log n)$

Case 3: if $c > \log_b a$ (ie $bc > a$) then $T(n) = \Theta(n^c)$

Example

Binary searching

```

int bs (int x, int z[], int l, int r) {
    if (l > r) // threshold, no element present
        return -1; // 0 verboten, da gültiger Indexwert!
    else { int m = (l + r) / 2; //
        gefunden! if (x == z[m]) return
        z[m]) return bs(x, z,           m; else if (x <
        l, m-1); else //
        x > z[m] return bs(x, z,
        m+1, r);

    }
    }
  
```

Case 1: if $c < \log b/a$ then $T(n) = \tilde{O}(n \log b/a)$
 Case 2: if $c = \log b/a$ then $T(n) = \tilde{O}(n c \log n)$
 Case 3: if $c > \log b/a$ then $T(n) = \tilde{O}(n c)$

Running time: $T(n) = T(n/2) + 1 = T(n/2) + \tilde{O}(1)$ a = 1, b = 2, c = 0

Case 2, since $c = \log b/a = 0 = \log 2/1$, gives $T(n) = \tilde{O}(\log n)$



Further examples

Example: merge sort

$$\begin{aligned} T(n) &= 2T(n/2) + n = 2T(n/2) + \tilde{\mathcal{O}}(n) \text{ a} \\ &= 2, b = 2, c = 1 \end{aligned}$$

Case 1: if $c < \log ba$ then $T(n) = \tilde{\mathcal{O}}(n \log ba)$
 Case 2: if $c = \log ba$ then $T(n) = \tilde{\mathcal{O}}(nc \log n)$
 Case 3: if $c > \log ba$ then $T(n) = \tilde{\mathcal{O}}(nc)$

Case 2, since $c = \log ba \approx 1 = \log 2^2$, gives $T(n) = \tilde{\mathcal{O}}(n \log n)$

Example: $T(n) = 4T(n/2) + n = 4T(n/2) + \tilde{\mathcal{O}}(n)$

$$a = 4, b = 2, c = 1$$

Case 1, since $c < \log ba \approx 1 < \log 2^4$, gives $T(n) = \tilde{\mathcal{O}}(n \log 2^4) = \tilde{\mathcal{O}}(n^2)$

Example: $T(n) = T(n/2) + n = T(n/2) + \tilde{\mathcal{O}}(n) \text{ a}$
 $= 1, b = 2, c = 1$

Case 3, since $c > \log ba \approx 1 > \log 2^1$, gives $T(n) = \tilde{\mathcal{O}}(n^1) = \tilde{\mathcal{O}}(n)$

1.3.6 Structural complexity

Evaluative statement about the structural structure of the program and the program parts among themselves, ie

Evaluation of programming style

interne Attribute

Generally assumed that programming style with the expected

Software maintenance costs are correlated.

Statements about the quality of a software product (external Attribute)

Susceptibility to errors

Maintenance effort

Cost

Assumption:

internal attributes are correlated with
external attributes!

These

complex program → high costs
program → lower costs



„When you can measure what you are speaking about and express it in numbers you know something about it, but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meager and unsatisfactory kind.“

Lord Kelvin



Software metrics

The goal is to find metrics (measures) that determine the structure, structure,
Have the style of a *module* (program piece) evaluated and compared .

Requirements

validity

Actually measures what it claims to measure

simplicity

Results are easy to understand and interpret

sensitivity

Reacts adequately to different manifestations

robustness

Does not react to characteristics that are uninteresting in the context

Measuring structural complexity

The focus of the measurement is the software module. Definition difficult - can be a function, method, class, etc. The *intra-modular complexity* describes the complexity of a individual SW module

Complexity module (internal)

LOC, Line-of-codes (simpel)

NCSS, non commenting source statements

McCabe (cyclomatic complexity), ...

Cohesion (external)

Henry-Kafura metric (information flow), ...

Inter-modular complexity describes complexity between modules - *coupling*

Fenton and Melton,...

Connection coupling and cohesion



universität
wien

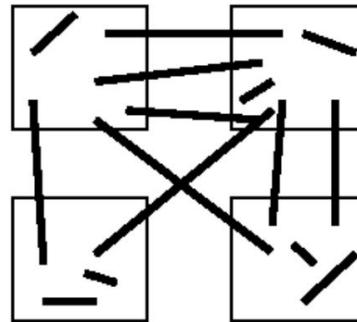
coupling

Measures complexity of relationships between modules

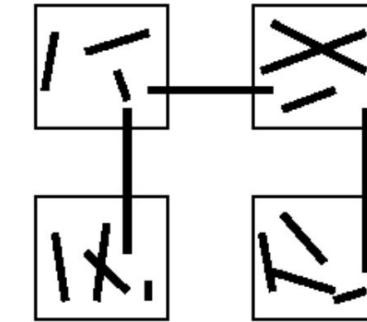
cohesion

Measures information flow to and from the outside depending on the
Module size

Mostly relationship between coupling and cohesion



Strong clutch
Weak cohesion



Weak clutch
Strong cohesion

(usually the goal of good software
Development)

1.3.6.1 Intra-modular complexity – McCabe's metric

McCabe's metric is a measure for assessing the module complexity

Based on *cyclomatic complexity* V = the number of independent paths in a program graph

With an independent path, at least one 'new' edge is taken in the program flowchart.

Experience values for cyclomatic complexity

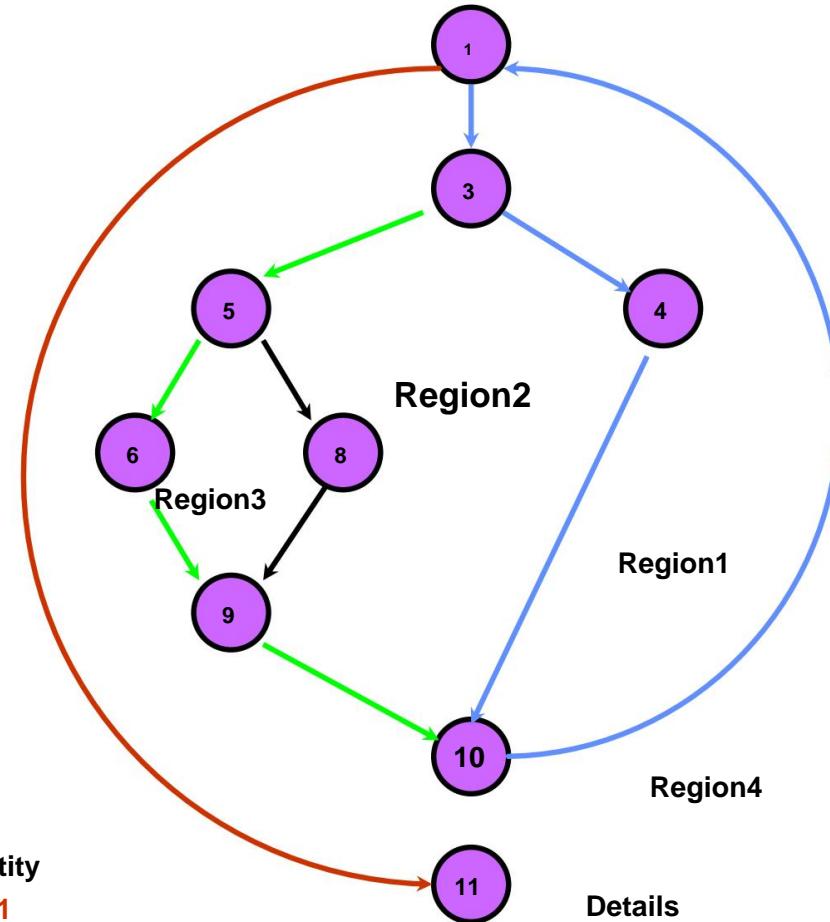
$V(G)$ assessment in normal cases	
< 5	simply
5-10	normal
> 10	complex, should be restructured
> 20	difficult to understand, probably incorrect

Program example

```

0: void foo (int a) {
1:     while (a < limit) {
2:         doit1();
3:         if(check1(a))
4:             doit2();
5:         else { if(check2(a))
6:             doit3();
7:             else
8:                 doit4();
9:         } // than else
10:    } // end while
11: } // end foo

```



Base quantity

Path 1: 1,11

Path 2: 1, 3,4,10,1,11

Path 3: 1,3,5,6,9,10,1,11

Path 4: 1,3,5,8,9,10,1,11

Details

Sides = 11

Node = 9

Condition node = 3

Cyclomatic complexity

Multiple calculation options

1. The number of regions in the program graph G
2. $V(G) = E - N + 2$ (E = number of edges, N = number of nodes)
3. $V(G) = P + 1$ (P = number of binary condition nodes)

Cyclomatic complexity of the example 1. Regions

$$= 4 \quad 2. \quad V(G) =$$

$$11 - 9 + 2 = 4 \quad 3. \quad V(G)$$

$= 3 + 1 = 4$ In our example the magic number is 4, i.e. “simple” program (Metric McCabe < 5)

1.3.6.2 Intra-modular complexity – Henry-Kafura Metric

Measure for determining cohesion

Describes the functional strength of the module; to what degree the
Module components perform the same task

The *Henry-Kafura Metric* (Sallie Henry and Dennis Kafura)
is based on the relationship between module complexity and
Connection complexity between modules

Measure of module complexity

PLACE

NCSS

McCabe

Connection complexity

Quantification of reading and modifying access
module to the environment

Counts the data flows between modules

FAN-IN_m: “Number of modules that use m”

more precisely: number of data flows that terminate in
module m + number of data structures from which
module m reads data

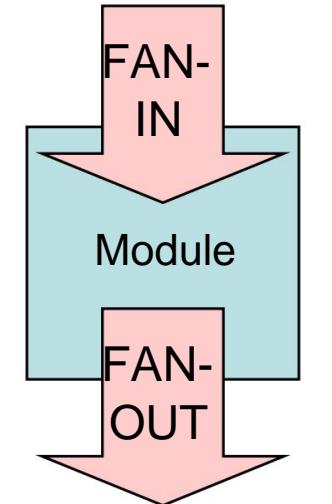
FAN-OUT_m: “Number of modules that m uses” more

precisely: number of data flows that originate from module m + number of data
structures that module m changes

Henry-Kafura Formula

$$C_{im} * (FAN-IN_m * FAN-OUT_m)^2$$

C_{im} ... module complexity (e.g. LOC, McCabe, ...)



Application

Applied to Unix code by Henry and Kafura

Assumption: connection between complexity and
 Frequency of changes (error correction) of a procedure

165 procedures investigated, patch information from newsgroups

Acceptance confirmed:

Take changes with you

Complexity class too

Weaknesses of HK:

Depends on the data flow

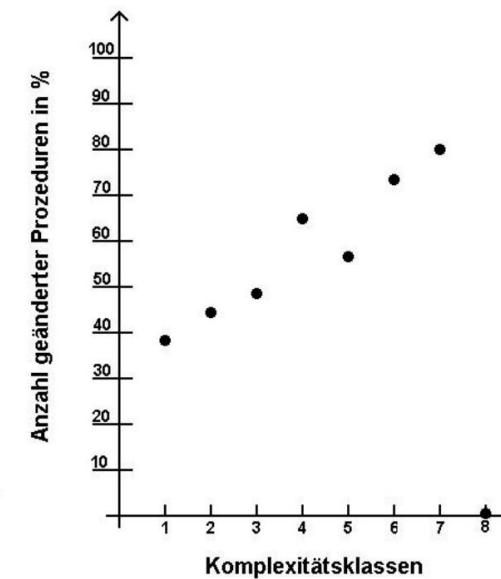
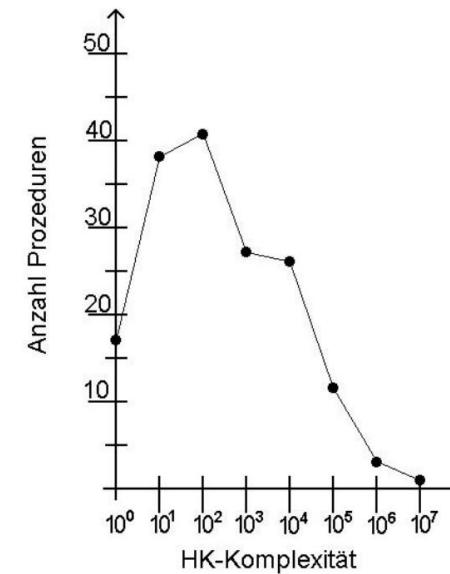
one FAN = 0, total 0

even at high

Module complexity

Reusability is “punished” by a high FAN

value



1.3.6.3 Inter-modular complexity – Fenton and Melton metric

Fenton and Melton metric is a measure for determining coupling, i.e. the independence between modules

Global coupling of a program is derived from the coupling values between all possible pairs of modules

Coupling types

Binary relations defined on pairs of modules x, y

Sorted according to the degree of “undesirability”.

0. No coupling: no communication between x and y
1. Data coupling: Communication via parameters (data)
2. Stamp coupling: accept the same record type as a parameter
3. Control coupling: Communication via parameters (control)
4. Common coupling: Access to the same global data structure
5. Content coupling: x directly accesses the internal structure of y (changes data, instructions)

Coupling calculation

Fenton dimension for the coupling between 2 modules

$$c(x,y) = i + n/(n+1)$$

i is the worst coupling type between module x and yn
is the number of “couplings” of type i

Measure $C(S)$ for the global coupling of a system S consisting of n modules D_1, \dots, D_n $C(S)$
 $= \text{median of the set of coupling values of all module pairs}$

What do we take with us?

Algorithmenparadigmen

Greedy, Divide and Conquer, Dynamic Programming

Analysis and evaluation of algorithms

Effectiveness, correctness, termination

Runtime complexity

Order notation, algorithmic gap, master theorem

Structural complexity

McCabe, Henry-Kafura, Fenton