Part I
Organizational Matters

▶ Modul: IN2003
▶ Name: “Efficient Algorithms and Data Structures”
  “Effiziente Algorithmen und Datenstrukturen”
▶ ECTS: 8 Credit points
▶ Lectures:
  ▶ 4 SWS
    Mon 10:00–12:00 (Room Interim2)
    Fri 10:00–12:00 (Room Interim2)
▶ Webpage: http://www14.in.tum.de/lehre/2016WS/ea/

▶ Required knowledge:
  ▶ IN0001, IN0003
    “Introduction to Informatics 1/2”
    “Einführung in die Informatik 1/2”
  ▶ IN0007
    “Fundamentals of Algorithms and Data Structures”
    “Grundlagen: Algorithmen und Datenstrukturen” (GAD)
  ▶ IN0011
    “Basic Theoretic Informatics”
    “Einführung in die Theoretische Informatik” (THEO)
  ▶ IN0015
    “Discrete Structures”
    “Diskrete Strukturen” (DS)
  ▶ IN0018
    “Discrete Probability Theory”
    “Diskrete Wahrscheinlichkeitstheorie” (DWT)
The Lecturer

- Harald Räcke
- Email: raecke@in.tum.de
- Room: 03.09.044
- Office hours: (by appointment)

Tutorials

- **A01** Monday, 12:00–14:00, 00.08.038 (Stotz)
- **A02** Monday, 12:00–14:00, 00.09.038 (Kohler)
- **A03** Monday, 14:00–16:00, 03.10.011 (Sperr)
- **B04** Tuesday, 12:00–14:00, 03.11.018 (Kohler)
- **B05** Tuesday, 14:00–16:00, 00.08.038 (Matl)
- **B06** Tuesday, 16:00–18:00, 00.08.036 (Sperr)
- **C07** Wednesday, 10:00–12:00, 01.13.010 (Stotz)
- **D08** Thursday, 10:00–12:00, 00.08.038 (Kraft)
- **E09** Friday, 12:00–14:00, 00.13.009 (Kraft)
- **E10** Friday, 14:00–16:00, 00.08.036 (Matl)

Assignment sheets

In order to pass the module you need to pass an exam.

Assessment

Assignment Sheets:

- An assignment sheet is usually made available on Monday on the module webpage.
- Solutions have to be handed in in the following week before the lecture on Monday.
- You can hand in your solutions by putting them in the mailbox "Efficient Algorithms" on the basement floor in the MI-building.
- Solutions have to be given in English.
- Solutions will be discussed in the tutorial of the week when the sheet has been handed in, i.e, sheet may not be corrected by this time.
- You can submit solutions in groups of up to 2 people.
### Assessment

**Assignment Sheets:**
- Submissions must be handwritten by a member of the group. Please indicate who wrote the submission.
- Don’t forget name and student id number for each group member.

### Assessment

Assignment can be used to improve you grade

- If you obtain a bonus your grade will improve according to the following function

\[
f(x) = \begin{cases} 
\frac{1}{10} \text{round} \left( 10 \left( \text{round} \left( \frac{3x}{3} \right) - 1 \right) \right) & 1 < x \leq 4 \\
\text{otw.} & 
\end{cases}
\]

- It will improve by 0.3 or 0.4, respectively.

Examples:
- 3.3 → 3.0
- 2.0 → 1.7
- 3.7 → 3.3
- 1.0 → 1.0
- > 4.0 no improvement

### Requirements for Bonus

- 50% of the points are achieved on submissions 1–7,
- 50% of the points are achieved on submissions 8–13,
- each group member has written at least 4 solutions.

### 1 Contents

- Foundations
  - Machine models
  - Efficiency measures
  - Asymptotic notation
  - Recursion
- Higher Data Structures
  - Search trees
  - Hashing
  - Priority queues
  - Union/Find data structures
- Cuts/Flows
- Matchings
2 Literatur

Alfred V. Aho, John E. Hopcroft, Jeffrey D. Ullman: *The design and analysis of computer algorithms*, Addison-Wesley Publishing Company: Reading (MA), 1974


Jon Kleinberg, Eva Tardos: *Algorithm Design*, Addison-Wesley, 2005


Uwe Schöning: *Algorithmik*, Spektrum Akademischer Verlag, 2001


Part II

Foundations
Vocabularies

- $a \cdot b$ “$a$ times $b$”
  - “$a$ multiplied by $b$”
  - “$a$ into $b$”
- $\frac{a}{b}$ “$a$ divided by $b$”
  - “$a$ by $b$”
  - “$a$ over $b$”
  (a: numerator (Zähler), b: denominator (Nenner))
- $a^b$ “$a$ raised to the $b$-th power”
  - “$a$ to the $b$-th”
  - “$a$ raised to the power of $b$”
  - “$a$ to the power of $b$”
  - “$a$ raised by the exponent of $b$”


Vocabularies

- $n!$ “$n$ factorial”
- $\binom{n}{k}$ “$n$ choose $k$”
- $x_i$ “$x$ subscript $i$”
  - “$x$ sub $i$”
  - “$x \ i$”
- $\log_b a$ “log to the base $b$ of $a$”
  - “log $a$ to the base $b$”

$f : X \rightarrow Y, x \rightarrow x^2$

$f$ is a function that maps from domain (Definitionsbereich) $X$ to codomain (Zielmenge) $Y$. The set $\{y \in Y \mid \exists x \in X : f(x) = y\}$ is the image or the range of the function (Bildbereich/Wertebereich).

3 Goals

- Gain knowledge about efficient algorithms for important problems, i.e., learn how to solve certain types of problems efficiently.
- Learn how to analyze and judge the efficiency of algorithms.
- Learn how to design efficient algorithms.

4 Modelling Issues

What do you measure?

- Memory requirement
- Running time
- Number of comparisons
- Number of multiplications
- Number of hard-disc accesses
- Program size
- Power consumption
- . . .
4 Modelling Issues

How do you measure?

- Implementing and testing on representative inputs
  - How do you choose your inputs?
  - May be very time-consuming.
  - Very reliable results if done correctly.
  - Results only hold for a specific machine and for a specific set of inputs.

- Theoretical analysis in a specific model of computation.
  - Gives asymptotic bounds like “this algorithm always runs in time $O(n^2)$”.
  - Typically focuses on the worst case.
  - Can give lower bounds like “any comparison-based sorting algorithm needs at least $\Omega(n \log n)$ comparisons in the worst case”.

Input length

The theoretical bounds are usually given by a function $f : \mathbb{N} \to \mathbb{N}$ that maps the input length to the running time (or storage space, comparisons, multiplications, program size etc.).

The input length may e.g.

- the size of the input (number of bits)
- the number of arguments

Example 1

Suppose $n$ numbers from the interval $\{1, \ldots, N\}$ have to be sorted. In this case we usually say that the input length is $n$ instead of e.g. $n \log N$, which would be the number of bits required to encode the input.

Model of Computation

How to measure performance

1. Calculate running time and storage space etc. on a simplified, idealized model of computation, e.g. Random Access Machine (RAM), Turing Machine (TM), . . .

2. Calculate number of certain basic operations: comparisons, multiplications, harddisc accesses, . . .

Version 2. is often easier, but focusing on one type of operation makes it more difficult to obtain meaningful results.

Turing Machine

- Very simple model of computation.
- Only the “current” memory location can be altered.
- Very good model for discussing computability, or polynomial vs. exponential time.
- Some simple problems like recognizing whether input is of the form $xx$, where $x$ is a string, have quadratic lower bound.

⇒ Not a good model for developing efficient algorithms.
Random Access Machine (RAM)

- Input tape and output tape (sequences of zeros and ones; unbounded length).
- Memory unit: infinite but countable number of registers \( R[0], R[1], R[2], \ldots \)
- Registers hold integers.
- Indirect addressing.

Note that in the picture on the right the tapes are one-directional, and that a READ- or WRITE-operation always advances its tape.

Operations

- input operations (input tape \( \rightarrow \) \( R[i] \))
  - \( \text{READ} \ i \)
- output operations (\( R[i] \) \( \rightarrow \) output tape)
  - \( \text{WRITE} \ i \)
- register-register transfers
  - \( R[j] := R[i] \)
  - \( R[j] := 4 \)
- indirect addressing
  - \( R[j] := R[R[i]] \)
    loads the content of the \( R[i] \)-th register into the \( j \)-th register
  - \( R[R[i]] := R[j] \)
    loads the content of the \( j \)-th into the \( R[i] \)-th register

branching (including loops) based on comparisons

- \( \text{jump} \ x \)
  jumps to position \( x \) in the program;
  sets instruction counter to \( x \);
  reads the next operation to perform from register \( R[x] \)
- \( \text{jumpz} \ x R[i] \)
  jump to \( x \) if \( R[i] = 0 \)
  if not the instruction counter is increased by 1;
- \( \text{jumpi} \ i \)
  jump to \( R[i] \) (indirect jump);
- arithmetic instructions: \( +, - , \times, / \)
  - \( R[i] := R[j] + R[k] \)
  - \( R[i] := -R[k] \)

The jump-directives are very close to the jump-instructions contained in the assembler language of real machines.

Model of Computation

- uniform cost model
  Every operation takes time 1.
- logarithmic cost model
  The cost depends on the content of memory cells:
  - The time for a step is equal to the largest operand involved;
  - The storage space of a register is equal to the length (in bits) of the largest value ever stored in it.

Bounded word RAM model: cost is uniform but the largest value stored in a register may not exceed \( 2^w \), where usually \( w = \log_2 n \).

The latter model is quite realistic as the word-size of a standard computer that handles a problem of size \( n \) must be at least \( \log_2 n \) as otherwise the computer could either not store the problem instance or not address all its memory.
There are different types of complexity bounds:
- **amortized** complexity:
  The average cost of data structure operations over a worst case sequence of operations.
- **randomized** complexity:
  The algorithm may use random bits. Expected running time (over all possible choices of random bits) for a fixed input $x$. Then take the worst-case over all $x$ with $|x| = n$. 

There are different types of complexity bounds:
- **best-case complexity**:
  
  \[
  C_{bc}(n) := \min\{C(x) \mid |x| = n\}
  \]

  Usually easy to analyze, but not very meaningful.
- **worst-case complexity**:
  
  \[
  C_{wc}(n) := \max\{C(x) \mid |x| = n\}
  \]

  Usually moderately easy to analyze; sometimes too pessimistic.
- **average case complexity**:
  
  \[
  C_{avg}(n) := \frac{1}{|I_n|} \sum_{|x| = n} C(x)
  \]

  more general: probability measure $\mu$
  
  \[
  C_{avg}(n) := \sum_{x \in I_n} \mu(x) \cdot C(x)
  \]

**Bibliography**


Chapter 2.1 and 2.2 of [MS08] and Chapter 2 of [CLRS90] are relevant for this section.

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### Algorithm 1: RepeatedSquaring($n$)

1. $r \leftarrow 2$
2. for $i = 1 \rightarrow n$
3. $r \leftarrow r^2$
4. return $r$

- running time:
  - uniform model: $n$ steps
  - logarithmic model: $1 + 2 + 4 + \cdots + 2^n = 2^{n+1} - 1 = \Theta(2^n)$
- space requirement:
  - uniform model: $\Theta(1)$
  - logarithmic model: $\Theta(2^n)$
5 Asymptotic Notation

We are usually not interested in exact running times, but only in an asymptotic classification of the running time, that ignores constant factors and constant additive offsets.

- We are usually interested in the running times for large values of $n$. Then constant additive terms do not play an important role.
- An exact analysis (e.g. exactly counting the number of operations in a RAM) may be hard, but wouldn’t lead to more precise results as the computational model is already quite a distance from reality.
- A linear speed-up (i.e., by a constant factor) is always possible by e.g. implementing the algorithm on a faster machine.
- Running time should be expressed by simple functions.

Asymptotic Notation

There is an equivalent definition using limes notation (assuming that the respective limes exists). $f$ and $g$ are functions from $\mathbb{N}_0$ to $\mathbb{R}_0^+$.

- $g \in \mathcal{O}(f)$: $0 \leq \lim_{n \to \infty} \frac{g(n)}{f(n)} < \infty$
- $g \in \Omega(f)$: $0 < \lim_{n \to \infty} \frac{g(n)}{f(n)} \leq \infty$
- $g \in \Theta(f)$: $0 < \lim_{n \to \infty} \frac{g(n)}{f(n)} < \infty$
- $g \in o(f)$: $\lim_{n \to \infty} \frac{g(n)}{f(n)} = 0$
- $g \in \omega(f)$: $\lim_{n \to \infty} \frac{g(n)}{f(n)} = \infty$

Asymptotic Notation

Abuse of notation

1. People write $f = \mathcal{O}(g)$, when they mean $f \in \mathcal{O}(g)$. This is not an equality (how could a function be equal to a set of functions).
2. People write $f(n) = \mathcal{O}(g(n))$, when they mean $f \in \mathcal{O}(g)$, with $f : \mathbb{N} \to \mathbb{R}^+, n \mapsto f(n)$, and $g : \mathbb{N} \to \mathbb{R}^+, n \mapsto g(n)$.
3. People write e.g. $h(n) = f(n) + o(g(n))$ when they mean that there exists a function $z : \mathbb{N} \to \mathbb{R}^+, n \mapsto z(n), z \in o(g)$ such that $h(n) = f(n) + z(n)$.

- Note that for the version of the Landau notation defined here, we assume that $f$ and $g$ are positive functions.
- There also exist versions for arbitrary functions, and for the case that the limes is not infinity.

Formal Definition

Let $f$ denote functions from $\mathbb{N}$ to $\mathbb{R}^+$.

- $\mathcal{O}(f) = \{g \mid \exists c > 0 \ \exists n_0 \in \mathbb{N}_0 \ \forall n \geq n_0 : [g(n) \leq c \cdot f(n)]\}$ (set of functions that asymptotically grow not faster than $f$)
- $\Omega(f) = \{g \mid \exists c > 0 \ \exists n_0 \in \mathbb{N}_0 \ \forall n \geq n_0 : [g(n) \geq c \cdot f(n)]\}$ (set of functions that asymptotically grow not slower than $f$)
- $\Theta(f) = \Omega(f) \cap \mathcal{O}(f)$ (functions that asymptotically have the same growth as $f$)
- $o(f) = \{g \mid \forall c > 0 \ \exists n_0 \in \mathbb{N}_0 \ \forall n \geq n_0 : [g(n) \leq c \cdot f(n)]\}$ (set of functions that asymptotically grow slower than $f$)
- $\omega(f) = \{g \mid \forall c > 0 \ \exists n_0 \in \mathbb{N}_0 \ \forall n \geq n_0 : [g(n) \geq c \cdot f(n)]\}$ (set of functions that asymptotically grow faster than $f$)
Abuse of notation

4. People write $O(f(n)) = O(g(n))$, when they mean $O(f(n)) \subseteq O(g(n))$. Again this is not an equality.

Asymptotic Notation in Equations

How do we interpret an expression like:

$$2n^2 + 3n + 1 = 2n^2 + \Theta(n)$$

Here, $\Theta(n)$ stands for an anonymous function in the set $\Theta(n)$ that makes the expression true.

Note that $\Theta(n)$ is on the right hand side, otw. this interpretation is wrong.

Asymptotic Notation in Equations

How do we interpret an expression like:

$$2n^2 + O(n) = \Theta(n^2)$$

Regardless of how we choose the anonymous function $f(n) \in O(n)$ there is an anonymous function $g(n) \in \Theta(n^2)$ that makes the expression true.

Asymptotic Notation in Equations

How do we interpret an expression like:

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

Careful!

“It is understood” that every occurrence of an $O$-symbol (or $\Theta, \Omega, o, \omega$) on the left represents one anonymous function.

Hence, the left side is not equal to

$$\Theta(1) + \Theta(2) + \cdots + \Theta(n-1) + \Theta(n)$$

$\Theta(1) + \Theta(2) + \cdots + \Theta(n-1) + \Theta(n)$ does not really have a reasonable interpretation.
**Asymptotic Notation in Equations**

We can view an expression containing asymptotic notation as generating a set:

\[ n^2 \cdot \Theta(n) + \Theta(\log n) \]

represents

\[ \{ f : \mathbb{N} \to \mathbb{R}^+ \mid f(n) = n^2 \cdot g(n) + h(n) \} \]

with \( g(n) \in \Theta(n) \) and \( h(n) \in \Theta(\log n) \)

Recall that according to the previous slide e.g. the expressions

\[ \sum_{i=1}^{n} \Theta(i) \quad \text{and} \quad \sum_{i=1}^{n/2} \Theta(i) + \sum_{i=n/2+1}^{n} \Theta(i) \]

generate different sets.

Asymptotic Notation

***Lemma 3***

Let \( f, g \) be functions with the property \( \exists n_0 > 0 \forall n \geq n_0 : f(n) > 0 \) (the same for \( g \)). Then

- \( c \cdot f(n) \in \Theta(f(n)) \) for any constant \( c \)
- \( \Theta(f(n)) + \Theta(g(n)) = \Theta(f(n) + g(n)) \)
- \( \Theta(f(n)) \cdot \Theta(g(n)) = \Theta(f(n) \cdot g(n)) \)
- \( \Theta(f(n)) + \Theta(g(n)) = \Theta(\max\{f(n), g(n)\}) \)

The expressions also hold for \( \Omega \). Note that this means that \( f(n) + g(n) \in \Theta(\max\{f(n), g(n)\}) \).

**Asymptotic Notation in Equations**

Then an asymptotic equation can be interpreted as containment btw. two sets:

\[ n^2 \cdot \Theta(n) + \Theta(\log n) = \Theta(n^2) \]

represents

\[ n^2 \cdot \Theta(n) + \Theta(\log n) \subseteq \Theta(n^2) \]

Note that the equation does not hold.

Asymptotic Notation

**Comments**

- Do not use asymptotic notation within induction proofs.
- For any constants \( a, b \) we have \( \log_a n = \Theta(\log_b n) \). Therefore, we will usually ignore the base of a logarithm within asymptotic notation.
- In general \( \log n = \log_2 n \), i.e., we use 2 as the default base for the logarithm.
Asymptotic Notation

In general asymptotic classification of running times is a good measure for comparing algorithms:

- If the running time analysis is tight and actually occurs in practice (i.e., the asymptotic bound is not a purely theoretical worst-case bound), then the algorithm that has better asymptotic running time will always outperform a weaker algorithm for large enough values of \( n \).

- However, suppose that I have two algorithms:
  - Algorithm A. Running time \( f(n) = 1000 \log n = O(\log n) \).
  - Algorithm B. Running time \( g(n) = \log^2 n \).

Clearly \( f = o(g) \). However, as long as \( \log n \leq 1000 \) Algorithm B will be more efficient.

6 Recurrences

Algorithm 2 mergesort(list \( L \))

1: \( n \leftarrow \text{size}(L) \)
2: if \( n \leq 1 \) return \( L \)
3: \( L_1 \leftarrow L[1 \cdot \cdot \cdot \left\lfloor n/2 \right\rfloor] \)
4: \( L_2 \leftarrow L[\left\lfloor n/2 \right\rfloor + 1 \cdot \cdot \cdot n] \)
5: mergesort(\( L_1 \))
6: mergesort(\( L_2 \))
7: \( L \leftarrow \text{merge}(L_1, L_2) \)
8: return \( L \)

This algorithm requires

\[
T(n) = T\left(\left\lfloor n/2 \right\rfloor \right) + T\left(\left\lceil n/2 \right\rceil \right) + O(n) \leq 2T\left(\left\lfloor n/2 \right\rfloor \right) + O(n)
\]

comparisons when \( n > 1 \) and 0 comparisons when \( n \leq 1 \).
Methods for Solving Recurrences

1. **Guessing+Induction**
   Guess the right solution and prove that it is correct via induction. It needs experience to make the right guess.

2. **Master Theorem**
   For a lot of recurrences that appear in the analysis of algorithms this theorem can be used to obtain tight asymptotic bounds. It does not provide exact solutions.

3. **Characteristic Polynomial**
   Linear homogenous recurrences can be solved via this method.

4. **Generating Functions**
   A more general technique that allows to solve certain types of linear inhomogenous relations and also sometimes non-linear recurrence relations.

5. **Transformation of the Recurrence**
   Sometimes one can transform the given recurrence relations so that it e.g. becomes linear and can therefore be solved with one of the other techniques.

6.1 Guessing+Induction

First we need to get rid of the $\Theta$-notation in our recurrence:

$$T(n) \leq \begin{cases} 2T\left(\left\lfloor \frac{n}{2} \right\rfloor \right) + cn & n \geq 2 \\ 0 & \text{otherwise} \end{cases}$$

Assume that instead we had

$$T(n) \leq \begin{cases} 2T\left(\frac{n}{2} \right) + cn & n \geq 2 \\ 0 & \text{otherwise} \end{cases}$$

One way of solving such a recurrence is to **guess** a solution, and check that it is correct by plugging it in.

Suppose we guess $T(n) \leq dn \log n$ for a constant $d$. Then

$$T(n) \leq 2T\left(\frac{n}{2} \right) + cn$$
$$\leq 2\left(d \frac{n}{2} \log \frac{n}{2} \right) + cn$$
$$= d\left(n \log n - 1 \right) + cn$$
$$= d\left(n \log n + (c - d)n \right)$$
$$\leq dn \log n$$

if we choose $d \geq c$.

Formally one would make an induction proof, where the above is the induction step. The base case is usually trivial.
### 6.1 Guessing+Induction

**Guess:** \( T(n) \leq dn \log n \).

**Proof.** (by induction)

- **base case** \((2 \leq n < 16)\): true if we choose \( d \geq b \).
- **induction step** \( 2 \ldots n - 1 \rightarrow n \):

  Suppose statem. is true for \( n' \in \{2, \ldots, n-1\} \), and \( n \geq 16 \).

  We prove it for \( n \):

  \[
  T(n) \leq 2T\left(\frac{n}{2}\right) + cn
  \leq 2(d \frac{n}{2} \log \frac{n}{2}) + cn
  = d(n \log n - 1) + cn
  = d(n \log n) + (c - d)n
  \leq d n \log n
  
  \]

  Hence, statement is true if we choose \( d \geq c \).

---

### 6.2 Master Theorem

**Lemma 4**

Let \( a \geq 1, b \geq 1 \) and \( \epsilon > 0 \) denote constants. Consider the recurrence

\[
T(n) = aT\left(\frac{n}{b}\right) + f(n) .
\]

**Case 1.**

If \( f(n) = \Theta(n^{\log_b a - \epsilon}) \) then \( T(n) = \Theta(n^{\log_b a}) \).

**Case 2.**

If \( f(n) = \Theta(n^{\log_b a} \log^k n) \) then \( T(n) = \Theta(n^{\log_b a} \log^{k+1} n) \), \( k \geq 0 \).

**Case 3.**

If \( f(n) = \Omega(n^{\log_b a + \epsilon}) \) and for sufficiently large \( n \\)

\[ af\left(\frac{n}{b}\right) \leq cf(n) \text{ for some constant } c < 1 \text{ then } T(n) = \Theta(f(n)) .
\]
6.2 Master Theorem

We prove the Master Theorem for the case that \( n \) is of the form \( b^\ell \), and we assume that the non-recursive case occurs for problem size \( 1 \) and incurs cost \( 1 \).

The Recursion Tree

The running time of a recursive algorithm can be visualized by a recursion tree:

Case 1. Now suppose that \( f(n) \leq cn^{\log_b a - \epsilon} \).

This gives

\[
T(n) = n^{\log_b a} + \sum_{i=0}^{\log_b n - 1} a^i f\left( \frac{n}{b^i} \right).
\]

Hence,

\[
T(n) \leq \left( \frac{c}{b^\epsilon - 1} + 1 \right) n^{\log_b a} \Rightarrow T(n) = \mathcal{O}(n^{\log_b a}).
\]
Case 2. Now suppose that \( f(n) \leq cn^{\log_b a} \).

\[
T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right)
\]

\[
\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a}
\]

\[
= c n^{\log_b a} \sum_{i=0}^{\log_b n - 1} \left(\log_b\left(\frac{n}{b^i}\right)\right)^k
\]

\[
\approx \frac{c}{k} n^{\log_b a} \cdot \sum_{i=0}^{k} i k \cdot \approx \frac{1}{k} \cdot \sum_{i=0}^{k} i k
\]

Hence, \( T(n) = \Theta(n^{\log_b a} \log_b n) \) \( \Rightarrow T(n) = \Theta(n^{\log_b a} \log n) \).

Case 2. Now suppose that \( f(n) \geq cn^{\log_b a} \).

\[
T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right)
\]

\[
\geq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a}
\]

\[
= c n^{\log_b a} \sum_{i=0}^{\log_b n - 1} 1
\]

\[
= c n^{\log_b a} \cdot \log_b n
\]

Hence, \( T(n) = \Omega(n^{\log_b a} \log_b n) \) \( \Rightarrow T(n) = \Omega(n^{\log_b a} \log n) \).

Case 3. Now suppose that \( f(n) \geq dn^{\log_b a + \epsilon} \), and that for sufficiently large \( n \): \( af(n/b) \leq cf(n) \), for \( c < 1 \).

From this we get \( a f(n/b^i) \leq c f(n) \), where we assume that \( n/b^{i-1} \geq n_0 \) is still sufficiently large.

\[
T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right)
\]

\[
\leq \sum_{i=0}^{\log_b n - 1} c f(n) + \Theta(n^{\log_b a})
\]

\[
\leq \frac{1}{c} f(n) + \Theta(n^{\log_b a})
\]

Hence, \( T(n) \leq \Theta(f(n)) \) \( \Rightarrow T(n) = \Theta(f(n)) \).

Where did we use \( f(n) \geq \Omega(n^{\log_b a + \epsilon}) \)?
Example: Multiplying Two Integers

Suppose we want to multiply two \( n \)-bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers \( A \) and \( B \):

\[
\begin{array}{c}
11011010101 A \\
1000100111 B \\
10110010000
\end{array}
\]

This gives that two \( n \)-bit integers can be added in time \( O(n) \).

Example: Multiplying Two Integers

Suppose that we want to multiply an \( n \)-bit integer \( A \) and an \( m \)-bit integer \( B \) \((m \leq n)\).

\[
\begin{array}{c}
10001 \times 1011 \\
10001 \\
010001 \\
0000000 \\
00010001 \\
11011101
\end{array}
\]

This is also known as the "school method" for multiplying integers.

- Note that the intermediate numbers that are generated can have at most \( m + n \leq 2n \) bits.

Time requirement:

- Computing intermediate results: \( O(nm) \).
- Adding \( m \) numbers of length \( \leq 2n \):
  \[ O((m + n)m) = O(nm) \].

Algorithm 3 \texttt{mult}(A,B)

1: if \(|A| = |B| = 1\) then
2: \hspace{1cm} return \( a_0 \cdot b_0 \)
3: split \( A \) into \( A_0 \) and \( A_1 \)
4: split \( B \) into \( B_0 \) and \( B_1 \)
5: \( Z_2 \leftarrow \text{mult}(A_1, B_1) \)
6: \( Z_1 \leftarrow \text{mult}(A_1, B_0) + \text{mult}(A_0, B_1) \)
7: \( Z_0 \leftarrow \text{mult}(A_0, B_0) \)
8: return \( Z_2 \cdot 2^n + Z_1 \cdot 2^\frac{n}{2} + Z_0 \)

We get the following recurrence:

\[ T(n) = 4T\left(\frac{n}{2}\right) + O(n) \]
Example: Multiplying Two Integers

We get the following recurrence:

\[ T[n] = a T\left(\frac{n}{b}\right) + f(n). \]

- **Case 1:** \( f(n) = \Theta(n^{\log_b a - \epsilon}) \) \( T(n) = \Theta(n^{\log_b a}) \)
- **Case 2:** \( f(n) = \Theta(n^{\log_b a \log k n}) \) \( T(n) = \Theta(n^{\log_b a \log k + 1} n) \)
- **Case 3:** \( f(n) = \Omega(n^{\log_b a + \epsilon}) \) \( T(n) = \Theta(f(n)) \)

In our case \( a = 4, b = 2 \), and \( f(n) = \Theta(n) \). Hence, we are in Case 1, since \( n = \Theta(n^{2 - \epsilon}) = \Theta(n^{\log_b a - \epsilon}). \)

We get a running time of \( \Theta(n^2) \) for our algorithm.

⇒ Not better then the “school method”.

---

Example: Multiplying Two Integers

Consider the recurrence relation:

\[ c_0 T(n) + c_1 T(n-1) + c_2 T(n-2) + \cdots + c_k T(n-k) = f(n) \]

This is the general form of a linear recurrence relation of order \( k \) with constant coefficients \( (c_0, c_k \neq 0) \).

- \( T(n) \) only depends on the \( k \) preceding values. This means the recurrence relation is of order \( k \).
- The recurrence is linear as there are no products of \( T[n] \)’s.
- If \( f(n) = 0 \) then the recurrence relation becomes a linear, homogenous recurrence relation of order \( k \).

Note that we ignore boundary conditions for the moment.

---

Algorithm 4 \( \text{mult}(A,B) \)

1: if \( |A| = |B| = 1 \) then
2: return \( a_0 \cdot b_0 \)
3: split \( A \) into \( A_0 \) and \( A_1 \)
4: split \( B \) into \( B_0 \) and \( B_1 \)
5: \( Z_2 \leftarrow \text{mult}(A_1, B_1) \)
6: \( Z_0 \leftarrow \text{mult}(A_0, B_0) \)
7: \( Z_1 \leftarrow \text{mult}(A_0 + A_1, B_0 + B_1) - Z_2 - Z_0 \)
8: return \( Z_2 \cdot 2^k + Z_1 \cdot 2^{k-1} + Z_0 \)

A more precise (correct) analysis would say that computing \( Z_1 \) needs time \( T(n) + \Theta(n) \). 

---

6.3 The Characteristic Polynomial

Consider the recurrence relation:

\[ c_0 T(n) + c_1 T(n-1) + c_2 T(n-2) + \cdots + c_k T(n-k) = f(n) \]

Note that we ignore boundary conditions for the moment.
6.3 The Characteristic Polynomial

Observations:
- The solution $T[1], T[2], T[3], \ldots$ is completely determined by a set of boundary conditions that specify values for $T[1], \ldots, T[k]$.
- In fact, any $k$ consecutive values completely determine the solution.
- $k$ non-consecutive values might not be an appropriate set of boundary conditions (depends on the problem).

Approach:
- First determine all solutions that satisfy recurrence relation.
- Then pick the right one by analyzing boundary conditions.
- First consider the homogenous case.

The Homogenous Case

The solution space
$$S = \{ \mathcal{T} = T[1], T[2], T[3], \ldots \mid \mathcal{T} \text{ fulfills recurrence relation} \}$$
is a vector space. This means that if $T_1, T_2 \in S$, then also $\alpha T_1 + \beta T_2 \in S$, for arbitrary constants $\alpha, \beta$.

How do we find a non-trivial solution?
We guess that the solution is of the form $\lambda^n$, $\lambda \neq 0$, and see what happens. In order for this guess to fulfill the recurrence we need
$$c_0 \lambda^n + c_1 \lambda^{n-1} + c_2 \cdot \lambda^{n-2} + \cdots + c_k \cdot \lambda^{n-k} = 0$$for all $n \geq k$.

Dividing by $\lambda^n$ gives that all these constraints are identical to
$$c_0 + c_1 + c_2 \cdot \lambda + \cdots + c_k \cdot \lambda^{k-1} = 0$$characteristic polynomial $P[\lambda]$
This means that if $\lambda_i$ is a root (Nullstelle) of $P[\lambda]$ then $T[n] = \lambda_i^n$ is a solution to the recurrence relation.

Let $\lambda_1, \ldots, \lambda_k$ be the $k$ (complex) roots of $P[\lambda]$. Then, because of the vector space property
$$\alpha_1 \lambda_1^n + \alpha_2 \lambda_2^n + \cdots + \alpha_k \lambda_k^n$$is a solution for arbitrary values $\alpha_i$.

Lemma 5
Assume that the characteristic polynomial has $k$ distinct roots $\lambda_1, \ldots, \lambda_k$. Then all solutions to the recurrence relation are of the form
$$\alpha_1 \lambda_1^n + \alpha_2 \lambda_2^n + \cdots + \alpha_k \lambda_k^n$$

Proof.
There is one solution for every possible choice of boundary conditions for $T[1], \ldots, T[k]$.
We show that the above set of solutions contains one solution for every choice of boundary conditions.
The Homogenous Case

Proof (cont.).
Suppose I am given boundary conditions $T[i]$ and I want to see whether I can choose the $\alpha_i$ such that these conditions are met:

$$\begin{align*}
\alpha_1 \cdot \lambda_1 + \alpha_2 \cdot \lambda_2 + \cdots + \alpha_k \cdot \lambda_k &= T[1] \\
\alpha_1 \cdot \lambda_1^2 + \alpha_2 \cdot \lambda_2^2 + \cdots + \alpha_k \cdot \lambda_k^2 &= T[2] \\
&
\vdots \\
\alpha_1 \cdot \lambda_1^k + \alpha_2 \cdot \lambda_2^k + \cdots + \alpha_k \cdot \lambda_k^k &= T[k]
\end{align*}$$

We show that the column vectors are linearly independent. Then the above equation has a solution.
Computing the Determinant

Repeating the above steps gives:

\[
\begin{vmatrix}
1 & \lambda_1 - \lambda_1 & 1 & \cdots & \lambda_k^{k-2} - \lambda_1 \cdot \lambda_k^{k-3} & \lambda_k^{k-1} - \lambda_1 \cdot \lambda_k^{k-2} \\
1 & \lambda_2 - \lambda_1 & 1 & \cdots & \lambda_k^{k-2} - \lambda_1 \cdot \lambda_k^{k-3} & \lambda_k^{k-1} - \lambda_1 \cdot \lambda_k^{k-2} \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
1 & \lambda_k - \lambda_1 & 1 & \cdots & \lambda_k^{k-2} - \lambda_1 \cdot \lambda_k^{k-3} & \lambda_k^{k-1} - \lambda_1 \cdot \lambda_k^{k-2}
\end{vmatrix} = \\
\begin{vmatrix}
1 & 0 & \cdots & 0 \\
1 & \lambda_2 - \lambda_1 & 1 & \cdots & \lambda_k^{k-3} - \lambda_1 \cdot \lambda_k^{k-2} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
1 & \lambda_k - \lambda_1 & 1 & \cdots & \lambda_k^{k-3} - \lambda_1 \cdot \lambda_k^{k-2}
\end{vmatrix}
\]

Hence, if all \(\lambda_i\)'s are different, then the determinant is non-zero.

The Homogeneous Case

What happens if the roots are not all distinct?

Suppose we have a root \(\lambda_i\) with multiplicity (Vielfachheit) at least 2. Then not only is \(\lambda_i^n\) a solution to the recurrence but also \(n\lambda_i^n\).

To see this consider the polynomial

\[
P[\lambda] \cdot \lambda^{n-k} = c_0 \lambda^n + c_1 \lambda^{n-1} + c_2 \lambda^{n-2} + \cdots + c_k \lambda^{n-k}
\]

Since \(\lambda_i\) is a root we can write this as \(Q[\lambda] \cdot (\lambda - \lambda_i)^2\). Calculating the derivative gives a polynomial that still has root \(\lambda_i\).
This means
\[ c_0 n\lambda_i^{n-1} + c_1 (n-1)\lambda_i^{n-2} + \cdots + c_k (n-k)\lambda_i^{n-k-1} = 0 \]
Hence,
\[ c_0 n\lambda_i^{n} + c_1 (n-1)\lambda_i^{n-1} + \cdots + c_k (n-k)\lambda_i^{n-k} = 0 \]

The Homogeneous Case

Lemma 6
Let \( P[\lambda] \) denote the characteristic polynomial to the recurrence
\[ c_0 T[n] + c_1 T[n-1] + \cdots + c_k T[n-k] = 0 \]
Let \( \lambda_i, i = 1, \ldots, m \) be the (complex) roots of \( P[\lambda] \) with multiplicities \( \ell_i \). Then the general solution to the recurrence is given by
\[ T[n] = \sum_{i=1}^{m} \sum_{j=0}^{\ell_i-1} \alpha_{ij} \cdot (n^j \lambda_i^n) \]
The full proof is omitted. We have only shown that any choice of \( \alpha_{ij} \)'s is a solution to the recurrence.

Example: Fibonacci Sequence
\[
\begin{align*}
T[0] &= 0 \\
T[1] &= 1 \\
T[n] &= T[n-1] + T[n-2] \text{ for } n \geq 2
\end{align*}
\]
The characteristic polynomial is
\[ \lambda^2 - \lambda - 1 \]
Finding the roots, gives
\[ \lambda_{1/2} = \frac{1}{2} \pm \sqrt{\frac{1}{4} + 1} = \frac{1}{2} (1 \pm \sqrt{5}) \]
**Example: Fibonacci Sequence**

Hence, the solution is of the form

$$\alpha \left( \frac{1 + \sqrt{5}}{2} \right)^n + \beta \left( \frac{1 - \sqrt{5}}{2} \right)^n$$

$T[0] = 0$ gives $\alpha + \beta = 0$.

$T[1] = 1$ gives

$$\alpha \left( \frac{1 + \sqrt{5}}{2} \right) + \beta \left( \frac{1 - \sqrt{5}}{2} \right) = 1 \implies \alpha - \beta = \frac{2}{\sqrt{5}}$$

---

**The Inhomogeneous Case**

Consider the recurrence relation:

$$c_0 T(n) + c_1 T(n - 1) + c_2 T(n - 2) + \cdots + c_k T(n - k) = f(n)$$

with $f(n) \neq 0$.

While we have a fairly general technique for solving homogeneous, linear recurrence relations the inhomogeneous case is different.

---

**Example: Fibonacci Sequence**

Hence, the solution is

$$\frac{1}{\sqrt{5}} \left( \left( \frac{1 + \sqrt{5}}{2} \right)^n - \left( \frac{1 - \sqrt{5}}{2} \right)^n \right)$$

**The Inhomogeneous Case**

The general solution of the recurrence relation is

$$T(n) = T_h(n) + T_p(n)$$

where $T_h$ is any solution to the homogeneous equation, and $T_p$ is one particular solution to the inhomogeneous equation.

There is no general method to find a particular solution.
The Inhomogeneous Case

Example:

\[ T[n] = T[n - 1] + 1 \quad T[0] = 1 \]

Then,

\[ T[n - 1] = T[n - 2] + 1 \quad (n \geq 2) \]

Subtracting the first from the second equation gives,

\[ T[n] - T[n - 1] = T[n - 1] - T[n - 2] \quad (n \geq 2) \]

or

\[ T[n] = 2T[n - 1] - T[n - 2] \quad (n \geq 2) \]

I get a completely determined recurrence if I add \( T[0] = 1 \) and \( T[1] = 2 \).

6.3 The Characteristic Polynomial

Ernst Mayr, Harald Räcke

Example: Characteristic polynomial:

\[ \lambda^2 - 2\lambda + 1 = 0 \]

Then the solution is of the form

\[ T[n] = \alpha 1^n + \beta n 1^n = \alpha + \beta n \]

\( T[0] = 1 \) gives \( \alpha = 1 \).

\( T[1] = 2 \) gives \( 1 + \beta = 2 \Rightarrow \beta = 1. \)

The Inhomogeneous Case

If \( f(n) \) is a polynomial of degree \( r \) this method can be applied \( r + 1 \) times to obtain a homogeneous equation:

\[ T[n] = T[n - 1] + n^2 \]

Shift:

\[ T[n - 1] = T[n - 2] + (n - 1)^2 = T[n - 2] + n^2 - 2n + 1 \]

Difference:


\[ T[n] = 2T[n - 1] - T[n - 2] + 2n - 1 \]

and so on...
6.4 Generating Functions

**Definition 7 (Generating Function)**
Let \((a_n)_{n \geq 0}\) be a sequence. The corresponding generating function (Erzeugendenfunktion) is
\[
F(z) := \sum_{n \geq 0} a_n z^n;
\]

exponential generating function (exponentielle Erzeugendenfunktion) is
\[
F(z) = \sum_{n \geq 0} \frac{a_n}{n!} z^n.
\]

**Example 8**
1. The generating function of the sequence \((1, 0, 0, \ldots)\) is
\[
F(z) = 1.
\]
2. The generating function of the sequence \((1, 1, 1, \ldots)\) is
\[
F(z) = \frac{1}{1 - z}.
\]

There are two different views:

A generating function is a formal power series (formale Potenzreihe).

Then the generating function is an algebraic object.

Let \(f = \sum_{n \geq 0} a_n z^n\) and \(g = \sum_{n \geq 0} b_n z^n\).

- **Equality**: \(f \) and \(g\) are equal if \(a_n = b_n\) for all \(n\).
- **Addition**: \(f + g := \sum_{n \geq 0} (a_n + b_n) z^n\).
- **Multiplication**: \(f \cdot g := \sum_{n \geq 0} c_n z^n\) with \(c_n = \sum_{p=0}^{n} a_p b_{n-p}\).

There are no convergence issues here.
6.4 Generating Functions

What does $\sum_{n \geq 0} z^n = \frac{1}{1-z}$ mean in the algebraic view?

It means that the power series $1 - z$ and the power series $\sum_{n \geq 0} z^n$ are invers, i.e.,

$$(1 - z) \cdot \left( \sum_{n \geq 0} z^n \right) = 1.$$

This is well-defined.

We can repeat this

$\sum_{n \geq 0} (n+1)z^n = \frac{1}{(1-z)^2}$.

Derivative:

$\sum_{n \geq 1} n(n+1)z^{n-1} = \frac{2}{(1-z)^3}$

Hence, the generating function of the sequence $a_n = (n+1)(n+2)$ is $\frac{2}{(1-z)^3}$.

6.4 Generating Functions

Suppose we are given the generating function

$$\sum_{n \geq 0} z^n = \frac{1}{1-z}.$$

We can compute the derivative:

$$\sum_{n \geq 1} n z^{n-1} = \frac{1}{(1-z)^2}.$$

Hence, the generating function of the sequence $a_n = n + 1$ is $1/(1-z)^2$.

6.4 Generating Functions

Computing the $k$-th derivative of $\sum z^n$.

$$\sum_{n \geq k} n(n-1) \cdot \ldots \cdot (n-k+1)z^{n-k} = \sum_{n \geq 0} (n+k) \cdot \ldots \cdot (n+1)z^n$$

$$= \frac{k!}{(1-z)^{k+1}}.$$

Hence:

$$\sum_{n \geq 0} \binom{n+k}{k} z^n = \frac{1}{(1-z)^{k+1}}.$$

The generating function of the sequence $a_n = \binom{n+k}{k}$ is $\frac{1}{(1-z)^{k+1}}$.
### 6.4 Generating Functions

The generating function of the sequence \(a_n = n\) is \(\frac{z}{(1-z)^2}\).

**Example:** \(a_n = a_{n-1} + 1, \quad a_0 = 1\)

Suppose we have the recurrence \(a_n = a_{n-1} + 1\) for \(n \geq 1\) and \(a_0 = 1\).

\[
A(z) = \sum_{n=0}^\infty a_n z^n
= a_0 + \sum_{n=1}^\infty (a_{n-1} + 1)z^n
= 1 + z \sum_{n=1}^\infty a_{n-1}z^{n-1} + \sum_{n=1}^\infty z^n
= z \sum_{n=0}^\infty a_n z^n + \sum_{n=0}^\infty z^n
= zA(z) + \sum_{n=0}^\infty z^n
= zA(z) + \frac{1}{1-z}
\]

Solving for \(A(z)\) gives

\[
\sum_{n=0}^\infty a_n z^n = A(z) = \frac{1}{(1-z)^2} = \sum_{n=0}^\infty (n+1)z^n
\]

Hence, \(a_n = n + 1\).
### Some Generating Functions

<table>
<thead>
<tr>
<th>$n$-th sequence element</th>
<th>generating function</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1$</td>
<td>$\frac{1}{1-z}$</td>
</tr>
<tr>
<td>$n+1$</td>
<td>$\frac{1}{(1-z)^2}$</td>
</tr>
<tr>
<td>$\binom{n+k}{k}$</td>
<td>$\frac{1}{(1-z)^{k+1}}$</td>
</tr>
<tr>
<td>$n$</td>
<td>$\frac{z}{(1-z)^2}$</td>
</tr>
<tr>
<td>$a^n$</td>
<td>$\frac{1}{1-az}$</td>
</tr>
<tr>
<td>$n^2$</td>
<td>$\frac{z(1+z)}{(1-z)^3}$</td>
</tr>
<tr>
<td>$\frac{1}{n!}$</td>
<td>$e^z$</td>
</tr>
</tbody>
</table>

### Solving Recursions with Generating Functions

1. Set $A(z) = \sum_{n \geq 0} a_n z^n$.
2. Transform the right hand side so that boundary condition and recurrence relation can be plugged in.
3. Do further transformations so that the infinite sums on the right hand side can be replaced by $A(z)$.
4. Solving for $A(z)$ gives an equation of the form $A(z) = f(z)$, where hopefully $f(z)$ is a simple function.
5. Write $f(z)$ as a formal power series.
   Techniques:
   - partial fraction decomposition (Partialbruchzerlegung)
   - lookup in tables
6. The coefficients of the resulting power series are the $a_n$.

### Example: $a_n = 2a_{n-1}$, $a_0 = 1$

1. Set up generating function:
   $$ A(z) = \sum_{n \geq 0} a_n z^n $$

2. Transform right hand side so that recurrence can be plugged in:
   $$ A(z) = a_0 + \sum_{n \geq 1} a_n z^n $$

2. Plug in:
   $$ A(z) = 1 + \sum_{n \geq 1} (2a_{n-1}) z^n $$
Example: \( a_n = 2a_{n-1}, a_0 = 1 \)

3. Transform right hand side so that infinite sums can be replaced by \( A(z) \) or by simple function.

\[
A(z) = 1 + \sum_{n \geq 1} (2a_{n-1})z^n
= 1 + 2z \sum_{n \geq 1} a_{n-1}z^{n-1}
= 1 + 2z \sum_{n \geq 0} a_nz^n
= 1 + 2z \cdot A(z)
\]

4. Solve for \( A(z) \).

\[
A(z) = \frac{1}{1 - 2z}
\]

Example: \( a_n = 3a_{n-1} + n, a_0 = 1 \)

1. Set up generating function:

\[
A(z) = \sum_{n \geq 0} a_n z^n
\]

2./3. Transform right hand side:

\[
A(z) = \sum_{n \geq 0} a_n z^n
= a_0 + \sum_{n \geq 1} a_n z^n
= 1 + \sum_{n \geq 1} (3a_{n-1} + n)z^n
= 1 + 3z \sum_{n \geq 1} a_{n-1}z^{n-1} + \sum_{n \geq 1} nz^n
= 1 + 3z \sum_{n \geq 0} a_n z^n + \sum_{n \geq 0} nz^n
= 1 + 3zA(z) + \frac{z}{(1-z)^2}
\]
Example: $a_n = 3a_{n-1} + n$, $a_0 = 1$

4. Solve for $A(z)$:

$$A(z) = 1 + 3zA(z) + \frac{z}{(1-z)^2}$$

gives

$$A(z) = \frac{(1-z)^2 + z}{(1-3z)(1-z)^2} = \frac{z^2 - z + 1}{(1-3z)(1-z)^2}$$

Example: $a_n = 3a_{n-1} + n$, $a_0 = 1$

5. Write $f(z)$ as a formal power series:

This leads to the following conditions:

$$A + B + C = 1$$
$$2A + 4B + 3C = 1$$
$$A + 3B = 1$$

which gives

$$A = \frac{7}{4}, \quad B = -\frac{1}{4}, \quad C = -\frac{1}{2}$$

Example: $a_n = 3a_{n-1} + n$, $a_0 = 1$

5. Write $f(z)$ as a formal power series:

We use partial fraction decomposition:

$$\frac{z^2 - z + 1}{(1-3z)(1-z)^2} = \frac{A}{1-3z} + \frac{B}{1-z} + \frac{C}{(1-z)^2}$$

This gives

$$z^2 - z + 1 = A(1-z)^2 + B(1-3z)(1-z) + C(1-3z)$$
$$= A(1-2z + z^2) + B(1-4z + 3z^2) + C(1-3z)$$
$$= (A + 3B)z^2 + (-2A - 4B - 3C)z + (A + B + C)$$

This means $a_n = \frac{7}{4}3^n - \frac{1}{2}n - \frac{3}{4}$. 

6.5 Transformation of the Recurrence

Example 9

\[ f_0 = 1 \]
\[ f_1 = 2 \]
\[ f_n = f_{n-1} \cdot f_{n-2} \text{ for } n \geq 2. \]

Define

\[ g_n := \log f_n. \]

Then

\[ g_n = g_{n-1} + g_{n-2} \text{ for } n \geq 2 \]
\[ g_1 = \log 2 = 1 \text{ (for } \log \text{ = log}_2) \]
\[ g_0 = 0 \]
\[ g_n = F_n \text{ (n-th Fibonacci number)} \]
\[ f_n = 2^{F_n} \]

6 Recurrences

We get

\[ g_k = 3 [g_{k-1}] + 2^k \]
\[ = 3 \left[ 3g_{k-2} + 2^{k-1} \right] + 2^k \]
\[ = 3^2 \left[ g_{k-2} \right] + 32^{k-1} + 2^k \]
\[ = 3^2 \left[ 3g_{k-3} + 2^{k-2} \right] + 32^{k-1} + 2^k \]
\[ = 3^3 g_{k-3} + 3^2 2^{k-2} + 32^{k-1} + 2^k \]
\[ = 2^k \cdot \sum_{i=0}^{k} \left( \frac{3}{2} \right)^i \]
\[ = 2^k \cdot \left( \frac{3^{k+1} - 1}{1/2} \right) = 3^{k+1} - 2^{k+1} \]

Example 10

\[ f_1 = 1 \]
\[ f_n = 3f_{\frac{n}{2}} + n; \text{ for } n = 2^k, k \geq 1; \]

Define

\[ g_k := f_{2^k}. \]

Then:

\[ g_0 = 1 \]
\[ g_k = 3g_{k-1} + 2^k, k \geq 1 \]

We get

\[ g_k = 3^{k+1} - 2^{k+1}, \text{ hence} \]
\[ f_n = 3 \cdot 3^k - 2 \cdot 2^k \]
\[ = 3(2^{\log 3})^k - 2 \cdot 2^k \]
\[ = 3(2^k)^{\log 3} - 2 \cdot 2^k \]
\[ = 3n^{\log 3} - 2n. \]
6 Recurrences

Bibliography


The Karatsuba method can be found in [MS08] Chapter 1. Chapter 4.3 of [CLRS90] covers the “Substitution method” which roughly corresponds to “Guessing+induction”. Chapters 4.4, 4.5, 4.6 of this book cover the master theorem. Methods using the characteristic polynomial and generating functions can be found in [Liu85] Chapter 10.

6.5 Transformation of the Recurrence

Abstract Data Type

An abstract data type (ADT) is defined by an interface of operations or methods that can be performed and that have a defined behavior.

The data types in this lecture all operate on objects that are represented by a [key, value] pair.

- The key comes from a totally ordered set, and we assume that there is an efficient comparison function.
- The value can be anything: it usually carries satellite information important for the application that uses the ADT.

Dynamic Set Operations

- \textbf{S. search(}k\textbf{)}: Returns pointer to object \textbf{x} from \textbf{S} with \textbf{key}[\textbf{x}] = \textbf{k} or \textbf{null}.
- \textbf{S. insert(}x\textbf{)}: Inserts object \textbf{x} into set \textbf{S}. \textbf{key}[\textbf{x}] must not currently exist in the data-structure.
- \textbf{S. delete(}x\textbf{)}: Given pointer to object \textbf{x} from \textbf{S}, delete \textbf{x} from the set.
- \textbf{S. minimum()}: Return pointer to object with smallest key-value in \textbf{S}.
- \textbf{S. maximum()}: Return pointer to object with largest key-value in \textbf{S}.
- \textbf{S. successor(}x\textbf{)}: Return pointer to the next larger element in \textbf{S} or \textbf{null} if \textbf{x} is maximum.
- \textbf{S. predecessor(}x\textbf{)}: Return pointer to the next smaller element in \textbf{S} or \textbf{null} if \textbf{x} is minimum.
Dynamic Set Operations

- **S. union($S'$):** Sets $S := S \cup S'$. The set $S'$ is destroyed.
- **S. merge($S'$):** Sets $S := S \cup S'$. Requires $S \cap S' = \emptyset$.
- **S. split($k, S'$):**
  - $S := \{x \in S \mid \text{key}[x] \leq k\}$,
  - $S' := \{x \in S \mid \text{key}[x] > k\}$.
  Requires $\text{key}[S.\text{maximum}()] \leq \text{key}[S'.\text{minimum}()]$.
- **S. decrease-key($x, k$):** Replace $\text{key}[x]$ by $k \leq \text{key}[x]$.

Examples of ADTs

**Stack:**
- **S. push($x$):** Insert an element.
- **S. pop():** Return the element from $S$ that was inserted most recently; delete it from $S$.
- **S. empty():** Tell if $S$ contains any object.

**Queue:**
- **S. enqueue($x$):** Insert an element.
- **S. dequeue():** Return the element that is longest in the structure; delete it from $S$.
- **S. empty():** Tell if $S$ contains any object.

**Priority-Queue:**
- **S. insert($x$):** Insert an element.
- **S. delete-min():** Return the element with lowest key-value; delete it from $S$.

Dictionary

**Dictionary:**
- **S. insert($x$):** Insert an element $x$.
- **S. delete($x$):** Delete the element pointed to by $x$.
- **S. search($k$):** Return a pointer to an element $e$ with $\text{key}[e] = k$ in $S$ if it exists; otherwise return null.

7.1 Binary Search Trees

An (internal) binary search tree stores the elements in a binary tree. Each tree-node corresponds to an element. All elements in the left sub-tree of a node $v$ have a smaller key-value than $\text{key}[v]$ and elements in the right sub-tree have a larger-key value. We assume that all key-values are different.

(External Search Trees store objects only at leaf-vertices)

Examples:
We consider the following operations on binary search trees. Note that this is a super-set of the dictionary-operations.

- \( T.\text{insert}(x) \)
- \( T.\text{delete}(x) \)
- \( T.\text{search}(k) \)
- \( T.\text{successor}(x) \)
- \( T.\text{predecessor}(x) \)
- \( T.\text{minimum}() \)
- \( T.\text{maximum}() \)
**Binary Search Trees: Successor**

Algorithm 7 TreeSucc(x)
1: if right[x] ≠ null return TreeMin(right[x])
2: y ← parent[x]
3: while y ≠ null and x = right[y] do
4: x ← y; y ← parent[x]
5: return y;

**Binary Search Trees: Insert**

Insert element not in the tree.

TreeInsert(root, 20)

Search for z. At some point the search stops at a null-pointer. This is the place to insert z.

Algorithm 8 TreeInsert(x, z)
1: if x = null then
2: root[T] ← z; parent[z] ← null;
3: return;
4: if key[x] > key[z] then
5: if left[x] = null then
6: left[x] ← z; parent[z] ← x;
7: else TreeInsert(left[x], z);
8: else
9: if right[x] = null then
10: right[x] ← z; parent[z] ← x;
11: else TreeInsert(right[x], z);

**Binary Search Trees: Delete**

Case 1:
Element does not have any children

- Simply go to the parent and set the corresponding pointer to null.
**Binary Search Trees: Delete**

Case 2:
Element has exactly one child
  - Splice the element out of the tree by connecting its parent to its successor.

**Algorithm 9** TreeDelete($z$)

1. if left[$z$] = null or right[$z$] = null
2. then $y' = z$ else $y' = $TreeSucc($z$); select $y'$ to splice out
3. if left[$y'$] ≠ null
4. then $x = $left[$y'$] else $x = $right[$y'$]; $x$ is child of $y'$ (or null)
5. if $x$ ≠ null then parent[$x$] ← parent[$y'$]; parent[$x$] is correct
6. if parent[$y'$] = null then
7. root[$T$] ← $x$
8. else
9. if $y = $left[parent[$y'$]] then fix pointer to $x$
10. left[parent[$y'$]] ← $x$
11. else
12. right[parent[$y'$]] ← $x$
13. if $y' ≠ z$ then copy $y'$-data to $z$

**Binary Search Trees: Delete**

Case 3:
Element has two children
  - Find the successor of the element
  - Splice successor out of the tree
  - Replace content of element by content of successor

**Balanced Binary Search Trees**

All operations on a binary search tree can be performed in time $O(h)$, where $h$ denotes the height of the tree.

However the height of the tree may become as large as $Θ(n)$.

**Balanced Binary Search Trees**

With each insert- and delete-operation perform local adjustments to guarantee a height of $O(\log n)$.

AVL-trees, Red-black trees, Scapegoat trees, 2-3 trees, B-trees, AA trees, Treaps
similar: SPLAY trees.
Binary Search Trees (BSTs)

Bibliography


Binary search trees can be found in every standard textbook. For example, Chapter 7.1 in [MS08] and Chapter 12 in [CLRS90].

7.1 Binary Search Trees

Ernst Mayr, Harald Räcke

7.2 Red Black Trees

Definition 11
A red-black tree is a balanced binary search tree in which each internal node has two children. Each internal node has a color, such that

1. The root is black.
2. All leaf nodes are black.
3. For each node, all paths to descendant leaves contain the same number of black nodes.
4. If a node is red then both its children are black.

The null-pointers in a binary search tree are replaced by pointers to special null-vertices, that do not carry any object-data.

7.2 Red Black Trees

Lemma 12
A red-black tree with \( n \) internal nodes has height at most \( O(\log n) \).

Definition 13
The black height \( bh(v) \) of a node \( v \) in a red black tree is the number of black nodes on a path from \( v \) to a leaf vertex (not counting \( v \)).

We first show:

Lemma 14
A sub-tree of black height \( bh(v) \) in a red black tree contains at least \( 2^{bh(v)} - 1 \) internal vertices.

Red Black Trees: Example

Ernst Mayr, Harald Räcke
7.2 Red Black Trees

Proof of Lemma 14.

Induction on the height of \( v \).

base case \((\text{height}(v) = 0)\)

- If \( \text{height}(v) \) (maximum distance btw. \( v \) and a node in the sub-tree rooted at \( v \)) is 0 then \( v \) is a leaf.
- The black height of \( v \) is 0.
- The sub-tree rooted at \( v \) contains \( 0 = 2^{\text{bh}(v)} - 1 \) inner vertices.

Proof (cont.)

induction step

- Suppose \( v \) is a node with \( \text{height}(v) > 0 \).
- \( v \) has two children with strictly smaller height.
- These children \((c_1, c_2)\) either have \( \text{bh}(c_i) = \text{bh}(v) \) or \( \text{bh}(c_i) = \text{bh}(v) - 1 \).
- By induction hypothesis both sub-trees contain at least \( 2^{\text{bh}(v) - 1} - 1 \) internal vertices.
- Then \( T_v \) contains at least \( 2(2^{\text{bh}(v) - 1} - 1) + 1 \geq 2^{\text{bh}(v)} - 1 \) vertices.

7.2 Red Black Trees

Definition 1

A red black tree is a balanced binary search tree in which each internal node has two children. Each internal node has a color, such that

1. The root is black.
2. All leaf nodes are black.
3. For each node, all paths to descendant leaves contain the same number of black nodes.
4. If a node is red then both its children are black.

The null-pointers in a binary search tree are replaced by pointers to special null-vertices, that do not carry any object-data.

7.2 Red Black Trees

Proof of Lemma 12.

Let \( h \) denote the height of the red-black tree, and let \( P \) denote a path from the root to the furthest leaf.

At least half of the node on \( P \) must be black, since a red node must be followed by a black node.

Hence, the black height of the root is at least \( h/2 \).

The tree contains at least \( 2^{h/2} - 1 \) internal vertices. Hence, \( 2^{h/2} - 1 \leq n \).

Hence, \( h \leq 2 \log(n + 1) = O(\log n) \).
Red Black Trees

We need to adapt the insert and delete operations so that the red black properties are maintained.

Rotations

The properties will be maintained through rotations:

\[
\text{LeftRotate}(x) \\
\text{RightRotate}(z)
\]

Red Black Trees: Insert

\[
\text{RB-Insert}(\text{root}, 18)
\]

Insert:
- first make a normal insert into a binary search tree
- then fix red-black properties

Invariant of the fix-up algorithm:
- \( z \) is a red node
- the black-height property is fulfilled at every node
- the only violation of red-black properties occurs at \( z \) and \( \text{parent}[z] \)
  - either both of them are red (most important case)
  - or the parent does not exist (violation since root must be black)

If \( z \) has a parent but no grand-parent we could simply color the parent/root black; however this case never happens.
**Algorithm 10 InsertFix(z)**

1: while parent[z] ≠ null and col[parent[z]] = red do
2: if parent[z] = left[gp[z]] then z in left subtree of grandparent
3: uncle ← right[grandparent[z]]
4: if col[uncle] = red then Case 1: uncle red
5: col[p[z]] ← black; col[u] ← black;
6: col[gp[z]] ← red; z ← grandparent[z];
7: else Case 2: uncle black
8: if z = right[parent[z]] then 2a: z right child
9: z ← p[z]; LeftRotate(z);
10: col[p[z]] ← black; col[gp[z]] ← red; 2b: z left child
11: RightRotate(gp[z]);
12: else same as then-clause but right and left exchanged
13: col(root[T]) ← black;

---

**Case 1: Red Uncle**

1. recolour
2. move z to grand-parent
3. invariant is fulfilled for new z
4. you made progress

---

**Case 2b: Black uncle and z is left child**

1. rotate around grandparent
2. re-colour to ensure that black height property holds
3. you have a red black tree

---

**Case 2a: Black uncle and z is right child**

1. rotate around parent
2. move z downwards
3. you have Case 2b.
Red Black Trees: Insert

Running time:
- Only Case 1 may repeat; but only $h/2$ many steps, where $h$ is the height of the tree.
- Case 2a $\rightarrow$ Case 2b $\rightarrow$ red-black tree
- Case 2b $\rightarrow$ red-black tree

Performing Case 1 at most $O(\log n)$ times and every other case at most once, we get a red-black tree. Hence $O(\log n)$ re-colorings and at most 2 rotations.

Red Black Trees: Delete

First do a standard delete.

If the spliced out node $x$ was red everything is fine.

If it was black there may be the following problems.
- Parent and child of $x$ were red; two adjacent red vertices.
- If you delete the root, the root may now be red.
- Every path from an ancestor of $x$ to a descendant leaf of $x$ changes the number of black nodes. Black height property might be violated.

Case 3:
Element has two children
- do normal delete
- when replacing content by content of successor, don’t change color of node

Delete:
- deleting black node messes up black-height property
- if $z$ is red, we can simply color it black and everything is fine
- the problem is if $z$ is black (e.g. a dummy-leaf); we call a fix-up procedure to fix the problem.
Red Black Trees: Delete

Invariant of the fix-up algorithm

- the node $z$ is black
- if we “assign” a fake black unit to the edge from $z$ to its parent then the black-height property is fulfilled

Goal: make rotations in such a way that you at some point can remove the fake black unit from the edge.

Case 1: Sibling of $z$ is red

1. left-rotate around parent of $z$
2. recolor nodes $b$ and $c$
3. the new sibling is black (and parent of $z$ is red)
4. Case 2 (special), or Case 3, or Case 4

Case 2: Sibling is black with two black children

1. re-color node $c$
2. move fake black unit upwards
3. move $z$ upwards
4. we made progress
5. if $b$ is red we color it black and are done

Case 3: Sibling black with one black child to the right

1. do a right-rotation at sibling
2. recolor $c$ and $d$
3. new sibling is black with red right child (Case 4)

Case 4: Sibling is black with two black children

1. right-rotate around sibling
2. recolor $c$ and $d$
3. the new sibling is red with black right child
4. the new sibling is black with red right child
5. we made progress
6. if $b$ is red we color it black and are done
Case 4: Sibling is black with red right child

1. left-rotate around $b$
2. remove the fake black unit
3. recolor nodes $b$, $c$, and $e$
4. you have a valid red black tree

- Here $b$ and $d$ are either red or black but have possibly different colors.
- We recolor $c$ by giving it the color of $b$.

**Running time:**
- only Case 2 can repeat; but only $h$ many steps, where $h$ is the height of the tree
- Case 1 → Case 2 (special) → red black tree
  - Case 1 → Case 3 → Case 4 → red black tree
  - Case 1 → Case 4 → red black tree
- Case 3 → Case 4 → red black tree
- Case 4 → red black tree

Performing Case 2 at most $\mathcal{O}(\log n)$ times and every other step at most once, we get a red black tree. Hence, $\mathcal{O}(\log n)$ re-colorings and at most 3 rotations.

Red-Black Trees

**Bibliography**


Red black trees are covered in detail in Chapter 13 of [CLRS90].

Splay Trees

**Disadvantage of balanced search trees:**
- worst case; no advantage for easy inputs
- additional memory required
- complicated implementation

**Splay Trees:**
- after access, an element is moved to the root; splay($x$) repeated accesses are faster
- only amortized guarantee
- read-operations change the tree
Splay Trees

**find(x)**
- search for \( x \) according to a search tree
- let \( \bar{x} \) be last element on search-path
- splay(\( \bar{x} \))

**insert(x)**
- search for \( x \); \( \bar{x} \) is last visited element during search (successor or predecessor of \( x \))
- splay(\( \bar{x} \)) moves \( \bar{x} \) to the root
- insert \( x \) as new root

**delete(x)**
- search for \( x \); splay(\( x \)); remove \( x \)
- search largest element \( \bar{x} \) in \( A \)
- splay(\( \bar{x} \)) (on subtree \( A \))
- connect root of \( B \) as right child of \( \bar{x} \)

**Move to Root**

- one (bad) option: moveToRoot(\( x \))
- iteratively do rotation around parent of \( x \) until \( x \) is root
- if \( x \) is left child do right rotation otw. left rotation
Splay: Zig Case

better option \text{splay}(x):

- zig case: if $x$ is child of root do left rotation or right rotation around parent

Note that \text{moveToRoot}(x) does the same.

Splay: Zigzag Case

better option \text{splay}(x):

- zigzag case: if $x$ is right child and parent of $x$ is left child (or $x$ left child parent of $x$ right child)
  - do double right rotation around grand-parent (resp. double left rotation)

Note that \text{moveToRoot}(x) does the same.

Splay: Zigzig Case

better option \text{splay}(x):

- zigzig case: if $x$ is left child and parent of $x$ is left child (or $x$ right child, parent of $x$ right child)
  - do right rotation around grand-parent followed by right rotation around parent (resp. left rotations)

This case is different between \text{moveToRoot}(x) and \text{splay}(x).
Input tree on which splay(x) and moveToRoot(x) is executed.

Result after moveToRoot(x).

Result after splay(x).

Static Optimality

Suppose we have a sequence of m find-operations. find(x) appears $h_x$ times in this sequence.

The cost of a static search tree $T$ is:

$$cost(T) = m + \sum_x h_x \text{depth}_T(x)$$

The total cost for processing the sequence on a splay-tree is $O(cost(T_{\text{min}}))$, where $T_{\text{min}}$ is an optimal static search tree.

Theorem given without proof.
Dynamic Optimality

Let $S$ be a sequence with $m$ find-operations.

Let $A$ be a data-structure based on a search tree:
- the cost for accessing element $x$ is $1 + \text{depth}(x)$;
- after accessing $x$ the tree may be re-arranged through rotations;

**Conjecture:**
A splay tree that only contains elements from $S$ has cost $O(\text{cost}(A,S))$, for processing $S$.

Amortized Analysis

**Definition 16**
A data structure with operations $\text{op}_1(), \ldots, \text{op}_k()$ has amortized running times $t_1, \ldots, t_k$ for these operations if the following holds.

Suppose you are given a sequence of operations (starting with an empty data-structure) that operate on at most $n$ elements, and let $k_i$ denote the number of occurrences of $\text{op}_i()$ within this sequence. Then the actual running time must be at most $\sum_i k_i \cdot t_i(n)$.

Potential Method

**Lemma 15**
Splay Trees have an amortized running time of $O(\log n)$ for all operations.

**Potential Method**

Introduce a potential for the data structure.
- $\Phi(D_i)$ is the potential after the $i$-th operation.
- Amortized cost of the $i$-th operation is
  $$\hat{c}_i = c_i + \Phi(D_i) - \Phi(D_{i-1})$$
- Show that $\Phi(D_i) \geq \Phi(D_0)$.

Then
$$\sum_{i=1}^{k} c_i \leq \sum_{i=1}^{k} \hat{c}_i - \Phi(D_0) = \sum_{i=1}^{k} \hat{c}_i$$

This means the amortized costs can be used to derive a bound on the total cost.
Example: Stack

**Stack**
- **S. push()**
- **S. pop()**
- **S. multipop(k):** removes $k$ items from the stack. If the stack currently contains less than $k$ items it empties the stack.
- The user has to ensure that pop and multipop do not generate an underflow.

**Actual cost:**
- **S. push():** cost 1.
- **S. pop():** cost 1.
- **S. multipop(k):** cost $\min\{\text{size},k\} = k$.

Example: Binary Counter

**Incrementing a binary counter:**
Consider a computational model where each bit-operation costs one time-unit.

Incrementing an $n$-bit binary counter may require to examine $n$-bits, and maybe change them.

**Actual cost:**
- **Changing bit from 0 to 1:** cost 1.
- **Changing bit from 1 to 0:** cost 1.
- **Increment:** cost is $k + 1$, where $k$ is the number of consecutive ones in the least significant bit-positions (e.g., 001101 has $k = 1$).

Example: Binary Counter

Choose potential function $\Phi(x) = k$, where $k$ denotes the number of ones in the binary representation of $x$.

**Amortized cost:**
- **Changing bit from 0 to 1:**
  \[ \hat{C}_{0 \to 1} = C_{0 \to 1} + \Delta \Phi = 1 + 1 \leq 2. \]

- **Changing bit from 1 to 0:**
  \[ \hat{C}_{1 \to 0} = C_{1 \to 0} + \Delta \Phi = 1 - 1 \leq 0. \]

- **Increment:** Let $k$ denotes the number of consecutive ones in the least significant bit-positions. An increment involves $k (1 \to 0)$-operations, and one $(0 \to 1)$-operation.
  Hence, the amortized cost is $k \hat{C}_{1 \to 0} + \hat{C}_{0 \to 1} \leq 2$. 
Splay Trees

potential function for splay trees:

- size \( s(x) = |T_x| \)
- rank \( r(x) = \log_2(s(x)) \)
- \( \Phi(T) = \sum_{v \in T} r(v) \)

amortized cost = real cost + potential change

The cost is essentially the cost of the splay-operation, which is 1 plus the number of rotations.

\[ \Delta \Phi = r'(x) + r'(p) - r(x) - r(p) \]
\[ = r'(p) - r(x) \]
\[ \leq r'(x) - r(x) \]
\[ \text{cost}_{zig} \leq 1 + 3(r'(x) - r(x)) \]
\[ \Delta \Phi = r'(x) + r'(p) + r'(g) - r(x) - r(p) - r(g) \]
\[ = r'(p) + r'(g) - r(x) - r(p) \]
\[ \leq r'(p) + r'(g) - r(x) - r(x) \]
\[ = r'(p) + r'(g) - 2r'(x) + 2r'(x) - 2r(x) \]
\[ \leq -2 + 2(r'(x) - r(x)) \quad \Rightarrow \text{cost}_{\text{zigzag}} \leq 3(r'(x) - r(x)) \]

Amortized cost of the whole splay operation:
\[ \leq 1 + 1 + \sum_{\text{steps } t} 3(r_t(x) - r_{t-1}(x)) \]
\[ = 2 + r(\text{root}) - r_0(x) \]
\[ \leq O(\log n) \]

1. The first one is added due to the fact that so far for each step of a splay-operation we have only counted the number of rotations, but the cost is \(1 + \#\text{rotations} \).
2. The second one comes from the zig-operation. Note that we have at most one zig-operation during a splay.
Suppose you want to develop a data structure with:

- **Insert(x)**: insert element \(x\).
- **Search(k)**: search for element with key \(k\).
- **Delete(x)**: delete element referenced by pointer \(x\).
- **find-by-rank(\(\ell\))**: return the \(\ell\)-th element; return “error” if the data-structure contains less than \(\ell\) elements.

Augment an existing data-structure instead of developing a new one.

### Goal: Design a data-structure that supports insert, delete, search, and find-by-rank in time \(O(\log n)\).

1. We choose a red-black tree as the underlying data-structure.
2. We store in each node \(v\) the size of the sub-tree rooted at \(v\).
3. We need to be able to update the size-field in each node without asymptotically affecting the running time of insert, delete, and search. We come back to this step later...

### How to augment a data-structure

1. choose an underlying data-structure
2. determine additional information to be stored in the underlying structure
3. verify/show how the additional information can be maintained for the basic modifying operations on the underlying structure.
4. develop the new operations

- Of course, the above steps heavily depend on each other. For example it makes no sense to choose additional information to be stored (Step 2), and later realize that either the information cannot be maintained efficiently (Step 3) or is not sufficient to support the new operations (Step 4).
- However, the above outline is a good way to describe/document a new data-structure.

### Goal: Design a data-structure that supports insert, delete, search, and find-by-rank in time \(O(\log n)\).

4. How does find-by-rank work?

Find-by-rank(\(k\)) = Select(root, \(k\)) with

```plaintext
Algorithm 11 Select(x, i)
1: if \(x = \text{null}\) then return \text{error}
2: if \(\text{left}[x] \neq \text{null}\) then \(r \leftarrow \text{left}[x].\text{size} + 1\) \text{ else } \(r \leftarrow 1\)
3: if \(i = r\) then return \(x\)
4: if \(i < r\) then
5: return Select(\(\text{left}[x]\), \(i\))
6: else
7: return Select(\(\text{right}[x]\), \(i - r\))
```
Select \((x, i)\)

Find-by-rank:
- decide whether you have to proceed into the left or right sub-tree
- adjust the rank that you are searching for if you go right

7.4 Augmenting Data Structures

Goal: Design a data-structure that supports insert, delete, search, and find-by-rank in time \(\theta(\log n)\).

3. How do we maintain information?

Search\((k)\): Nothing to do.

Insert\((x)\): When going down the search path increase the size field for each visited node. Maintain the size field during rotations.

Delete\((x)\): Directly after splicing out a node traverse the path from the spliced out node upwards, and decrease the size counter on every node on this path. Maintain the size field during rotations.

Rotations

The only operation during the fix-up procedure that alters the tree and requires an update of the size-field:

The nodes \(x\) and \(z\) are the only nodes changing their size-fields. The new size-fields can be computed locally from the size-fields of the children.

Augmenting Data Structures

Bibliography


See Chapter 14 of [CLRS90].
### 7.5 \((a, b)\)-trees

**Definition 17**

For \(b \geq 2a - 1\) an \((a, b)\)-tree is a search tree with the following properties:

1. all leaves have the same distance to the root
2. every internal non-root vertex \(v\) has at least \(a\) and at most \(b\) children
3. the root has degree at least 2 if the tree is non-empty
4. the internal vertices do not contain data, but only keys (external search tree)
5. there is a special dummy leaf node with key-value \(\infty\)

### Example 18

```
10 19
1 3 5 14 28
0 1 3 5 14 19 28 \infty
```

### Variants

- The dummy leaf element may not exist; it only makes implementation more convenient.
- Variants in which \(b = 2a\) are commonly referred to as \(B\)-trees.
- A \(B\)-tree usually refers to the variant in which keys and data are stored at internal nodes.
- A \(B^+\) tree stores the data only at leaf nodes as in our definition. Sometimes the leaf nodes are also connected in a linear list data structure to speed up the computation of successors and predecessors.
- A \(B^*\) tree requires that a node is at least \(2/3\)-full as opposed to \(1/2\)-full (the requirement of a \(B\)-tree).
Lemma 19
Let $T$ be an $(a,b)$-tree for $n > 0$ elements (i.e., $n + 1$ leaf nodes) and height $h$ (number of edges from root to a leaf vertex). Then

1. $2a^{h-1} \leq n + 1 \leq b^h$
2. $\log_b(n + 1) \leq h \leq 1 + \log_a \left(\frac{n+1}{2}\right)$

Proof.

- If $n > 0$ the root has degree at least 2 and all other nodes have degree at least $a$. This gives that the number of leaf nodes is at least $2a^{h-1}$.
- Analogously, the degree of any node is at most $b$ and, hence, the number of leaf nodes at most $b^h$.

Search

Search(8)

The search is straightforward. It is only important that you need to go all the way to the leaf.

Time: $O(b \cdot h) = O(b \cdot \log n)$, if the individual nodes are organized as linear lists.

Insert

Insert element $x$:

- Follow the path as if searching for key[$x$].
- If this search ends in leaf $\ell$, insert $x$ before this leaf.
- For this add key[$x$] to the key-list of the last internal node $v$ on the path.
- If after the insert $v$ contains $b$ nodes, do Rebalance($v$).
Insert

Rebalance($v$):

- Let $k_i, i = 1, \ldots, b$ denote the keys stored in $v$.
- Let $j := \lfloor \frac{b+1}{2} \rfloor$ be the middle element.
- Create two nodes $v_1$ and $v_2$. $v_1$ gets all keys $k_1, \ldots, k_{j-1}$ and $v_2$ gets keys $k_{j+1}, \ldots, k_b$.
- Both nodes get at least $\lfloor \frac{b-1}{2} \rfloor$ keys, and have therefore degree at least $\lfloor \frac{b-1}{2} \rfloor + 1 \geq a$ since $b \geq 2a - 1$.
- They get at most $\lceil \frac{b-1}{2} \rceil$ keys, and have therefore degree at most $\lceil \frac{b-1}{2} \rceil + 1 \leq b$ (since $b \geq 2$).
- The key $k_j$ is promoted to the parent of $v$. The current pointer to $v$ is altered to point to $v_1$, and a new pointer (to the right of $k_j$) in the parent is added to point to $v_2$.
- Then, re-balance the parent.
**Insert**

Insert(7)

- Insertion process into an (a, b)-tree.

**Delete**

Delete element \( x \) (pointer to leaf vertex):

- Let \( v \) denote the parent of \( x \). If \( \text{key}[x] \) is contained in \( v \), remove the key from \( v \), and delete the leaf vertex.
- Otherwise delete the key of the predecessor of \( x \) from \( v \); delete the leaf vertex; and replace the occurrence of \( \text{key}[x] \) in internal nodes by the predecessor key. (Note that it appears in exactly one internal vertex).
- If now the number of keys in \( v \) is below \( a - 1 \) perform Rebalance'(v).

**Rebalance' (v):**

- If there is a neighbour of \( v \) that has at least \( a \) keys take over the largest (if right neighbour) or smallest (if left neighbour) and the corresponding sub-tree.
- If not: merge \( v \) with one of its neighbours.
- The merged node contains at most \((a - 2) + (a - 1) + 1\) keys, and has therefore at most \(2a - 1 \leq b\) successors.
- Then rebalance the parent.
- During this process the root may become empty. In this case the root is deleted and the height of the tree decreases.

Animation for deleting in an \((a, b)\)-tree is only available in the lecture version of the slides.
There is a close relation between red-black trees and (2,4)-trees:

First make it into an internal search tree by moving the satellite-data from the leaves to internal nodes. Add dummy leaves.

Then, color one key in each internal node \( v \) black. If \( v \) contains 3 keys you need to select the middle key otherwise choose a black key arbitrarily. The other keys are colored red.

Re-attach the pointers to individual keys. A pointer that is between two keys is attached as a child of the red key. The incoming pointer points to the black key.

Note that this correspondence is not unique. In particular, there are different red-black trees that correspond to the same (2,4)-tree.
Augmenting Data Structures

Bibliography


A description of B-trees (a specific variant of \((a,b)\)-trees) can be found in Chapter 18 of [CLRS90]. Chapter 7.2 of [MS08] discusses \((a,b)\)-trees as discussed in the lecture.

7.6 Skip Lists

Why do we not use a list for implementing the ADT Dynamic Set?

- time for search \(\Theta(n)\)
- time for insert \(\Theta(n)\) (dominated by searching the item)
- time for delete \(\Theta(1)\) if we are given a handle to the object, otw. \(\Theta(n)\)

Add more express lanes. Lane \(L_1\) contains roughly every \(\frac{L_{i+1}}{L_i}\)-th item from list \(L_{i-1}\).

Search(x) \((k + 1\) lists \(L_0, \ldots, L_k)\)

- Find the largest item in list \(L_k\) that is smaller than \(x\). At most \(|L_k| + 2\) steps.
- Find the largest item in list \(L_{k-1}\) that is smaller than \(x\). At most \(|L_{k-1}| + 1\) + 2 steps.
- Find the largest item in list \(L_{k-2}\) that is smaller than \(x\). At most \(|L_{k-2}| + 1\) + 2 steps.
- \(\ldots\)
- At most \(|L_k| + \sum_{i=1}^{k} \frac{L_{i+1}}{L_i} + 3(k + 1)\) steps.

Let \(|L_1|\) denote the number of elements in the “express lane”, and \(|L_0| = n\) the number of all elements (ignoring dummy elements).

Worst case search time: \(|L_1| + \frac{|L_0|}{L_1}\) (ignoring additive constants)

Choose \(|L_1| = \sqrt{n}\). Then search time \(\Theta(\sqrt{n})\).
Choose ratios between list-lengths evenly, i.e., \( \frac{|L_{i+1}|}{|L_i|} = r \), and, hence, \( L_k \approx r^{-k}n \).

Worst case running time is: \( O(r^{-k}n + kr) \). Choose \( r = n^{\frac{1}{1+k}} \). Then
\[
    r^{-k}n + kr = \left( n^{\frac{1}{1+k}} \right)^{-k} n + kn^{\frac{1}{1+k}}
    = n^{1 - \frac{k}{1+k}} + kn^{\frac{1}{1+k}}
    = (k + 1)n^{\frac{1}{1+k}}.
\]

Choosing \( k = \Theta(\log n) \) gives a logarithmic running time.

How to do insert and delete?

- If we want that in \( L_i \) we always skip over roughly the same number of elements in \( L_{i-1} \) an insert or delete may require a lot of re-organisation.

Use randomization instead!

**Insert:**

- A search operation gives you the insert position for element \( x \) in every list.
- Flip a coin until it shows head, and record the number \( t \in \{1, 2, \ldots \} \) of trials needed.
- Insert \( x \) into lists \( L_0, \ldots, L_{t-1} \).

**Delete:**

- You get all predecessors via backward pointers.
- Delete \( x \) in all lists it actually appears in.

The time for both operations is dominated by the search time.
**High Probability**

**Definition 20 (High Probability)**
We say a randomized algorithm has running time $O(\log n)$ with high probability if for any constant $\alpha$ the running time is at most $O(\log n)$ with probability at least $1 - \frac{1}{n^\alpha}$.

Here the $O$-notation hides a constant that may depend on $\alpha$.

**High Probability**

Suppose there are a polynomially many events $E_1, E_2, \ldots, E_\ell$, $\ell = n^c$ each holding with high probability (e.g. $E_i$ may be the event that the $i$-th search in a skip list takes time at most $O(\log n)$).

Then the probability that all $E_i$ hold is at least

$$\Pr[E_1 \land \cdots \land E_\ell] = 1 - \Pr[\bar{E}_1 \lor \cdots \lor \bar{E}_\ell] \geq 1 - n^c \cdot n^{-\alpha} = 1 - n^{c-\alpha}.$$ 

This means $\Pr[E_1 \land \cdots \land E_\ell]$ holds with high probability.

**7.6 Skip Lists**

**Lemma 21**
A search (and, hence, also insert and delete) in a skip list with $n$ elements takes time $O(\log n)$ with high probability (w. h. p.).

**7.6 Skip Lists**

**Backward analysis:**

At each point the path goes up with probability $1/2$ and left with probability $1/2$.

We show that w.h.p:
- A “long” search path must also go very high.
- There are no elements in high lists.

From this it follows that w.h.p. there are no long paths.
7.6 Skip Lists

Let $E_{z,k}$ denote the event that a search path is of length $z$ (number of edges) but does not visit a list above $L_k$.

In particular, this means that during the construction in the backward analysis we see at most $k$ heads (i.e., coin flips that tell you to go up) in $z$ trials.

\[ \Pr[E_{z,k}] \leq \Pr[\text{at most } k \text{ heads in } z \text{ trials}] \leq \left( \frac{2e}{k} \right)^{k} n^{-\alpha} \]

choosing $k = \gamma \log n$ with $\gamma \geq 1$ and $z = (\beta + \alpha) \gamma \log n$

\[ \leq \left( \frac{2e}{k} \right)^{k} 2^{-k} n^{-\alpha} \leq \left( \frac{2e}{2^\beta k} \right)^{k} n^{-\alpha} \]

now choosing $\beta = 6\alpha$ gives

\[ \leq \left( \frac{42\alpha}{64\alpha} \right)^{k} n^{-\alpha} \leq n^{-\alpha} \]

for $\alpha \geq 1$.

This means, the search requires at most $z$ steps, w.h.p.
Skip Lists

Bibliography

[GT98] Michael T. Goodrich, Roberto Tamassia
Data Structures and Algorithms in JAVA.
John Wiley, 1998

Skip lists are covered in Chapter 7.5 of [GT98].

7.7 Hashing

Dictionary:

- \( S.\ insert(x) \): Insert an element \( x \).
- \( S.\ delete(x) \): Delete the element pointed to by \( x \).
- \( S.\ search(k) \): Return a pointer to an element \( e \) with
  \( \text{key}[e] = k \) in \( S \) if it exists; otherwise return null.

So far we have implemented the search for a key by carefully choosing split-elements.

Then the memory location of an object \( x \) with key \( k \) is determined by successively comparing \( k \) to split-elements.

Hashing tries to directly compute the memory location from the given key. The goal is to have constant search time.

7.7 Hashing

Definitions:

- Universe \( U \) of keys, e.g., \( U \subseteq \mathbb{N}_0 \). \( U \) very large.
- Set \( S \subseteq U \) of keys, \( |S| = m \leq |U| \).
- Array \( T[0,\ldots,n-1] \) hash-table.
- Hash function \( h: U \rightarrow [0,\ldots,n-1] \).

The hash-function \( h \) should fulfill:

- Fast to evaluate.
- Small storage requirement.
- Good distribution of elements over the whole table.

Direct Addressing

Ideally the hash function maps all keys to different memory locations.

This special case is known as Direct Addressing. It is usually very unrealistic as the universe of keys typically is quite large, and in particular larger than the available memory.
Perfect Hashing

Suppose that we know the set $S$ of actual keys (no insert/no delete). Then we may want to design a simple hash-function that maps all these keys to different memory locations.

Such a hash function $h$ is called a perfect hash function for set $S$.

Collisions

If we do not know the keys in advance, the best we can hope for is that the hash function distributes keys evenly across the table.

Problem: Collisions

Usually the universe $U$ is much larger than the table-size $n$.

Hence, there may be two elements $k_1,k_2$ from the set $S$ that map to the same memory location (i.e., $h(k_1) = h(k_2)$). This is called a collision.

Lemma 22

The probability of having a collision when hashing $m$ elements into a table of size $n$ under uniform hashing is at least

$$1 - e^{-\frac{m(m-1)}{2n}} \approx 1 - e^{-\frac{m^2}{2n}}.$$

Uniform hashing:

Choose a hash function uniformly at random from all functions $f : U \rightarrow [0,\ldots,n-1]$.

Proof.

Let $A_{m,n}$ denote the event that inserting $m$ keys into a table of size $n$ does not generate a collision. Then

$$\Pr[A_{m,n}] = \prod_{\ell=1}^{m} \frac{n-\ell+1}{n} = \prod_{j=0}^{m-1} (1 - \frac{j}{n}) \leq \prod_{j=0}^{m-1} e^{-\frac{j}{n}} = e^{-\sum_{j=0}^{m-1}\frac{j}{n}} = e^{-\frac{m(m-1)}{2n}}.$$

Here the first equality follows since the $\ell$-th element that is hashed has a probability of $\frac{n-\ell+1}{n}$ to not generate a collision under the condition that the previous elements did not induce collisions.
The inequality $1 - x \leq e^{-x}$ is derived by stopping the Taylor-expansion of $e^{-x}$ after the second term.

## Hashing with Chaining

Arrange elements that map to the same position in a linear list.

- Access: compute $h(x)$ and search list for $key[x]$.
- Insert: insert at the front of the list.

Let $A$ denote a strategy for resolving collisions. We use the following notation:

- $A^+$ denotes the average time for a **successful** search when using $A$;
- $A^-$ denotes the average time for an **unsuccessful** search when using $A$;
- We parameterize the complexity results in terms of $\alpha := \frac{m}{n}$, the so-called **fill factor** of the hash-table.

We assume **uniform hashing** for the following analysis.
Hashing with Chaining

The time required for an unsuccessful search is 1 plus the length of the list that is examined. The average length of a list is \( \alpha = \frac{m}{n} \). Hence, if \( A \) is the collision resolving strategy “Hashing with Chaining” we have

\[
A^- = 1 + \alpha.
\]

Hashing with Chaining

For a successful search observe that we do not choose a list at random, but we consider a random key \( k \) in the hash-table and ask for the search-time for \( k \).

This is 1 plus the number of elements that lie before \( k \) in \( k \)’s list.

Let \( k_\ell \) denote the \( \ell \)-th key inserted into the table.

Let for two keys \( k_i \) and \( k_j \), \( X_{ij} \) denote the indicator variable for the event that \( k_i \) and \( k_j \) hash to the same position. Clearly, \( \Pr[X_{ij} = 1] = 1/n \) for uniform hashing.

The expected successful search cost is

\[
E \left[ \frac{1}{m} \sum_{i=1}^{m} \left( 1 + \sum_{j=i+1}^{m} X_{ij} \right) \right] \text{ keys before } k_i
\]

\[
E \left[ \frac{1}{m} \sum_{i=1}^{m} \left( 1 + \sum_{j=i+1}^{m} X_{ij} \right) \right] \text{ cost for key } k_i
\]

Hence, the expected cost for a successful search is \( A^+ \leq 1 + \frac{\alpha}{2} \).

Disadvantages:

- pointers increase memory requirements
- pointers may lead to bad cache efficiency

Advantages:

- no à priori limit on the number of elements
- deletion can be implemented efficiently
- by using balanced trees instead of linked list one can also obtain worst-case guarantees.
Open Addressing

All objects are stored in the table itself.

Define a function $h(k, j)$ that determines the table-position to be examined in the $j$-th step. The values $h(k, 0), \ldots, h(k, n - 1)$ must form a permutation of $0, \ldots, n - 1$.

**Search**($k$): Try position $h(k, 0)$; if it is empty your search fails; otw. continue with $h(k, 1), h(k, 2), \ldots$.

**Insert**($x$): Search until you find an empty slot; insert your element there. If your search reaches $h(k, n - 1)$, and this slot is non-empty then your table is full.

Linear Probing

- **Advantage**: Cache-efficiency. The new probe position is very likely to be in the cache.
- **Disadvantage**: Primary clustering. Long sequences of occupied table-positions get longer as they have a larger probability to be hit. Furthermore, they can merge forming larger sequences.

**Lemma 23**

Let $L$ be the method of linear probing for resolving collisions:

$$L^+ \approx \frac{1}{2} \left(1 + \frac{1}{1 - \alpha}\right)$$

$$L^- \approx \frac{1}{2} \left(1 + \frac{1}{(1 - \alpha)^2}\right)$$

Quadratic Probing

- **Not as cache-efficient as Linear Probing**.
- **Secondary clustering**: caused by the fact that all keys mapped to the same position have the same probe sequence.

**Lemma 24**

Let $Q$ be the method of quadratic probing for resolving collisions:

$$Q^+ \approx 1 + \ln \left(\frac{1}{1 - \alpha}\right) - \frac{\alpha}{2}$$

$$Q^- \approx \frac{1}{1 - \alpha} + \ln \left(\frac{1}{1 - \alpha}\right) - \alpha$$
Double Hashing

- Any probe into the hash-table usually creates a cache-miss.

Lemma 25
Let \( A \) be the method of double hashing for resolving collisions:

\[
D^+ \approx \frac{1}{\alpha} \ln \left( \frac{1}{1 - \alpha} \right)
\]

\[
D^- \approx \frac{1}{1 - \alpha}
\]

Open Addressing

Some values:

<table>
<thead>
<tr>
<th>( \alpha )</th>
<th>Linear Probing</th>
<th>Quadratic Probing</th>
<th>Double Hashing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( L^+ )</td>
<td>( L^- )</td>
<td>( Q^+ )</td>
</tr>
<tr>
<td>0.5</td>
<td>1.5</td>
<td>2.5</td>
<td>1.44</td>
</tr>
<tr>
<td>0.9</td>
<td>5.5</td>
<td>50.5</td>
<td>2.85</td>
</tr>
<tr>
<td>0.95</td>
<td>10.5</td>
<td>200.5</td>
<td>3.52</td>
</tr>
</tbody>
</table>

Analysis of Idealized Open Address Hashing

We analyze the time for a search in a very idealized Open Addressing scheme.

- The probe sequence \( h(k, 0), h(k, 1), h(k, 2), \ldots \) is equally likely to be any permutation of \( (0, 1, \ldots, n - 1) \).
Analysis of Idealized Open Address Hashing

Let $X$ denote a random variable describing the number of probes in an unsuccessful search.

Let $A_i$ denote the event that the $i$-th probe occurs and is to a non-empty slot.

$$\Pr[A_1 \cap A_2 \cap \cdots \cap A_{i-1}] = \Pr[A_1] \cdot \Pr[A_2 | A_1] \cdot \Pr[A_3 | A_1 \cap A_2] \cdots \Pr[A_{i-1} | A_1 \cap \cdots \cap A_{i-2}]$$

$$\Pr[X \geq i] = \frac{m}{n} \cdot \frac{m-1}{n-1} \cdot \frac{m-2}{n-2} \cdots \frac{m-i+2}{n-i+2}$$

$$\leq \left( \frac{m}{n} \right)^{i-1} = \alpha^{i-1}.$$
Analysis of Idealized Open Address Hashing

The number of probes in a successful search for \( k \) is equal to the number of probes made in an unsuccessful search for \( k \) at the time that \( k \) is inserted.

Let \( k \) be the \( i+1 \)-st element. The expected time for a search for \( k \) is at most
\[
1 - i/n = \frac{n}{n-i}.
\]

\[
\frac{1}{m} \sum_{i=0}^{m-1} \frac{n}{n-i} = \frac{n}{m} \sum_{i=0}^{m-1} \frac{1}{n-i} = \frac{1}{\alpha} \sum_{k=n-m+1}^{n} \frac{1}{k}.
\]

\[
\leq \frac{1}{\alpha} \int_{n-m}^{n} \frac{1}{x} \, dx = \frac{1}{\alpha} \ln \frac{n}{n-m} = \frac{1}{\alpha} \ln \frac{1}{1-\alpha}.
\]

Deletions in Hashables

How do we delete in a hash-table?

- For hashing with chaining this is not a problem. Simply search for the key, and delete the item in the corresponding list.
- For open addressing this is difficult.
Deletions for Linear Probing

- For Linear Probing one can delete elements without using deletion-markers.
- Upon a deletion elements that are further down in the probe-sequence may be moved to guarantee that they are still found during a search.

### Algorithm 12 delete(p)

1: $T[p] \leftarrow \text{null}$
2: $p \leftarrow \text{succ}(p)$
3: while $T[p] \neq \text{null}$ do
4: $y \leftarrow T[p]$
5: $T[p] \leftarrow \text{null}$
6: $p \leftarrow \text{succ}(p)$
7: $\text{insert}(y)$

$p$ is the index into the table-cell that contains the object to be deleted.

Pointers into the hash-table become invalid.

Universal Hashing

Regardless, of the choice of hash-function there is always an input (a set of keys) that has a very poor worst-case behaviour.

Therefore, so far we assumed that the hash-function is random so that regardless of the input the average case behaviour is good.

However, the assumption of uniform hashing that $h$ is chosen randomly from all functions $f : U \rightarrow [0, \ldots, n-1]$ is clearly unrealistic as there are $n^{|U|}$ such functions. Even writing down such a function would take $|U| \log n$ bits.

Universal hashing tries to define a set $\mathcal{H}$ of functions that is much smaller but still leads to good average case behaviour when selecting a hash-function uniformly at random from $\mathcal{H}$.

### Definition 26

A class $\mathcal{H}$ of hash-functions from the universe $U$ into the set $\{0, \ldots, n-1\}$ is called universal if for all $u_1, u_2 \in U$ with $u_1 \neq u_2$

$$\Pr[h(u_1) = h(u_2)] \leq \frac{1}{n},$$

where the probability is w. r. t. the choice of a random hash-function from set $\mathcal{H}$.

Note that this means that the probability of a collision between two arbitrary elements is at most $\frac{1}{n}$. 
Universal Hashing

Definition 27
A class $H$ of hash-functions from the universe $U$ into the set $\{0, \ldots, n-1\}$ is called 2-independent (pairwise independent) if the following two conditions hold:

- For any key $u \in U$, and $t \in \{0, \ldots, n-1\}$ $\Pr[h(u) = t] = \frac{1}{n}$, i.e., a key is distributed uniformly within the hash-table.
- For all $u_1, u_2 \in U$ with $u_1 \neq u_2$, and for any two hash-positions $t_1, t_2$:
  $$\Pr[h(u_1) = t_1 \land h(u_2) = t_2] \leq \frac{1}{n^2}.$$ 

This requirement clearly implies a universal hash-function.

Universal Hashing

Definition 28
A class $H$ of hash-functions from the universe $U$ into the set $\{0, \ldots, n-1\}$ is called $k$-independent if for any choice of $\ell \leq k$ distinct keys $u_1, \ldots, u_\ell \in U$, and for any set of $\ell$ not necessarily distinct hash-positions $t_1, \ldots, t_\ell$:

$$\Pr[h(u_1) = t_1 \land \cdots \land h(u_\ell) = t_\ell] \leq \frac{1}{n^\ell},$$

where the probability is w. r. t. the choice of a random hash-function from set $H$.

Let $U := \{0, \ldots, p-1\}$ for a prime $p$. Let $\mathbb{Z}_p := \{0, \ldots, p-1\}$, and let $\mathbb{Z}_p^* := \{1, \ldots, p-1\}$ denote the set of invertible elements in $\mathbb{Z}_p$.

Define

$$h_{a,b}(x) := (ax + b \mod p) \mod n$$

Lemma 30
The class

$$\mathcal{H} = \{h_{a,b} \mid a \in \mathbb{Z}_p^*, b \in \mathbb{Z}_p\}$$

is a universal class of hash-functions from $U$ to $\{0, \ldots, n-1\}$. 
Proof.
Let $x, y \in U$ be two distinct keys. We have to show that the probability of a collision is only $1/n$.

- $ax + b \not\equiv ay + b \pmod{p}$

If $x \neq y$ then $(x - y) \not\equiv 0 \pmod{p}$.

Multiplying with $a \not\equiv 0 \pmod{p}$ gives $a(x - y) \not\equiv 0 \pmod{p}$

where we use that $\mathbb{Z}_p$ is a field (Körper) and, hence, has no zero divisors (nullteilerfrei).

There is a one-to-one correspondence between hash-functions (pairs $(a,b), a \neq 0$) and pairs $(t_x, t_y), t_x \neq t_y$.

Therefore, we can view the first step (before the mod $n$-operation) as choosing a pair $(t_x, t_y), t_x \neq t_y$ uniformly at random.

What happens when we do the mod $n$ operation?

Fix a value $t_x$. There are $p - 1$ possible values for choosing $t_y$.

From the range $0, \ldots, p - 1$ the values $t_x, t_x + n, t_x + 2n, \ldots$ map to $t_x$ after the modulo-operation. These are at most $\lceil p/n \rceil$ values.

As $t_y \neq t_x$ there are

$$\left\lceil \frac{p}{n} \right\rceil - 1 \leq \frac{p}{n} + \frac{n-1}{n} - 1 \leq \frac{p-1}{n}$$

possibilities for choosing $t_y$ such that the final hash-value creates a collision.

This happens with probability at most $\frac{1}{n}$.
Universal Hashing

It is also possible to show that $\mathcal{H}$ is an (almost) pairwise independent class of hash-functions.

$$\frac{\left\lceil \frac{p}{n} \right\rceil^2}{p(p-1)} \leq \Pr_{t_x \neq t_y \in \mathbb{Z}_p^n} \left[ t_x \mod n = h_1 \quad t_y \mod n = h_2 \right] \leq \frac{\left\lceil \frac{p}{n} \right\rceil^2}{p(p-1)}$$

Note that the middle is the probability that $h(x) = h_1$ and $h(y) = h_2$. The total number of choices for $(t_x, t_y)$ is $p(p-1)$.

The number of choices for $t_x (t_y)$ such that $t_x \mod n = h_1 (t_y \mod n = h_2)$ lies between $\left\lfloor \frac{p}{n} \right\rfloor$ and $\left\lceil \frac{p}{n} \right\rceil$.

Universal Hashing

Definition 31

Let $d \in \mathbb{N}; q \geq (d + 1)n$ be a prime; and let $\bar{a} \in \{0, \ldots, q-1\}^{d+1}$. Define for $x \in \{0, \ldots, q-1\}$

$$h_{\bar{a}}(x) := \left( \sum_{i=0}^{d} a_i x^i \mod q \right) \mod n$$

Let $\mathcal{H}_H^d := \{h_{\bar{a}} \mid \bar{a} \in \{0, \ldots, q-1\}^{d+1}\}$. The class $\mathcal{H}_H^d$ is $(e, d + 1)$-independent.

Note that in the previous case we had $d = 1$ and chose $a_d \neq 0$.

Universal Hashing

Fix $\ell \leq d + 1$; let $x_1, \ldots, x_\ell \in \{0, \ldots, q-1\}$ be keys, and let $t_1, \ldots, t_\ell$ denote the corresponding hash-function values.

Let $A^\ell = \{h_{\bar{a}} \in \mathcal{H} \mid h_{\bar{a}}(x_i) = t_i \text{ for all } i \in \{1, \ldots, \ell\}\}$

Then $h_{\bar{a}} \in A^\ell \iff h_{\bar{a}} = f_{\bar{a}} \mod n$ and

$$f_{\bar{a}}(x_i) \in \{ t_i + \alpha \cdot n \mid \alpha \in \{0, \ldots, \left\lceil \frac{q}{n} \right\rceil - 1\} \} =: B_i$$

In order to obtain the cardinality of $A^\ell$ we choose our polynomial by fixing $d + 1$ points.

We first fix the values for inputs $x_1, \ldots, x_\ell$.

We have

$$|B_1| \cdot \cdots \cdot |B_\ell|$$

possibilities to do this (so that $h_{\bar{a}}(x_i) = t_i$).
Universal Hashing

Now, we choose \( d - \ell + 1 \) other inputs and choose their value arbitrarily. We have \( q^{d-\ell+1} \) possibilities to do this.

Therefore we have

\[
|B_1| \cdot \ldots \cdot |B_{\ell}| \cdot q^{d-\ell+1} \leq \left\lfloor \frac{q}{n} \right\rfloor^\ell \cdot q^{d-\ell+1}
\]

possibilities to choose \( \bar{a} \) such that \( h_{\bar{a}} \in A_\ell \).

Perfect Hashing

Suppose that we know the set \( S \) of actual keys (no insert/no delete). Then we may want to design a simple hash-function that maps all these keys to different memory locations.

Let \( m = |S| \). We could simply choose the hash-table size very large so that we don’t get any collisions.

Using a universal hash-function the expected number of collisions is

\[
E[\#\text{Collisions}] = \binom{m}{2} \cdot \frac{1}{n}.
\]

If we choose \( n = m^2 \) the expected number of collisions is strictly less than \( \frac{1}{2} \).

Can we get an upper bound on the probability of having collisions?

The probability of having 1 or more collisions can be at most \( \frac{1}{2} \) as otherwise the expectation would be larger than \( \frac{1}{2} \).
Perfect Hashing

We can find such a hash-function by a few trials.

However, a hash-table size of $n = m^2$ is very very high.

We construct a two-level scheme. We first use a hash-function that maps elements from $S$ to $m$ buckets.

Let $m_j$ denote the number of items that are hashed to the $j$-th bucket. For each bucket we choose a second hash-function that maps the elements of the bucket into a table of size $m_j^2$. The second function can be chosen such that all elements are mapped to different locations.

The total memory that is required by all hash-tables is $\mathcal{O}(\sum m_j^2)$. Note that $m_j$ is a random variable.

$$E\left[\sum m_j^2\right] = E\left[2 \sum \left(\frac{m_j}{2}\right) + \sum m_j\right]$$

$$= 2 E\left[\sum \left(\frac{m_j}{2}\right)\right] + E\left[\sum m_j\right]$$

The first expectation is simply the expected number of collisions, for the first level. Since we use universal hashing we have

$$= 2 \left(\frac{m}{2}\right) \frac{1}{m} + m = 2m - 1.$$
Cuckoo Hashing

Goal:
Try to generate a hash-table with constant worst-case search time in a dynamic scenario.

▶ Two hash-tables $T_1[0,\ldots,n-1]$ and $T_2[0,\ldots,n-1]$, with hash-functions $h_1$, and $h_2$.
▶ An object $x$ is either stored at location $T_1[h_1(x)]$ or $T_2[h_2(x)]$.
▶ A search clearly takes constant time if the above constraint is met.

Algorithm 13 Cuckoo-Insert($x$)
1: if $T_1[h_1(x)] = x \lor T_2[h_2(x)] = x$ then return
2: steps $\leftarrow 1$
3: while steps $\leq$ maxsteps do
4: exchange $x$ and $T_1[h_1(x)]$
5: if $x = \text{null}$ then return
6: exchange $x$ and $T_2[h_2(x)]$
7: if $x = \text{null}$ then return
8: steps $\leftarrow$ steps + 1
9: rehash() // change hash-functions; rehash everything
10: Cuckoo-Insert($x$)

▶ We call one iteration through the while-loop a step of the algorithm.
▶ We call a sequence of iterations through the while-loop without the termination condition becoming true a phase of the algorithm.
▶ We say a phase is successful if it is not terminated by the maxstep-condition, but the while loop is left because $x = \text{null}$.
Cuckoo Hashing

What is the expected time for an insert-operation?

We first analyze the probability that we end-up in an infinite loop (that is then terminated after \( \maxsteps \) steps).

Formally what is the probability to enter an infinite loop that touches \( s \) different keys?

A cycle-structure of size \( s \) is defined by

- \( s - 1 \) different cells (alternating btw. cells from \( T_1 \) and \( T_2 \)).
- \( s \) distinct keys \( x = x_1, x_2, \ldots, x_s \), linking the cells.
- The leftmost cell is “linked forward” to some cell on the right.
- The rightmost cell is “linked backward” to a cell on the left.
- One link represents key \( x \); this is where the counting starts.

A cycle-structure is active if for every key \( x_\ell \) (linking a cell \( p_i \) from \( T_1 \) and a cell \( p_j \) from \( T_2 \)) we have

\[
 h_1(x_\ell) = p_i \quad \text{and} \quad h_2(x_\ell) = p_j
\]

Observation:
If during a phase the insert-procedure runs into a cycle there must exist an active cycle structure of size \( s \geq 3 \).
Cuckoo Hashing

What is the probability that all keys in a cycle-structure of size \( s \) correctly map into their \( T_1 \)-cell?

This probability is at most \( \frac{\mu}{m^2} \) since \( h_1 \) is a \((\mu, s)\)-independent hash-function.

What is the probability that all keys in the cycle-structure of size \( s \) correctly map into their \( T_2 \)-cell?

This probability is at most \( \frac{\mu}{m^2} \) since \( h_2 \) is a \((\mu, s)\)-independent hash-function.

These events are independent.

Cuckoo Hashing

The number of cycle-structures of size \( s \) is at most

\[
  s^3 \cdot n^{s-1} \cdot m^{s-1} .
\]

- There are at most \( s^2 \) possibilities where to attach the forward and backward links.
- There are at most \( s \) possibilities to choose where to place key \( x \).
- There are \( m^{s-1} \) possibilities to choose the keys apart from \( x \).
- There are \( n^{s-1} \) possibilities to choose the cells.

Cuckoo Hashing

The probability that a given cycle-structure of size \( s \) is active is at most \( \frac{\mu}{m^2} \).

What is the probability that there exists an active cycle structure of size \( s \)?

The probability that there exists an active cycle-structure is therefore at most

\[
\sum_{s=3}^{\infty} s^3 \cdot n^{s-1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}} = \frac{\mu^2}{nm} \sum_{s=3}^{\infty} s^3 \left( \frac{m}{n} \right)^s \leq \frac{\mu^2}{m^2} \sum_{s=3}^{\infty} s^3 \left( \frac{1}{1+\epsilon} \right)^s \leq O \left( \frac{1}{m^2} \right) .
\]

Here we used the fact that \((1+\epsilon)m \leq n\).

Hence,

\[
\Pr[\text{cycle}] = O \left( \frac{1}{m^2} \right) .
\]
Now, we analyze the probability that a phase is not successful without running into a closed cycle.

Consider the sequence of not necessarily distinct keys starting with $x$ in the order that they are visited during the phase.

**Lemma 32**

If the sequence is of length $p$ then there exists a sub-sequence of at least $\frac{p+2}{3}$ keys starting with $x$ of distinct keys.

Proof.

Let $i$ be the number of keys (including $x$) that we see before the first repeated key. Let $j$ denote the total number of distinct keys.

The sequence is of the form:

$x = x_1 \rightarrow x_2 \rightarrow \cdots \rightarrow x_i \rightarrow x_r \rightarrow x_{r-1} \rightarrow \cdots \rightarrow x_1 \rightarrow x_{i+1} \rightarrow \cdots \rightarrow x_j$

As $r \leq i - 1$ the length $p$ of the sequence is

$$p = i + r + (j - i) \leq i + j - 1.$$  

Either sub-sequence $x_1 \rightarrow x_2 \rightarrow \cdots \rightarrow x_i$ or sub-sequence $x_1 \rightarrow x_{i+1} \rightarrow \cdots \rightarrow x_j$ has at least $\frac{p+2}{3}$ elements.

A path-structure of size $s$ is defined by

- $s + 1$ different cells (alternating btw. cells from $T_1$ and $T_2$).
- $s$ distinct keys $x = x_1, x_2, \ldots, x_s$, linking the cells.
- The leftmost cell is either from $T_1$ or $T_2$.

The probability that a given path-structure of size $s$ is active is at most $\mu^2 n^{2s}$.

The probability that there exists an active path-structure of size $s$ is at most

$$2 \cdot n^{s+1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}} \leq 2 \mu^2 \left(\frac{m}{n}\right)^{s-1} \leq 2 \mu^2 \left(\frac{1}{1+\epsilon}\right)^{s-1}$$

Plugging in $s = (2t + 2)/3$ gives

$$\leq 2 \mu^2 \left(\frac{1}{1+\epsilon}\right)^{(2t+2)/3-1} = 2 \mu^2 \left(\frac{1}{1+\epsilon}\right)^{(2t-1)/3}.$$
Cuckoo Hashing

So far we estimated
\[ \Pr[\text{cycle}] \leq O\left(\frac{1}{m^2}\right) \]
and
\[ \Pr[\text{unsuccessful} \mid \text{no cycle}] \leq O\left(\frac{1}{m^2}\right) \]

Observe that
\[ \Pr[\text{successful}] = \Pr[\text{no cycle}] - \Pr[\text{unsuccessful} \mid \text{no cycle}] \geq c \cdot \Pr[\text{no cycle}] \]
for a suitable constant \( c > 0 \).

This is a very weak (and trivial) statement but still sufficient for our asymptotic analysis.

Hence,
\[
\mathbb{E}[\text{number of steps} \mid \text{phase successful}] \leq \frac{1}{c} \sum_{t=1}^{\text{maxsteps}} \Pr[\text{search takes at least } t \text{ steps} \mid \text{phase successful}]
\]
\[ \leq \frac{1}{c} \sum_{t=1}^{\text{maxsteps}} \frac{2^t}{(1+\epsilon)^{(2^t-1)/3}} \leq \frac{2^t}{c(1+\epsilon)^{1/3}} \sum_{t=0}^{\infty} \left(\frac{1}{1+\epsilon}\right)^{2^t/3} = \Theta(1) . \]

This means the expected cost for a successful phase is constant (even after accounting for the cost of the incomplete step that finishes the phase).

Cuckoo Hashing

The expected number of complete steps in the **successful phase** of an insert operation is:
\[
\mathbb{E}[\text{number of steps} \mid \text{phase successful}] = \sum_{t=1}^{\text{maxsteps}} \Pr[\text{search takes at least } t \text{ steps} \mid \text{phase successful}]
\]

We have
\[ \Pr[\text{search at least } t \text{ steps} \mid \text{successful}] \]
\[ = \frac{\Pr[\text{search at least } t \text{ steps} \land \text{successful}]}{\Pr[\text{successful}]} \]
\[ \leq \frac{1}{c} \frac{\Pr[\text{search at least } t \text{ steps} \land \text{successful}]}{\Pr[\text{no cycle}]} \]
\[ \leq \frac{1}{c} \frac{\Pr[\text{search at least } t \text{ steps} \land \text{no cycle}]}{\Pr[\text{no cycle}]} \]
\[ = \frac{1}{c} \Pr[\text{search at least } t \text{ steps} \mid \text{no cycle}] . \]

A phase that is not successful induces cost for doing a complete rehash (this dominates the cost for the steps in the phase).

The probability that a phase is not successful is \( p = O\left(\frac{1}{m^2}\right) \) (probability \( O\left(\frac{1}{m^2}\right) \) of running into a cycle and probability \( O\left(\frac{1}{m^2}\right) \) of reaching \( \text{maxsteps} \) without running into a cycle).

A rehash try requires \( m \) insertions and takes expected constant time per insertion. It fails with probability \( p := \Theta\left(\frac{1}{m}\right) \).

The expected number of unsuccessful rehashes is
\[ \sum_{t=1}^{\text{maxsteps}} p^t = \frac{1}{1-p} - 1 = \frac{p}{1-p} = \Theta(p) . \]

Therefore the expected cost for re-hashes is \( \Theta(m) \cdot \Theta(p) = \Theta(1) \).
Formal Proof

Let \( Y_i \) denote the event that the \( i \)-th rehash does not lead to a valid configuration (assuming \( i \)-th rehash occurs) (i.e., one of the \( m + 1 \) insertions fails):

\[
\Pr[Y_i] \leq (m + 1) \cdot \Theta(1/m^2) = \Theta(1/m) =: p.
\]

Let \( Z_i \) denote the event that the \( i \)-th rehash occurs:

\[
\Pr[Z_i] \leq \Pr[\bigwedge_{j=1}^{i-1} Y_j] \leq p^{i-1}
\]

Let \( X_s^i, s \in \{1, \ldots, m + 1\} \) denote the cost for inserting the \( s \)-th element during the \( i \)-th rehash (assuming \( i \)-th rehash occurs):

\[
E[X_s^i] = E[\text{steps | phase successful}] \cdot \Pr[\text{phase successful}]
+ \maxsteps \cdot \Pr[\text{not successful}] = \Theta(1).
\]

The expected cost for all rehashes is

\[
E \left[ \sum_i \sum_s Z_i X_s^i \right]
\]

Note that \( Z_i \) is independent of \( X_j^i, j \geq i \) (however, it is not independent of \( X_j^s, j < i \)). Hence,

\[
E \left[ \sum_i \sum_s Z_i X_s^i \right] = \sum_i \sum_s E[Z_i] \cdot E[X_s^i]
\]

\[
\leq \Theta(1) \cdot \sum_i p^{i-1}
\]

\[
\leq \Theta(1) \cdot \frac{1}{1 - p}
\]

\[
= \Theta(1).
\]

Cuckoo Hashing

What kind of hash-functions do we need?

Since \( \maxsteps \) is \( \Theta(\log m) \) the largest size of a path-structure or cycle-structure contains just \( \Theta(\log m) \) different keys. Therefore, it is sufficient to have \( (\mu, \Theta(\log m)) \)-independent hash-functions.

Cuckoo Hashing

How do we make sure that \( n \geq (1 + \epsilon)m \)?

- Let \( \alpha := 1/(1 + \epsilon) \).
- Keep track of the number of elements in the table. When \( m \geq \alpha n \) we double \( n \) and do a complete re-hash (table-expand).
- Whenever \( m \) drops below \( \alpha n / 4 \) we divide \( n \) by 2 and do a rehash (table-shrink).
- Note that right after a change in table-size we have \( m = \alpha n / 2 \). In order for a table-expand to occur at least \( \alpha n / 2 \) insertions are required. Similar, for a table-shrink at least \( \alpha n / 4 \) deletions must occur.
- Therefore we can amortize the rehash cost after a change in table-size against the cost for insertions and deletions.
Cuckoo Hashing

Lemma 33

Cuckoo Hashing has an expected constant insert-time and a worst-case constant search-time.

Note that the above lemma only holds if the fill-factor (number of keys/total number of hash-table slots) is at most \( \frac{1}{2(1+\epsilon)} \).

[The \( 1/2(1+\epsilon) \) fill-factor comes from the fact that the total hash-table is of size \( 2n \) (because we have two tables of size \( n \)); moreover \( m \leq (1+\epsilon)n \).]

8 Priority Queues

A Priority Queue \( S \) is a dynamic set data structure that supports the following operations:

- \( S\text{-build}(x_1, \ldots, x_n) \): Creates a data-structure that contains just the elements \( x_1, \ldots, x_n \).
- \( S\text{-insert}(x) \): Adds element \( x \) to the data-structure.
- \( \text{element } S\text{-minimum}() \): Returns an element \( x \in S \) with minimum key-value \( \text{key}[x] \).
- \( \text{element } S\text{-delete-min()} \): Deletes the element with minimum key-value from \( S \) and returns it.
- \( \text{boolean } S\text{-is-empty()} \): Returns \( \text{true} \) if the data-structure is empty and \( \text{false} \) otherwise.

Sometimes we also have

- \( S\text{-merge}(S') \): \( S := S \cup S' \); \( S' := \emptyset \).

Hashing

Bibliography


Chapter 4 of [M508] contains a detailed description about Hashing with Linear Probing and Hashing with Chaining. Also the Perfect Hashing scheme can be found there.

The analysis of Hashing with Chaining under the assumption of uniform hashing can be found in Chapter 11.2 of [CLRS90]. Chapter 11.3.3 describes Universal Hashing. Collision resolution with Open Addressing is described in Chapter 11.4. Chapter 11.5 describes the Perfect Hashing scheme.

Reference for Cuckoo Hashing???
Dijkstra’s Shortest Path Algorithm

Algorithm 14 Shortest-Path($G = (V, E, d), s \in V$)

1: Input: weighted graph $G = (V, E, d)$; start vertex $s$
2: Output: key-field of every node contains distance from $s$
3: $S$.build(); // build empty priority queue
4: for all $v \in V \setminus \{s\}$ do
5: $v$.key $\leftarrow \infty$
6: $h_v \leftarrow S$.insert($v$)
7: $s$.key $\leftarrow 0$; $S$.insert($s$)
8: while $S$.is-empty() = false do
9: $v \leftarrow S$.delete-min()
10: for all $x \in V$ s.t. $(v, x) \in E$ do
11: if $x$.key $> v$.key $+ d(v, x)$ then
12: $S$.decrease-key($h_x$, $v$.key $+ d(v, x)$);
13: $x$.key $\leftarrow v$.key $+ d(v, x)$;

Prim’s Minimum Spanning Tree Algorithm

Algorithm 15 Prim-MST($G = (V, E, d), s \in V$)

1: Input: weighted graph $G = (V, E, d)$; start vertex $s$
2: Output: pred-fields encode MST
3: $S$.build(); // build empty priority queue
4: for all $v \in V \setminus \{s\}$ do
5: $v$.key $\leftarrow \infty$
6: $h_v \leftarrow S$.insert($v$)
7: $s$.key $\leftarrow 0$; $S$.insert($s$)
8: while $S$.is-empty() = false do
9: $v \leftarrow S$.delete-min()
10: for all $x \in V$ s.t. $(v, x) \in E$ do
11: if $x$.key $> d(v, x)$ then
12: $S$.decrease-key($h_x$, $d(v, x)$);
13: $x$.key $\leftarrow d(v, x)$;
14: $x$.pred $\leftarrow v$;

Analysis of Dijkstra and Prim

Both algorithms require:
- 1 build() operation
- $|V|$ insert() operations
- $|V|$ delete-min() operations
- $|V|$ is-empty() operations
- $|E|$ decrease-key() operations

How good a running time can we obtain?

<table>
<thead>
<tr>
<th>Operation</th>
<th>Binary Heap</th>
<th>BST</th>
<th>Binomial Heap</th>
<th>Fibonacci Heap*</th>
</tr>
</thead>
<tbody>
<tr>
<td>build</td>
<td>$n$</td>
<td>$n \log n$</td>
<td>$n \log n$</td>
<td>$n$</td>
</tr>
<tr>
<td>minimum</td>
<td>1</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>1</td>
</tr>
<tr>
<td>is-empty</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>insert</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>1</td>
</tr>
<tr>
<td>delete</td>
<td>$\log n^{**}$</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
</tr>
<tr>
<td>delete-min</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
</tr>
<tr>
<td>decrease-key</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>1</td>
</tr>
<tr>
<td>merge</td>
<td>$n$</td>
<td>$n \log n$</td>
<td>$n \log n$</td>
<td>1</td>
</tr>
</tbody>
</table>

Note that most applications use build() only to create an empty heap which then costs time 1.

* Fibonacci heaps only give an amortized guarantee.
** The standard version of binary heaps is not addressable. Hence, it does not support a delete.
8 Priority Queues

Using Binary Heaps, Prim and Dijkstra run in time $O((|V| + |E|) \log |V|)$.

Using Fibonacci Heaps, Prim and Dijkstra run in time $O(|V| \log |V| + |E|)$.

8.1 Binary Heaps

- Nearly complete binary tree; only the last level is not full, and this one is filled from left to right.
- **Heap property**: A node’s key is not larger than the key of one of its children.

Binary Heaps

Operations:
- **minimum()**: return the root-element. Time $O(1)$.
- **is-empty()**: check whether root-pointer is null. Time $O(1)$.

Maintain a pointer to the **last element $x$**.
- We can compute the predecessor of $x$ (last element when $x$ is deleted) in time $O(\log n)$.
  - go up until the last edge used was a right edge.
  - go left; go right until you reach a leaf
  - if you hit the root on the way up, go to the rightmost element
8.1 Binary Heaps

Maintain a pointer to the last element \( x \).

- We can compute the successor of \( x \) (last element when an element is inserted) in time \( O(\log n) \).
  - go up until the last edge used was a left edge.
  - go right; go left until you reach a null-pointer.
  - if you hit the root on the way up, go to the leftmost element; insert a new element as a left child;

![Binary Heap Diagram]

Insert

1. Insert element at successor of \( x \).
2. Exchange with parent until heap property is fulfilled.

![Insert Diagram]

Note that an exchange can either be done by moving the data or by changing pointers. The latter method leads to an addressable priority queue.

Delete

1. Exchange the element to be deleted with the element \( e \) pointed to by \( x \).
2. Restore the heap-property for the element \( e \).

![Delete Diagram]

At its new position \( e \) may either travel up or down in the tree (but not both directions).

Binary Heaps

Operations:

- **minimum()**: return the root-element. Time \( O(1) \).
- **is-empty()**: check whether root-pointer is null. Time \( O(1) \).
- **insert(k)**: insert at successor of \( x \) and bubble up. Time \( O(\log n) \).
- **delete(h)**: swap with \( x \) and bubble up or sift-down. Time \( O(\log n) \).
Build Heap

We can build a heap in linear time:

$$\sum_{\text{levels } \ell} 2^\ell \cdot (h - \ell) = \sum_i i 2^{h-i} = O(2^h) = O(n)$$

Binary Heaps

Operations:

- **minimum()**: Return the root-element. Time $O(1)$.
- **is-empty()**: Check whether root-pointer is null. Time $O(1)$.
- **insert(k)**: Insert at $x$ and bubble up. Time $O(\log n)$.
- **delete(h)**: Swap with $x$ and bubble up or sift-down. Time $O(\log n)$.
- **build(x_1, \ldots, x_n)**: Insert elements arbitrarily; then do sift-down operations starting with the lowest layer in the tree. Time $O(n)$.

Binary Heaps

The standard implementation of binary heaps is via arrays. Let $A[0, \ldots, n-1]$ be an array

- The parent of $i$-th element is at position $\lfloor \frac{i-1}{2} \rfloor$.
- The left child of $i$-th element is at position $2i+1$.
- The right child of $i$-th element is at position $2i+2$.

Finding the successor of $x$ is much easier than in the description on the previous slide. Simply increase or decrease $x$.

The resulting binary heap is not addressable. The elements don’t maintain their positions and therefore there are no stable handles.

8.2 Binomial Heaps

<table>
<thead>
<tr>
<th>Operation</th>
<th>Binary Heap</th>
<th>BST</th>
<th>Binomial Heap</th>
<th>Fibonacci Heap</th>
</tr>
</thead>
<tbody>
<tr>
<td>build</td>
<td>$n$</td>
<td>$n \log n$</td>
<td>$n \log n$</td>
<td>$n$</td>
</tr>
<tr>
<td>minimum</td>
<td>$1$</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$1$</td>
</tr>
<tr>
<td>is-empty</td>
<td>$1$</td>
<td>$1$</td>
<td>$1$</td>
<td>$1$</td>
</tr>
<tr>
<td>insert</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$1$</td>
</tr>
<tr>
<td>delete</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
</tr>
<tr>
<td>delete-min</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
</tr>
<tr>
<td>decrease-key</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$1$</td>
</tr>
<tr>
<td>merge</td>
<td>$n$</td>
<td>$n \log n$</td>
<td>$\log n$</td>
<td>$1$</td>
</tr>
</tbody>
</table>
Binomial Trees

Properties of Binomial Trees

- $B_k$ has $2^k$ nodes.
- $B_k$ has height $k$.
- The root of $B_k$ has degree $k$.
- $B_k$ has $\binom{k}{\ell}$ nodes on level $\ell$.
- Deleting the root of $B_k$ gives trees $B_0, B_1, \ldots, B_{k-1}$.

Deleting the root of $B_5$ leaves sub-trees $B_4, B_3, B_2, B_1$, and $B_0$.

Deleting the leaf furthest from the root (in $B_5$) leaves a path that connects the roots of sub-trees $B_4, B_3, B_2, B_1$, and $B_0$. 
Binomial Trees

The number of nodes on level \( \ell \) in tree \( B_k \) is therefore

\[
\binom{k-1}{\ell-1} + \binom{k-1}{\ell} = \binom{k}{\ell}
\]

8.2 Binomial Heaps

How do we implement trees with non-constant degree?

- The children of a node are arranged in a circular linked list.
- A child-pointer points to an arbitrary node within the list.
- A parent-pointer points to the parent node.
- Pointers \( x.\text{left} \) and \( x.\text{right} \) point to the left and right sibling of \( x \) (if \( x \) does not have siblings then \( x.\text{left} = x.\text{right} = x \)).

The binomial tree \( B_k \) is a sub-graph of the hypercube \( H_k \).

The parent of a node with label \( b_n, \ldots, b_1, b_0 \) is obtained by setting the least significant 1-bit to 0.

The \( \ell \)-th level contains nodes that have \( \ell \) 1’s in their label.

8.2 Binomial Heaps

- Given a pointer to a node \( x \) we can splice out the sub-tree rooted at \( x \) in constant time.
- We can add a child-tree \( T \) to a node \( x \) in constant time if we are given a pointer to \( x \) and a pointer to the root of \( T \).
In a binomial heap the keys are arranged in a collection of binomial trees.

Every tree fulfills the heap-property

There is at most one tree for every dimension/order. For example the above heap contains trees $B_0$, $B_1$, and $B_4$.

Properties of a heap with $n$ keys:

- Let $n = b_d b_{d-1} \ldots b_0$ denote binary representation of $n$.
- The heap contains tree $B_i$ iff $b_i = 1$.
- Hence, at most $\lceil \log n \rceil + 1$ trees.
- The minimum must be contained in one of the roots.
- The height of the largest tree is at most $\lceil \log n \rceil$.
- The trees are stored in a single-linked list; ordered by dimension/size.

The merge-operation is instrumental for binomial heaps.

A merge is easy if we have two heaps with different binomial trees. We can simply merge the tree-lists.

Otherwise, we cannot do this because the merged heap is not allowed to contain two trees of the same order.

Merging two trees of the same size: Add the tree with larger root-value as a child to the other tree.

For more trees the technique is analogous to binary addition.

Note that we do not just do a concatenation as we want to keep the trees in the list sorted according to size.
8.2 Binomial Heaps

**S. merge(S2):**
- Analogous to binary addition.
- Time is proportional to the number of trees in both heaps.
- Time: $O(\log n)$.

All other operations can be reduced to `merge()`.

**S. insert(x):**
- Create a new heap $S'$ that contains just the element $x$.
- Execute $S.\text{merge}(S')$.
- Time: $O(\log n)$.

**S. minimum():**
- Find the minimum key-value among all roots.
- Time: $O(\log n)$. 
8.2 Binomial Heaps

S. delete-min():
▶ Find the minimum key-value among all roots.
▶ Remove the corresponding tree $T_{\text{min}}$ from the heap.
▶ Create a new heap $S'$ that contains the trees obtained from $T_{\text{min}}$ after deleting the root (note that these are just $O(\log n)$ trees).
▶ Compute $S$.merge($S'$).
▶ Time: $O(\log n)$.

S. decrease-key(handle $h$):
▶ Decrease the key of the element pointed to by $h$.
▶ Bubble the element up in the tree until the heap property is fulfilled.
▶ Time: $O(\log n)$ since the trees have height $O(\log n)$.

8.3 Fibonacci Heaps

Collection of trees that fulfill the heap property.
Structure is much more relaxed than binomial heaps.
8.3 Fibonacci Heaps

Additional implementation details:

- Every node $x$ stores its degree in a field $x\.degree$. Note that this can be updated in constant time when adding a child to $x$.
- Every node stores a boolean value $x\.marked$ that specifies whether $x$ is marked or not.

The potential function:

- $t(S)$ denotes the number of trees in the heap.
- $m(S)$ denotes the number of marked nodes.
- We use the potential function $\Phi(S) = t(S) + 2m(S)$.

The potential is $\Phi(S) = 5 + 2 \cdot 3 = 11$.

We assume that one unit of potential can pay for a constant amount of work, where the constant is chosen “big enough” (to take care of the constants that occur).

To make this more explicit we use $c$ to denote the amount of work that a unit of potential can pay for.

8.3 Fibonacci Heaps

$S\.minimum()$

- Access through the min-pointer.
- Actual cost $\mathcal{O}(1)$.
- No change in potential.
- Amortized cost $\mathcal{O}(1)$. 
### 8.3 Fibonacci Heaps

#### S. merge($S'$)
- Merge the root lists.
- Adjust the min-pointer

In the figure below the dashed edges are replaced by red edges.
The minimum of the left heap becomes the new minimum of the merged heap.

#### Running time:
- Actual cost $O(1)$.
- No change in potential.
- Hence, amortized cost is $O(1)$.

---

#### S. insert($x$)
- Create a new tree containing $x$.
- Insert $x$ into the root-list.
- Update min-pointer, if necessary.

$x$ is inserted next to the min-pointer as this is our entry point into the root-list.

#### Running time:
- Actual cost $O(1)$.
- Change in potential is +1.
- Amortized cost is $c + O(1) = O(1)$.

---

#### S. delete-min($x$)
- Delete minimum; add child-trees to heap; time: $D(\text{min}) \cdot O(1)$.
- Update min-pointer; time: $(t + D(\text{min})) \cdot O(1)$.

$D(\text{min})$ is the number of children of the node that stores the minimum.

#### Running time:
- Delete minimum; add child-trees to heap; time: $D(\text{min}) \cdot O(1)$.
- Update min-pointer; time: $(t + D(\text{min})) \cdot O(1)$.

$D(\text{min})$ is the number of children of the node that stores the minimum.

- Consolidate root-list so that no roots have the same degree. Time $t \cdot O(1)$ (see next slide).
During the consolidation we traverse the root list. Whenever we discover two trees that have the same degree we merge these trees. In order to efficiently check whether two trees have the same degree, we use an array that contains for every degree value \( d \) a pointer to a tree left of the current pointer whose root has degree \( d \) (if such a tree exist).
8.3 Fibonacci Heaps

Consolidate:

Consolidate:
8.3 Fibonacci Heaps

Consolidate:

\[
\begin{array}{c}
0 & 1 & 2 & 3 \\
\downarrow & \downarrow & \downarrow & \downarrow \\
\text{min} & 7 & 23 & 30
\end{array}
\]

### Actual cost for delete-min()
- At most \( D_n + t \) elements in root-list before consolidate.
- Actual cost for a delete-min is at most \( O(1) \cdot (D_n + t) \).
- Hence, there exists \( c_1 \) s.t. actual cost is at most \( c_1 \cdot (D_n + t) \).

### Amortized cost for delete-min()
- \( t' \leq D_n + 1 \) as degrees are different after consolidating.
- Therefore \( \Delta \Phi \leq D_n + 1 - t \);
- We can pay \( c \cdot (t - D_n - 1) \) from the potential decrease.
- The amortized cost is
  \[
  c_1 \cdot (D_n + t) - c \cdot (t - D_n - 1) 
  \leq (c_1 + c)D_n + (c_1 - c)t + c \leq 2c(D_n + 1) \leq O(D_n)
  \]
  for \( c \geq c_1 \).

---

8.3 Fibonacci Heaps

If the input trees of the consolidation procedure are binomial trees (for example only singleton vertices) then the output will be a set of distinct binomial trees, and, hence, the Fibonacci heap will be (more or less) a Binomial heap right after the consolidation.

If we do not have delete or decrease-key operations then \( D_n \leq \log n \).

---

**Fibonacci Heaps: decrease-key(handle h, v)**

### Case 1: decrease-key does not violate heap-property
- Just decrease the key-value of element referenced by \( h \).
  Nothing else to do.
Fibonacci Heaps: decrease-key(handle h, v)

Case 2: heap-property is violated, but parent is not marked
- Decrease key-value of element x reference by h.
- If the heap-property is violated, cut the parent edge of x, and make x into a root.
- Adjust min-pointers, if necessary.
- Mark the (previous) parent of x (unless it’s a root).

Case 3: heap-property is violated, and parent is marked
- Decrease key-value of element x reference by h.
- Cut the parent edge of x, and make x into a root.
- Adjust min-pointers, if necessary.
- Continue cutting the parent until you arrive at an unmarked node.
Fibonacci Heaps: decrease-key(handle $h, v$)

**Case 3: heap-property is violated, and parent is marked**
- Decrease key-value of element $x$ reference by $h$.
- Cut the parent edge of $x$, and make $x$ into a root.
- Adjust min-pointers, if necessary.
- Execute the following:
  - $p ← \text{parent}[x]$;
  - while ($p$ is marked)
    - $pp ← \text{parent}[p]$;
    - cut of $p$; make it into a root; unmark it;
    - $p ← pp$;
  - if $p$ is unmarked and not a root mark it;

Amortized cost:
- $t' = t + \ell$, as every cut creates one new root.
- $m' \leq m - (\ell - 1) + 1 = m - \ell + 2$, since all but the first cut unmarks a node; the last cut may mark a node.
- $\Delta \Phi \leq \ell + 2(-\ell + 2) = 4 - \ell$
- Amortized cost is at most $c_2(\ell + 1) + c(4 - \ell) \leq (c_2 - c)\ell + 4c + c_2 = O(1)$, if $c \geq c_2$.

**Delete node**

$H. \text{delete}(x)$:
- decrease value of $x$ to $-\infty$.
- delete-min.

Amortized cost: $O(D_n)$
- $O(1)$ for decrease-key.
- $O(D_n)$ for delete-min.

**Lemma 34**

Let $x$ be a node with degree $k$ and let $y_1, \ldots, y_k$ denote the children of $x$ in the order that they were linked to $x$. Then

$$\text{degree}(y_i) = \begin{cases} 0 & \text{if } i = 1 \\ i - 2 & \text{if } i > 1 \end{cases}$$

The marking process is very important for the proof of this lemma. It ensures that a node can have lost at most one child since the last time it became a non-root node. When losing a first child the node gets marked; when losing the second child it is cut from the parent and made into a root.
8.3 Fibonacci Heaps

Proof

- When \( y_i \) was linked to \( x \), at least \( y_1, \ldots, y_{i-1} \) were already linked to \( x \).
- Hence, at this time \( \deg(x) \geq i - 1 \), and therefore also \( \deg(y_i) \geq i - 1 \) as the algorithm links nodes of equal degree only.
- Since, then \( y_i \) has lost at most one child.
- Therefore, \( \deg(y_i) \geq i - 2 \).

\[
\phi = \frac{1}{2}(1 + \sqrt{5}) \text{ denotes the golden ratio.}
\]

Note that \( \phi^2 = 1 + \phi \).

Definition 35
Consider the following non-standard Fibonacci type sequence:

\[
F_k = \begin{cases} 
1 & \text{if } k = 0 \\
2 & \text{if } k = 1 \\
F_{k-1} + F_{k-2} & \text{if } k \geq 2 
\end{cases}
\]

Facts:
1. \( F_k \geq \phi^k \).
2. For \( k \geq 2 \): \( F_k = 2 + \sum_{i=0}^{k-2} F_i \).

The above facts can be easily proved by induction. From this it follows that \( s_k \geq F_k \geq \phi^k \), which gives that the maximum degree in a Fibonacci heap is logarithmic.
Priority Queues

Bibliography


Binary heaps are covered in [CLRS90] in combination with the heapsort algorithm in Chapter 6. Fibonacci heaps are covered in detail in Chapter 19. Problem 19-2 in this chapter introduces Binomial heaps.

Chapter 6 in [MS08] covers Priority Queues. Chapter 6.2.2 discusses Fibonacci heaps. Binomial heaps are dealt with in Exercise 6.11.

9 Union Find

Applications:

- Keep track of the connected components of a dynamic graph that changes due to insertion of nodes and edges.
- Kruskal’s Minimum Spanning Tree Algorithm

Algorithm 16 Kruskal-MST \( G = (V, E), w \)

1: \( A \leftarrow \emptyset \);
2: \textbf{for all} \( v \in V \) \textbf{do}
3: \( v.\text{set} \leftarrow {\mathcal P}.\text{makeset}(v.\text{label}) \)
4: \text{sort edges in non-decreasing order of weight} \( w \)
5: \textbf{for all} \( (u, v) \in E \) in non-decreasing order \textbf{do}
6: \textbf{if} \( {\mathcal P}.\text{find}(u.\text{set}) \neq {\mathcal P}.\text{find}(v.\text{set}) \) \textbf{then}
7: \( A \leftarrow A \cup \{(u, v)\} \)
8: \( {\mathcal P}.\text{union}(u.\text{set}, v.\text{set}) \)

9 Union Find
List Implementation

- The elements of a set are stored in a list; each node has a backward pointer to the head.
- The head of the list contains the identifier for the set and a field that stores the size of the set.

- makerset(x) can be performed in constant time.
- find(x) can be performed in constant time.

union(x, y)

- Determine sets $S_x$ and $S_y$.
- Traverse the smaller list (say $S_y$), and change all backward pointers to the head of list $S_x$.
- Insert list $S_y$ at the head of $S_x$.
- Adjust the size-field of list $S_x$.
- Time: $\min\{|S_x|, |S_y|\}$. 

List Implementation

- for $S_x$:
  - $x$'s backward pointer is set to be the head of the list.
  - Size of $S_x$ is increased by 1.

- for $S_y$:
  - Size of $S_y$ is decreased by 1.
  - $S_y$ is moved to the head of $S_x$.

- For other elements:
  - The backward pointers are unchanged.

- Time: $\min\{|S_x|, |S_y|\}$. 

List Implementation

Running times:
- find(x): constant
- makeset(x): constant
- union(x, y): O(n), where n denotes the number of elements contained in the set system.

The Accounting Method for Amortized Time Bounds

- There is a bank account for every element in the data structure.
- Initially the balance on all accounts is zero.
- Whenever for an operation the amortized time bound exceeds the actual cost, the difference is credited to some bank accounts of elements involved.
- Whenever for an operation the actual cost exceeds the amortized time bound, the difference is charged to bank accounts of some of the elements involved.
- If we can find a charging scheme that guarantees that balances always stay positive the amortized time bounds are proven.

List Implementation

Lemma 36
The list implementation for the ADT union find fulfills the following amortized time bounds:
- find(x): O(1).
- makeset(x): O(log n).
- union(x, y): O(1).

List Implementation

- For an operation whose actual cost exceeds the amortized cost we charge the excess to the elements involved.
- In total we will charge at most O(log n) to an element (regardless of the request sequence).
- For each element a makeset operation occurs as the first operation involving this element.
- We inflate the amortized cost of the makeset operation to O(log n), i.e., at this point we fill the bank account of the element to O(log n).
- Later operations charge the account but the balance never drops below zero.
**List Implementation**

makeset(x): The actual cost is $O(1)$. Due to the cost inflation the amortized cost is $O(\log n)$.

find(x): For this operation we define the amortized cost and the actual cost to be the same. Hence, this operation does not change any accounts. Cost: $O(1)$.

union(x, y):
- If $S_x = S_y$ the cost is constant; no bank accounts change.
- Otw. the actual cost is $O(\min\{|S_x|, |S_y|\})$.
- Assume wlog. that $S_x$ is the smaller set; let $c$ denote the hidden constant, i.e., the actual cost is at most $c \cdot |S_x|$.
- Charge $c$ to every element in set $S_x$.

**Implementation via Trees**

- Maintain nodes of a set in a tree.
- The root of the tree is the label of the set.
- Only pointer to parent exists; we cannot list all elements of a given set.
- Example:

```
10
  12 5
  2

6
  9 7
  3 17

16
  19 23
  8

Set system \{2, 5, 10, 12\}, \{3, 6, 7, 8, 9, 14, 17\}, \{16, 19, 23\}.
```

**Lemma 37**

An element is charged at most $\lceil \log_2 n \rceil$ times, where $n$ is the total number of elements in the set system.

**Proof.** Whenever an element $x$ is charged the number of elements in $x$'s set doubles. This can happen at most $\lceil \log n \rceil$ times.

**Implementation via Trees**

makeset(x)
- Create a singleton tree. Return pointer to the root.
- Time: $O(1)$.

find(x)
- Start at element $x$ in the tree. Go upwards until you reach the root.
- Time: $O(\text{level}(x))$, where $\text{level}(x)$ is the distance of element $x$ to the root in its tree. Not constant.
Implementation via Trees

To support union we store the size of a tree in its root.

\[
\text{union}(x, y)
\]

- Perform \(a \leftarrow \text{find}(x); \ b \leftarrow \text{find}(y)\). Then: \(\text{link}(a, b)\).
- \(\text{link}(a, b)\) attaches the smaller tree as the child of the larger.
- In addition it updates the size-field of the new root.

\[
\begin{array}{c}
\text{5} \\
\text{3} \\
\text{2} \\
\text{1}
\end{array}
\]

\[
\begin{array}{c}
\text{11} \\
\text{7} \\
\text{3} \\
\text{2}
\end{array}
\]

\[
\begin{array}{c}
\text{10} \\
\text{5} \\
\text{1} \\
\text{2}
\end{array}
\]

- Time: constant for \(\text{link}(a, b)\) plus two find-operations.

Path Compression

\text{find}(x):

- Go upward until you find the root.
- Re-attach all visited nodes as children of the root.
- Speeds up successive find-operations.

\[
\begin{array}{c}
\text{5} \\
\text{3} \\
\text{2} \\
\text{1}
\end{array}
\]

\[
\begin{array}{c}
\text{11} \\
\text{7} \\
\text{3} \\
\text{2}
\end{array}
\]

\[
\begin{array}{c}
\text{10} \\
\text{5} \\
\text{1} \\
\text{2}
\end{array}
\]

- Note that the size-fields now only give an upper bound on the size of a sub-tree.
**Path Compression**

Asymptotically the cost for a find-operation does not increase due to the path compression heuristic.

However, for a worst-case analysis there is no improvement on the running time. It can still happen that a find-operation takes time $O(\log n)$.

---

**Amortized Analysis**

**Definitions:**

- $\text{size}(v)$ = the number of nodes that were in the sub-tree rooted at $v$ when $v$ became the child of another node (or the number of nodes if $v$ is the root).

Note that this is the same as the size of $v$’s subtree in the case that there are no find-operations.

- $\text{rank}(v) = \lceil \log(\text{size}(v)) \rceil$.

- $\Rightarrow \text{size}(v) \geq 2^{\text{rank}(v)}$.

**Lemma 39**
The rank of a parent must be strictly larger than the rank of a child.

---

**Lemma 40**

There are at most $n/2^s$ nodes of rank $s$.

**Proof.**

- Let’s say a node $v$ sees node $x$ if $v$ is in $x$’s sub-tree at the time that $x$ becomes a child.

- A node $v$ sees at most one node of rank $s$ during the running time of the algorithm.

- This holds because the rank-sequence of the roots of the different trees that contain $v$ during the running time of the algorithm is a strictly increasing sequence.

- Hence, every node sees at most one rank $s$ node, but every rank $s$ node is seen by at least $2^s$ different nodes.

---

**Theorem 41**

Union find with path compression fulfills the following amortized running times:

- $\text{makeset}(x) : \mathcal{O}(\log^*(n))$

- $\text{find}(x) : \mathcal{O}(\log^*(n))$

- $\text{union}(x, y) : \mathcal{O}(\log^*(n))$
Amortized Analysis

In the following we assume $n \geq 2$.

**rank-group:**
- A node with rank $\text{rank}(v)$ is in rank group $\log^*(\text{rank}(v))$.
- The rank-group $g = 0$ contains only nodes with rank 0 or rank 1.
- A rank group $g \geq 1$ contains ranks $\text{tow}(g) + 1, \ldots, \text{tow}(g)$.
- The maximum non-empty rank group is $\log^*(\lfloor \log n \rfloor) \leq \log^*(n) - 1$ (which holds for $n \geq 2$).
- Hence, the total number of rank-groups is at most $\log^* n$.

**Accounting Scheme:**
- create an account for every find-operation
- create an account for every node $v$

The cost for a find-operation is equal to the length of the path traversed. We charge the cost for going from $v$ to $\text{parent}[v]$ as follows:
- If $\text{parent}[v]$ is the root we charge the cost to the find-account.
- If the group-number of $\text{rank}(v)$ is the same as that of $\text{rank}(\text{parent}[v])$ (before starting path compression) we charge the cost to the node-account of $v$.
- Otherwise we charge the cost to the find-account.

**Observations:**
- A find-account is charged at most $\log^*(n)$ times (once for the root and at most $\log^*(n) - 1$ times when increasing the rank-group).
- After a node $v$ is charged its parent-edge is re-assigned.
  The rank of the parent strictly increases.
- After some charges to $v$ the parent will be in a larger rank-group. $\Rightarrow v$ will never be charged again.
- The total charge made to a node in rank-group $g$ is at most $\text{tow}(g) - \text{tow}(g) - 1 \leq \text{tow}(g)$.

**What is the total charge made to nodes?**
- The total charge is at most
  \[ \sum_g n(g) \cdot \text{tow}(g) , \]
  where $n(g)$ is the number of nodes in group $g$.\]
Amortized Analysis

For \( g \geq 1 \) we have

\[
\sum_{s=tow(g)+1}^{tow(g)} \frac{n}{2^s} \leq \sum_{s=tow(g)+1}^{\infty} \frac{n}{2^s} = \frac{n}{2^{tow(g)-1}} \cdot 2
\]

\[
= \frac{n}{2^{tow(g)-1}} = \frac{n}{tow(g)}
\]

Hence,

\[
\sum_{g} n(g) \cdot tow(g) \leq n(0) \cdot tow(0) + \sum_{g=1}^{\infty} n(g) \cdot tow(g) \leq n \log^* (n)
\]

Without loss of generality we can assume that all `makeset`-operations occur at the start.

This means if we inflate the cost of `makeset` to \( \log^* n \) and add this to the node account of \( v \) then the balances of all node accounts will sum up to a positive value (this is sufficient to obtain an amortized bound).

The analysis is not tight. In fact it has been shown that the amortized time for the union-find data structure with path compression is \( O(\alpha(m, n)) \), where \( \alpha(m, n) \) is the inverse Ackermann function which grows a lot lot slower than \( \log^* n \).

(Here, we consider the average running time of \( m \) operations on at most \( n \) elements).

There is also a lower bound of \( \Omega(\alpha(m, n)) \).

\[
\alpha(m, n) = \min\{i \geq 1 : A(i, \lfloor m/n \rfloor) \geq \log n\}
\]

\[
\begin{align*}
A(0, y) &= y + 1 \\
A(1, y) &= y + 2 \\
A(2, y) &= 2y + 3 \\
A(3, y) &= 2y + 3 - 3 \\
A(4, y) &= \frac{2^{2^y} - 3}{\gamma + 3} \\
\end{align*}
\]
Union Find

Bibliography


Union find data structures are discussed in Chapter 21 of [CLRS90b] and [CLRS90c] and in Chapter 22 of [CLRS90a]. The analysis of union by rank with path compression can be found in [CLRS90a] but neither in [CLRS90b] nor in [CLRS90c]. The latter books contain a more involved analysis that gives a better bound than $O(\log^* n)$.

A description of the $O(\log^* n)$-bound can also be found in Chapter 4.8 of [AHU74].

The following slides are partially based on slides by Kevin Wayne.

10 Introduction

Flow Network

- directed graph $G = (V, E)$; edge capacities $c(e)$
- two special nodes: source $s$; target $t$
- no edges entering $s$ or leaving $t$
- at least for now: no parallel edges;
Cuts

Definition 42
An \((s,t)\)-cut in the graph \(G\) is given by a set \(A \subset V\) with \(s \in A\) and \(t \in V \setminus A\).

Definition 43
The capacity of a cut \(A\) is defined as
\[
\text{cap}(A,V \setminus A) := \sum_{e \in \text{out}(A)} c(e),
\]
where \(\text{out}(A)\) denotes the set of edges of the form \(A \times V \setminus A\) (i.e. edges leaving \(A\)).

Minimum Cut Problem: Find an \((s,t)\)-cut with minimum capacity.

Example 44

The capacity of the cut is \(\text{cap}(A,V \setminus A) = 28\).

Flows

Definition 45
An \((s,t)\)-flow is a function \(f : E \rightarrow \mathbb{R}^+\) that satisfies
1. For each edge \(e\)
   \[
   0 \leq f(e) \leq c(e).
   \]
   (capacity constraints)
2. For each \(v \in V \setminus \{s,t\}\)
   \[
   \sum_{e \in \text{out}(v)} f(e) = \sum_{e \in \text{into}(v)} f(e).
   \]
   (flow conservation constraints)

Definition 46
The value of an \((s,t)\)-flow \(f\) is defined as
\[
\text{val}(f) = \sum_{e \in \text{out}(s)} f(e).
\]

Maximum Flow Problem: Find an \((s,t)\)-flow with maximum value.
The value of the flow is $\text{val}(f) = 24$.

Proof.

$$\text{val}(f) = \sum_{e \in \text{out}(s)} f(e)$$

$$= \sum_{e \in \text{out}(s)} f(e) + \sum_{v \in A \setminus \{s\}} \left( \sum_{e \in \text{out}(v)} f(e) - \sum_{e \in \text{in}(v)} f(e) \right)$$

$$= \sum_{e \in \text{out}(A)} f(e) - \sum_{e \in \text{in}(A)} f(e)$$

The last equality holds since every edge with both end-points in $A$ contributes negatively as well as positively to the sum in Line 2. The only edges whose contribution doesn’t cancel out are edges leaving or entering $A$.  

Corollary 50

Let $f$ be an $(s,t)$-flow and let $A$ be an $(s,t)$-cut, such that

$$\text{val}(f) = \text{cap}(A, V \setminus A).$$

Then $f$ is a maximum flow.

Proof.

Suppose that there is a flow $f'$ with larger value. Then

$$\text{cap}(A, V \setminus A) < \text{val}(f')$$

$$= \sum_{e \in \text{out}(A)} f'(e) - \sum_{e \in \text{into}(A)} f'(e)$$

$$\leq \sum_{e \in \text{out}(A)} f'(e)$$

$$\leq \text{cap}(A, V \setminus A).$$

The Residual Graph

From the graph $G = (V,E,c)$ and the current flow $f$ we construct an auxiliary graph $G_f = (V,E_f,c_f)$ (the residual graph):

- Suppose the original graph has edges $e_1 = (u,v)$, and $e_2 = (v,u)$ between $u$ and $v$.
- $G_f$ has edge $e'_1$ with capacity $\max\{0,c(e_1) - f(e_1) + f(e_2)\}$ and $e'_2$ with with capacity $\max\{0,c(e_2) - f(e_2) + f(e_1)\}$.

Augmenting Path Algorithm

Definition 51

An augmenting path with respect to flow $f$, is a path from $s$ to $t$ in the auxiliary graph $G_f$ that contains only edges with non-zero capacity.

Algorithm 1 FordFulkerson($G = (V,E,c)$)

1: Initialize $f(e) = 0$ for all edges.
2: while $\exists$ augmenting path $p$ in $G_f$ do
3: augment as much flow along $p$ as possible.
Augmenting Path Algorithm

Animation for augmenting path algorithms is only available in the lecture version of the slides.

11.1 The Generic Augmenting Path Algorithm

Theorem 52
A flow $f$ is a maximum flow iff there are no augmenting paths.

Theorem 53
The value of a maximum flow is equal to the value of a minimum cut.

Proof.
Let $f$ be a flow. The following are equivalent:
1. There exists a cut $A, B$ such that $\text{val}(f) = \text{cap}(A, B)$.
2. Flow $f$ is a maximum flow.
3. There is no augmenting path w.r.t. $f$.

$\square$

Augmenting Path Algorithm

1. $\Rightarrow$ 2.
This we already showed.

2. $\Rightarrow$ 3.
If there were an augmenting path, we could improve the flow. Contradiction.

3. $\Rightarrow$ 1.

- Let $f$ be a flow with no augmenting paths.
- Let $A$ be the set of vertices reachable from $s$ in the residual graph along non-zero capacity edges.
- Since there is no augmenting path we have $s \in A$ and $t \notin A$.

\[
\text{val}(f) = \sum_{e \in \text{out}(A)} f(e) - \sum_{e \in \text{into}(A)} f(e) = \sum_{e \in \text{out}(A)} c(e) = \text{cap}(A, V \setminus A)
\]

This finishes the proof.

Here the first equality uses the flow value lemma, and the second exploits the fact that the flow along incoming edges must be 0 as the residual graph does not have edges leaving $A$. 
Analysis

Assumption:
All capacities are integers between 1 and $C$.

Invariant:
Every flow value $f(e)$ and every residual capacity $c_f(e)$ remains integral throughout the algorithm.

Lemma 54
The algorithm terminates in at most $\text{val}(f^*) \leq nC$ iterations, where $f^*$ denotes the maximum flow. Each iteration can be implemented in time $O(m)$. This gives a total running time of $O(nmC)$.

Theorem 55
If all capacities are integers, then there exists a maximum flow for which every flow value $f(e)$ is integral.

A Bad Input

Problem: The running time may not be polynomial.

Question:
Can we tweak the algorithm so that the running time is polynomial in the input length?

See the lecture-version of the slides for the animation.
A Pathological Input

Let \( r = \frac{1}{2}(\sqrt{5} - 1) \). Then \( r^{n+2} = r^n - r^{n+1} \).

How to choose augmenting paths?

- We need to find paths efficiently.
- We want to guarantee a small number of iterations.

Several possibilities:

- Choose path with maximum bottleneck capacity.
- Choose path with sufficiently large bottleneck capacity.
- Choose the shortest augmenting path.

Running time may be infinite!!!

Overview: Shortest Augmenting Paths

Lemma 56
The length of the shortest augmenting path never decreases.

Lemma 57
After at most \( O(m) \) augmentations, the length of the shortest augmenting path strictly increases.

These two lemmas give the following theorem:

Theorem 58
The shortest augmenting path algorithm performs at most \( O(mn) \) augmentations. This gives a running time of \( O(m^2n) \).

Proof.

- We can find the shortest augmenting paths in time \( O(m) \) via BFS.
- \( O(m) \) augmentations for paths of exactly \( k < n \) edges.
Shortest Augmenting Paths

Define the level $\ell(v)$ of a node as the length of the shortest $s$-$v$ path in $G_f$.

Let $L_G$ denote the subgraph of the residual graph $G_f$ that contains only those edges $(u,v)$ with $\ell(v) = \ell(u) + 1$.

A path $P$ is a shortest $s$-$u$ path in $G_f$ if it is a $s$-$u$ path in $L_G$.

In the following we assume that the residual graph $G_f$ does not contain zero capacity edges.

This means, we construct it in the usual sense and then delete edges of zero capacity.

Shortest Augmenting Path

First Lemma:
The length of the shortest augmenting path never decreases.

After an augmentation $G_f$ changes as follows:
- Bottleneck edges on the chosen path are deleted.
- Back edges are added to all edges that don’t have back edges so far.

These changes cannot decrease the distance between $s$ and $t$.

Second Lemma: After at most $m$ augmentations the length of the shortest augmenting path strictly increases.

Let $E_L$ denote the set of edges in graph $L_G$ at the beginning of a round when the distance between $s$ and $t$ is $k$.

An $s$-$t$ path in $G_f$ that uses edges not in $E_L$ has length larger than $k$, even when considering edges added to $G_f$ during the round.

In each augmentation one edge is deleted from $E_L$. 
Theorem 59
The shortest augmenting path algorithm performs at most \( O(mn) \) augmentations. Each augmentation can be performed in time \( O(m) \).

Theorem 60 (without proof)
There exist networks with \( m = \Theta(n^2) \) that require \( O(mn) \) augmentations, when we restrict ourselves to only augment along shortest augmenting paths.

Note:
There always exists a set of \( m \) augmentations that gives a maximum flow (why?).

We maintain a subset \( E_L \) of the edges of \( G_f \) with the guarantee that a shortest \( s-t \) path using only edges from \( E_L \) is a shortest augmenting path.

With each augmentation some edges are deleted from \( E_L \).

When \( E_L \) does not contain an \( s-t \) path anymore the distance between \( s \) and \( t \) strictly increases.

Note that \( E_L \) is not the set of edges of the level graph but a subset of level-graph edges.

Suppose that the initial distance between \( s \) and \( t \) in \( G_f \) is \( k \).

\( E_L \) is initialized as the level graph \( L_G \).

Perform a DFS search to find a path from \( s \) to \( t \) using edges from \( E_L \).

Either you find \( t \) after at most \( n \) steps, or you end at a node \( v \) that does not have any outgoing edges.

You can delete incoming edges of \( v \) from \( E_L \).
Let a phase of the algorithm be defined by the time between two augmentations during which the distance between \( s \) and \( t \) strictly increases.

Initializing \( E_L \) for the phase takes time \( O(m) \).

The total cost for searching for augmenting paths during a phase is at most \( O(mn) \), since every search (successful (i.e., reaching \( t \)) or unsuccessful) decreases the number of edges in \( E_L \) and takes time \( O(n) \).

The total cost for performing an augmentation during a phase is only \( O(n) \). For every edge in the augmenting path one has to update the residual graph \( G_f \) and has to check whether the edge is still in \( E_L \) for the next search.

There are at most \( n \) phases. Hence, total cost is \( O(mn^2) \).

How to choose augmenting paths?

- We need to find paths efficiently.
- We want to guarantee a small number of iterations.

Several possibilities:

- Choose path with maximum bottleneck capacity.
- Choose path with sufficiently large bottleneck capacity.
- Choose the shortest augmenting path.

### Capacity Scaling

Intuition:

- Choosing a path with the highest bottleneck increases the flow as much as possible in a single step.
- Don’t worry about finding the exact bottleneck.
- Maintain scaling parameter \( \Delta \).
- \( G_f(\Delta) \) is a sub-graph of the residual graph \( G_f \) that contains only edges with capacity at least \( \Delta \).

\[
\begin{align*}
G_f & \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad **Algorithm 2 maxflow(G, s, t, c)**

1: foreach \( e \in E \) do \( f_e \leftarrow 0 \);
2: \( \Delta \leftarrow 2^{\lceil \log_2 C \rceil} \)
3: while \( \Delta \geq 1 \) do
4: \( G_f(\Delta) \) \leftarrow \( \Delta \)-residual graph
5: while there is augmenting path \( P \) in \( G_f(\Delta) \) do
6: \( f \leftarrow \text{augment}(f, c, P) \)
7: \( \text{update}(G_f(\Delta)) \)
8: \( \Delta \leftarrow \Delta / 2 \)
9: return \( f \)
**Capacity Scaling**

**Assumption:**
All capacities are integers between 1 and $C$.

**Invariant:**
All flows and capacities are/remain integral throughout the algorithm.

**Correctness:**
The algorithm computes a maxflow:
- because of integrality we have $G_f(1) = G_f$
- therefore after the last phase there are no augmenting paths anymore
- this means we have a maximum flow.

---

**Lemma 61**
There are $\lceil \log C \rceil$ iterations over $\Delta$.

**Proof:** obvious.

**Lemma 62**
Let $f$ be the flow at the end of a $\Delta$-phase. Then the maximum flow is smaller than $\val(f) + m\Delta$.

**Proof:** less obvious, but simple:
- There must exist an $s$-$t$ cut in $G_f(\Delta)$ of zero capacity.
- In $G_f$ this cut can have capacity at most $m\Delta$.
- This gives me an upper bound on the flow that I can still add.

---

**Lemma 63**
There are at most $2m$ augmentations per scaling-phase.

**Proof:**
- Let $f$ be the flow at the end of the previous phase.
- $\val(f^*) \leq \val(f) + 2m\Delta$
- Each augmentation increases flow by $\Delta$.

**Theorem 64**
We need $\mathcal{O}(m \log C)$ augmentations. The algorithm can be implemented in time $\mathcal{O}(m^2 \log C)$.

---

**Matching**

- Input: undirected graph $G = (V, E)$.
- $M \subseteq E$ is a matching if each node appears in at most one edge in $M$.
- Maximum Matching: find a matching of maximum cardinality
Bipartite Matching

- Input: undirected, bipartite graph $G = (L \cup R, E)$.
- $M \subseteq E$ is a matching if each node appears in at most one edge in $M$.
- Maximum Matching: find a matching of maximum cardinality

Maxflow Formulation

- Input: undirected, bipartite graph $G = (L \cup R \cup \{s, t\}, E')$.
- Direct all edges from $L$ to $R$.
- Add source $s$ and connect it to all nodes on the left.
- Add $t$ and connect all nodes on the right to $t$.
- All edges have unit capacity.

Proof

Max cardinality matching in $G \leq$ value of maxflow in $G'$

- Given a maximum matching $M$ of cardinality $k$.
- Consider flow $f$ that sends one unit along each of $k$ paths.
- $f$ is a flow and has cardinality $k$. 
Proof

Max cardinality matching in $G \geq$ value of maxflow in $G'$

- Let $f$ be a maxflow in $G'$ of value $k$
- Integrality theorem $\Rightarrow$ $k$ integral; we can assume $f$ is 0/1.
- Consider $M =$ set of edges from $L$ to $R$ with $f(e) = 1$.
- Each node in $L$ and $R$ participates in at most one edge in $M$.
- $|M| = k$, as the flow must use at least $k$ middle edges.

Baseball Elimination

Which team can end the season with most wins?

- Montreal is eliminated, since even after winning all remaining games there are only 80 wins.
- But also Philadelphia is eliminated. Why?
**Baseball Elimination**

Flow network for $z = 3$. $M$ is number of wins Team 3 can still obtain.

![Flow network diagram](image)

Idea. Distribute the results of remaining games in such a way that no team gets too many wins.

**Theorem 65**

A team $z$ is eliminated if and only if the flow network for $z$ does not allow a flow of value $\sum_{i<j \in T} r_{ij}$.

**Proof (⇐)**

Consider the mincut $A$ in the flow network. Let $T$ be the set of team-nodes in $A$.

- If for node $x \cdot y$ not both team-nodes $x$ and $y$ are in $T$, then $x \cdot y \not\in A$ as otw. the cut would cut an infinite capacity edge.
- We don’t find a flow that saturates all source edges:

\[
\begin{align*}
r(S \setminus \{z\}) &> \text{cap}(A, V \setminus A) \\
&\geq \sum_{i<j \in T \setminus j \notin T} r_{ij} + \sum_{i \in T} (M - w_i) \\
&\geq r(S \setminus \{z\}) - r(T) + |T| M - w(T)
\end{align*}
\]

- This gives $M \leq (w(T) + r(T))/|T|$, i.e., $z$ is eliminated.

**Certificate of Elimination**

Let $T \subseteq S$ be a subset of teams. Define

\[
\begin{align*}
w(T) &:= \sum_{i \in T} w_i, \\
r(T) &:= \sum_{i,j \in T, i<j} r_{ij}
\end{align*}
\]

wins of teams in $T$ remaining games among teams in $T$

If $\frac{w(T)+r(T)}{|T|} > M$ then one of the teams in $T$ will have more than $M$ wins in the end. A team that can win at most $M$ games is therefore eliminated.

**Baseball Elimination**

**Proof (⇒)**

- Suppose we have a flow that saturates all source edges.
- We can assume that this flow is integral.
- For every pairing $x \cdot y$ it defines how many games team $x$ and team $y$ should win.
- The flow leaving the team-node $x$ can be interpreted as the additional number of wins that team $x$ will obtain.
- This is less than $M - w_x$ because of capacity constraints.
- Hence, we found a set of results for the remaining games, such that no team obtains more than $M$ wins in total.
- Hence, team $z$ is not eliminated.
Project Selection

Project selection problem:
- Set $P$ of possible projects. Project $v$ has an associated profit $p_v$ (can be positive or negative).
- Some projects have requirements (taking course EA2 requires course EA1).
- Dependencies are modelled in a graph. Edge $(u, v)$ means "can't do project $u$ without also doing project $v$.
- A subset $A$ of projects is feasible if the prerequisites of every project in $A$ also belong to $A$.

Goal: Find a feasible set of projects that maximizes the profit.

The prerequisite graph:
- $\{x, a, z\}$ is a feasible subset.
- $\{x, a\}$ is infeasible.

Min-cut formulation:
- Edges in the prerequisite graph get infinite capacity.
- Add edge $(s, v)$ with capacity $p_v$ for nodes $v$ with positive profit.
- Create edge $(v, t)$ with capacity $-p_v$ for nodes $v$ with negative profit.

Theorem 66
$A$ is a mincut if $A \setminus \{s\}$ is the optimal set of projects.

Proof.
- $A$ is feasible because of capacity infinity edges.
- $\text{cap}(A, V \setminus A) = \sum_{v \in A} p_v + \sum_{v \in A, p_v < 0} (-p_v) = \sum_{v : p_v > 0} p_v - \sum_{v \in A} p_v$.

For the formula we define $p_s := 0$.
- The step follows by adding $\sum_{v \in A} p_v - \sum_{v \in A, p_v > 0} p_v = 0$.
- Note that minimizing the capacity of the cut $(A, V \setminus A)$ corresponds to maximizing profits of projects in $A$. 
Preflows

**Definition 67**

An \((s,t)\)-preflow is a function \(f : E \rightarrow \mathbb{R^+}\) that satisfies

1. For each edge \(e\)
   \[0 \leq f(e) \leq c(e)\]  
   (capacity constraints)

2. For each \(v \in V \setminus \{s,t\}\)
   \[\sum_{e \in \text{out}(v)} f(e) \leq \sum_{e \in \text{into}(v)} f(e)\]  

**Example 68**

A node that has \(\sum_{e \in \text{out}(v)} f(e) < \sum_{e \in \text{into}(v)} f(e)\) is called an active node.

**Preflows**

**Definition:**

A labelling is a function \(\ell : V \rightarrow \mathbb{N}\). It is valid for preflow \(f\) if

- \(\ell(u) \leq \ell(v) + 1\) for all edges \((u,v)\) in the residual graph \(G_f\) (only non-zero capacity edges!!)
- \(\ell(s) = n\)
- \(\ell(t) = 0\)

**Intuition:**

The labelling can be viewed as a height function. Whenever the height from node \(u\) to node \(v\) decreases by more than 1 (i.e., it goes very steep downhill from \(u\) to \(v\)), the corresponding edge must be saturated.
Preflows

Lemma 69
A preflow that has a valid labeling saturates a cut.

Proof:
▶ There are \( n \) nodes but \( n+1 \) different labels from \( 0, \ldots, n \).
▶ There must exist a label \( d \in \{0, \ldots, n\} \) such that none of the nodes carries this label.
▶ Let \( A = \{v \in V \mid \ell(v) > d\} \) and \( B = \{v \in V \mid \ell(v) < d\} \).
▶ We have \( s \in A \) and \( t \in B \) and there is no edge from \( A \) to \( B \) in the residual graph \( G_f \); this means that \((A, B)\) is a saturated cut.

Lemma 70
A flow that has a valid labeling is a maximum flow.

Push Relabel Algorithms

Idea:
▶ start with some preflow and some valid labelling
▶ successively change the preflow while maintaining a valid labelling
▶ stop when you have a flow (i.e., no more active nodes)

Note that this is somewhat dual to an augmenting path algorithm. The former maintains the property that it has a feasible flow. It successively changes this flow until it saturates some cut in which case we conclude that the flow is maximum. A preflow push algorithm maintains the property that it has a saturated cut. The preflow is changed iteratively until it fulfills conservation constraints in which case we can conclude that we have a maximum flow.

Changing a Preflow

An arc \((u, v)\) with \( c_f(u, v) > 0 \) in the residual graph is admissible if \( \ell(u) = \ell(v) + 1 \) (i.e., it goes downwards w.r.t. labeling \( \ell \)).

The push operation
Consider an active node \( u \) with excess flow 
\[
f(u) = \sum_{e \in \text{int}(u)} f(e) - \sum_{e \in \text{out}(u)} f(e)
\]
and suppose \( e = (u, v) \) is an admissible arc with residual capacity \( c_f(e) \).

We can send flow \( \min\{c_f(e), f(u)\} \) along \( e \) and obtain a new preflow. The old labelling is still valid (!!!).

▶ saturating push: \( \min\{f(u), c_f(e)\} = c_f(e) \)
  the arc \( e \) is deleted from the residual graph
▶ non-saturating push: \( \min\{f(u), c_f(e)\} = f(u) \)
  the node \( u \) becomes inactive

Note that a push-operation may be saturating and non-saturating at the same time.
Push Relabel Algorithms

Intuition:
We want to send flow downwards, since the source has a
height/label of $n$ and the target a height/label of $0$. If we see an
active node $u$ with an admissible arc we push the flow at $u$
towards the other end-point that has a lower height/label. If we
do not have an admissible arc but excess flow into $u$ it should
roughly mean that the level/height/label of $u$ should rise. (If we
consider the flow to be water then this would be natural.)

Note that the above intuition is very incorrect as the labels are
integral, i.e., they cannot really be seen as the height of a node.

Reminder

- In a preflow nodes may not fulfill conservation constraints;
a node may have more incoming flow than outgoing flow.
- Such a node is called active.
- A labelling is valid if for every edge $(u, v)$ in the residual
graph $\ell(u) \leq \ell(v) + 1$.
- An arc $(u, v)$ in residual graph is admissible if
$\ell(u) = \ell(v) + 1$.
- A saturating push along $e$ pushes an amount of $c(e)$ flow
along the edge, thereby saturating the edge (and making it
dissappear from the residual graph).
- A non-saturating push along $e = (u, v)$ pushes a flow of
$f(u)$, where $f(u)$ is the excess flow of $u$. This makes $u$
inactive.

Push Relabel Algorithms

Algorithm 3 maxflow($G, s, t, c$)
1: find initial preflow $f$
2: while there is active node $u$ do
3: if there is admiss. arc $e$ out of $u$ then
4: push($G, e, f, c$)
5: else
6: relabel($u$)
7: return $f$

In the following example we always stick to the same active node
$u$ until it becomes inactive but this is not required.
Note that the lemma is almost trivial. A node \( v \) having excess flow means that the current preflow ships something to \( v \). The residual graph allows to undo flow. Therefore, there must exist a path that can undo the shipment and move it back to \( s \). However, a formal proof is required.

Lemma 71
An active node has a path to \( s \) in the residual graph.

Proof.
- Let \( A \) denote the set of nodes that can reach \( s \), and let \( B \) denote the remaining nodes. Note that \( s \in A \).
- In the following we show that a node \( b \in B \) has excess flow \( f(b) = 0 \) which gives the lemma.
- In the residual graph there are no edges into \( A \), and, hence, no edges leaving \( A \) entering \( B \) can carry any flow.
- Let \( f(B) = \sum_{v \in B} f(v) \) be the excess flow of all nodes in \( B \).

Hence, the excess flow \( f(b) \) must be 0 for every node \( b \in B \).

Let \( f : E \rightarrow \mathbb{R}_0^+ \) be a preflow. We introduce the notation
\[
f(x, y) = \begin{cases} 0 & (x, y) \notin E \\ f((x, y)) & (x, y) \in E 
\end{cases}
\]

We have
\[
f(B) = \sum_{b \in B} f(b)
= \sum_{b \in B} \left( \sum_{v \in V} f(v, b) - \sum_{v \in V} f(b, v) \right)
= \sum_{b \in B} \left( \sum_{v \in A} f(v, b) + \sum_{v \in B} f(v, b) - \sum_{v \in A} f(b, v) - \sum_{v \in B} f(b, v) \right)
= - \sum_{b \in B} \sum_{v \in A} f(b, v)
\leq 0
\]

Lemma 72
The label of a node cannot become larger than \( 2n - 1 \).

Proof.
- When increasing the label at a node \( u \) there exists a path from \( u \) to \( s \) of length at most \( n - 1 \). Along each edge of the path the height/label can at most drop by 1, and the label of the source is \( n \).

Lemma 73
There are only \( O(n^2) \) relabel operations.

Lemma 74
The number of saturating pushes performed is at most \( O(mn) \).

Proof.
- Suppose that we just made a saturating push along \((u, v)\).
- Hence, the edge \((u, v)\) is deleted from the residual graph.
- For the edge to appear again, a push from \( v \) to \( u \) is required.
- Currently, \( \ell(u) = \ell(v) + 1 \), as we only make pushes along admissible edges.
- For a push from \( v \) to \( u \) the edge \((v, u)\) must become admissible. The label of \( v \) must increase by at least 2.
- Since the label of \( v \) is at most \( 2n - 1 \), there are at most \( n \) pushes along \((u, v)\).
Lemma 75
The number of non-saturating pushes performed is at most $O(n^2m)$.

Proof.
- Define a potential function $\Phi(f) = \sum_{\text{active nodes}} \ell(v)$
- A saturating push increases $\Phi$ by $\leq 2n$ (when the target node becomes active it may contribute at most $2n$ to the sum).
- A relabel increases $\Phi$ by at most $1$.
- A non-saturating push decreases $\Phi$ by at least $1$ as the node that is pushed from becomes inactive and has a label that is strictly larger than the target.
- Hence,

$$\text{#non-saturating_pushes} \leq \text{#relabels} + 2n \cdot \text{#saturating_pushes} \leq O(n^2m).$$

Analysis

Theorem 76
There is an implementation of the generic push relabel algorithm with running time $O(n^2m)$.

Analysis

For special variants of push relabel algorithms we organize the neighbours of a node into a linked list (possible neighbours in the residual graph $G_f$). Then we use the discharge-operation:

Algorithm 20 discharge$(u)$
1: while $u$ is active do
2: $v \leftarrow u$.current-neighbour
3: if $v =$ null then
4: relabel$(u)$
5: $u$.current-neighbour $\leftarrow u$.neighbour-list-head
6: else
7: if $(u, v)$ admissible then push$(u, v)$
8: else $u$.current-neighbour $\leftarrow v$.next-in-list

Note that $u$.current-neighbour is a global variable. It is only changed within the discharge routine, but keeps its value between consecutive calls to discharge.
Lemma 77
If $v = \text{null}$ in Line 3, then there is no outgoing admissible edge from $u$.

Proof.

- While pushing from $u$ the current-neighbour pointer is only advanced if the current edge is not admissible.
- The only thing that could make the edge admissible again would be a relabel at $u$.
- If we reach the end of the list ($v = \text{null}$) all edges are not admissible.

This shows that discharge($u$) is correct, and that we can perform a relabel in Line 4.

13.2 Relabel to Front

Lemma 78 (Invariant)
In Line 6 of the relabel-to-front algorithm the following invariant holds.

1. The sequence $L$ is topologically sorted w.r.t. the set of admissible edges; this means for an admissible edge $(x, y)$ the node $x$ appears before $y$ in sequence $L$.

2. No node before $u$ in the list $L$ is active.

Proof:

- Initialization:
  1. In the beginning $s$ has label $m \geq 2$, and all other nodes have label 0. Hence, no edge is admissible, which means that any ordering $L$ is permitted.
  2. We start with $u$ being the head of the list; hence no node before $u$ can be active

- Maintenance:
  1. Pushes do not create any new admissible edges. Therefore, if discharge() does not relabel $u$, $L$ is still topologically sorted.
  2. After relabeling, $u$ cannot have admissible incoming edges as such an edge $(x, u)$ would have had a difference $\ell(x) - \ell(u) \geq 2$ before the re-labeling (such edges do not exist in the residual graph).

Hence, moving $u$ to the front does not violate the sorting property for any edge; however it fixes this property for all admissible edges leaving $u$ that were generated by the relabeling.

Algorithm 21 relabel-to-front($G, s, t$)

1: initialize preflow
2: initialize node list $L$ containing $V \setminus \{s, t\}$ in any order
3: foreach $u \in V \setminus \{s, t\}$ do
4:   $u$.current-neighbour ← $u$.neighbour-list-head
5: $u ← L$.head
6: while $u \neq \text{null}$ do
7:   old-height ← $\ell(u)$
8:   discharge($u$)
9:   if $\ell(u) > \text{old-height}$ then // relabel happened
10:     move $u$ to the front of $L$
11: $u ← u$.next
13.2 Relabel to Front

Proof:

- Maintenance:

  2. If we do a relabel there is nothing to prove because the only node before $u'$ ($u$ in the next iteration) will be the current $u$; the discharge($u$) operation only terminates when $u$ is not active anymore.

  For the case that we do not relabel, observe that the only way a predecessor could be active is that we push flow to it via an admissible arc. However, all admissible arc point to successors of $u$.

  Note that the invariant means that for $u = \text{null}$ we have a preflow with a valid labelling that does not have active nodes. This means we have a maximum flow.

Note that by definition a saturating push operation ($\min\{c_f(e), f(u)\} = c_f(e)$) can at the same time be a non-saturating push operation ($\min\{c_f(e), f(u)\} = f(u)$).

Lemma 79

There are at most $O(n^3)$ calls to discharge($u$).

Every discharge operation without a relabel advances $u$ (the current node within list $I$). Hence, if we have $n$ discharge operations without a relabel we have $u = \text{null}$ and the algorithm terminates.

Therefore, the number of calls to discharge is at most $n(\#\text{relabels} + 1) = O(n^3)$.

Lemma 80

The cost for all relabel-operations is only $O(n^2)$.

A relabel-operation at a node is constant time (increasing the label and resetting $u\.\text{current-neighbour}$). In total we have $O(n^2)$ relabel-operations.

Lemma 81

The cost for all saturating push-operations that are not also non-saturating push-operations is only $O(mn)$.

Note that such a push-operation leaves the node $u$ active but makes the edge $e$ disappear from the residual graph. Therefore the push-operation is immediately followed by an increase of the pointer $u\.\text{current-neighbour}$.

This pointer can traverse the neighbour-list at most $O(n)$ times (upper bound on number of relabels) and the neighbour-list has only $\text{degree}(u) + 1$ many entries (+1 for $\text{null}$-entry).
13.2 Relabel to Front

Lemma 82
The cost for all non-saturating push-operations is only $O(n^3)$.

A non-saturating push-operation takes constant time and ends the current call to discharge(). Hence, there are only $O(n^3)$ such operations.

Theorem 83
The push-relabel algorithm with the rule relabel-to-front takes time $O(n^3)$.

13.3 Highest Label

Lemma 84
When using highest label the number of non-saturating pushes is only $O(n^3)$.

A push from a node on level $\ell$ can only “activate” nodes on levels strictly less than $\ell$.

This means, after a non-saturating push from $u$ a relabel is required to make $u$ active again.

Hence, after $n$ non-saturating pushes without an intermediate relabel there are no active nodes left.

Therefore, the number of non-saturating pushes is at most $n(\#\text{relabels} + 1) = O(n^3)$.

Algorithm 6 highest-label($G, s, t$)
1: initialize preflow
2: foreach $u \in V \setminus \{s, t\}$ do
3: \hspace{1cm} $u.\text{current-neighbour} \leftarrow u.\text{neighbour-list-head}$
4: while $\exists$ active node $u$ do
5: \hspace{1cm} select active node $u$ with highest label
6: discharge($u$)

Since a discharge-operation is terminated by a non-saturating push this gives an upper bound of $O(n^3)$ on the number of discharge-operations.

The cost for relabels and saturating pushes can be estimated in exactly the same way as in the case of the generic push-relabel algorithm.

Question:
How do we find the next node for a discharge operation?
13.3 Highest Label

Maintain lists $L_i$, $i \in \{0, \ldots, 2n\}$, where list $L_i$ contains active
nodes with label $i$ (maintaining these lists induces only constant
additional cost for every push-operation and for every
relabel-operation).

After a discharge operation terminated for a node $u$ with label $k$,
traverse the lists $L_k, L_{k-1}, \ldots, L_0$, (in that order) until you find a
non-empty list.

Unless the last (non-saturating) push was to $s$ or $t$ the list $k-1$
must be non-empty (i.e., the search takes constant time).

13.3 Highest Label

Hence, the total time required for searching for active nodes is
at most $O(n^3) + n(\#\text{non-saturating pushes to } s \text{ or } t)$

Lemma 85
The number of non-saturating pushes to $s$ or $t$ is at most $O(n^2)$.

With this lemma we get

Theorem 86
The push-relabel algorithm with the rule highest-label takes time
$O(n^3)$.

Mincost Flow

Problem Definition:

$$\begin{align*}
\text{min} & \quad \sum_{e} c(e) f(e) \\
\text{s.t.} & \quad \forall e \in E : \ 0 \leq f(e) \leq u(e) \\
& \quad \forall v \in V : \ f(v) = b(v)
\end{align*}$$

$G = (V, E)$ is a directed graph.
$u : E \to \mathbb{R}^+ \cup \{\infty\}$ is the capacity function.
$c : E \to \mathbb{R}$ is the cost function
(note that $c(e)$ may be negative).
$b : V \to \mathbb{R}$, $\sum_{v \in V} b(v) = 0$ is a demand function.
Solve Maxflow Using Mincost Flow

▶ Given a flow network for a standard maxflow problem.
▶ Set \( b(v) = 0 \) for every node. Keep the capacity function \( u \) for all edges. Set the cost \( c(e) \) for every edge to 0.
▶ Add an edge from \( t \) to \( s \) with infinite capacity and cost \( -1 \).
▶ Then, \( \text{val}(f^*) = -\text{cost}(f_{\text{min}}) \), where \( f^* \) is a maxflow, and \( f_{\text{min}} \) is a mincost-flow.

Solve decision version of maxflow:
▶ Given a flow network for a standard maxflow problem, and a value \( k \).
▶ Set \( b(v) = 0 \) for every node apart from \( s \) or \( t \). Set \( b(s) = -k \) and \( b(t) = k \).
▶ Set edge-costs to zero, and keep the capacities.
▶ There exists a maxflow of value at least \( k \) if and only if the mincost-flow problem is feasible.

Generalization

Our model:
\[
\begin{align*}
\min & \quad \sum_e c(e) f(e) \\
\text{s.t.} & \quad \forall e \in E: \quad 0 \leq f(e) \leq u(e) \\
& \quad \forall v \in V: \quad f(v) = b(v)
\end{align*}
\]
where \( b : V \to \mathbb{R} \), \( \sum_v b(v) = 0 \); \( u : E \to \mathbb{R}_+ \cup \{\infty\} \); \( c : E \to \mathbb{R} \);

A more general model?
\[
\begin{align*}
\min & \quad \sum_e c(e) f(e) \\
\text{s.t.} & \quad \forall e \in E: \quad \ell(e) \leq f(e) \leq u(e) \\
& \quad \forall v \in V: \quad a(v) \leq f(v) \leq b(v)
\end{align*}
\]
where \( a : V \to \mathbb{R} \), \( b : V \to \mathbb{R} \); \( \ell : E \to \mathbb{R} \cup \{-\infty\} \), \( u : E \to \mathbb{R} \cup \{\infty\} \)
\( c : E \to \mathbb{R} \);
Reduction I

\[
\begin{align*}
\min & \quad \sum_e c(e) f(e) \\
\text{s.t.} & \quad \forall e \in E: \; \ell(e) \leq f(e) \leq u(e) \\
& \quad \forall v \in V: \; a(v) \leq f(v) \leq b(v)
\end{align*}
\]

We can assume that \(a(v) = b(v)\):

Add new node \(r\).

Add edge \((r,v)\) for all \(v \in V\).

Set \(u(e) = b(v) - a(v)\) for edge \((r,v)\).

Set \(a(v) = b(v)\) for all \(v \in V\).

Set \(b(r) = -\sum_{v \in V} b(v)\).

\(-\sum_v b(v)\) is negative; hence \(r\) is only sending flow.

Reduction II

We can transform any network so that a particular edge has cost \(c(e) = 0\):

Additionally we set \(b(u) = 0\).

Reduction III

We can assume that either \(\ell(e) \neq -\infty\) or \(u(e) \neq \infty\):

If \(c(e) = 0\) we can contract the edge/identify nodes \(u\) and \(v\).

If \(c(e) \neq 0\) we can transform the graph so that \(c(e) = 0\).

Replace the edge by an edge in opposite direction.
Reduction IV

\[
\min \sum_{e} c(e)f(e)
\]
\[
s.t. \quad \forall e \in E: \quad \ell(e) \leq f(e) \leq u(e)
\]
\[
\forall v \in V: \quad f(v) = b(v)
\]

We can assume that \(\ell(e) = 0\):

The added edges have infinite capacity and cost \(c(e)/2\).

Applications

Caterer Problem

- She needs to supply \(r_i\) napkins on \(N\) successive days.
- She can buy new napkins at \(p\) cents each.
- She can launder them at a fast laundry that takes \(m\) days and cost \(f\) cents a napkin.
- She can use a slow laundry that takes \(k > m\) days and costs \(s\) cents each.
- At the end of each day she should determine how many to send to each laundry and how many to buy in order to fulfill demand.
- Minimize cost.
forward edges:
upper bound: $u(e_i) = \infty$;
lower bound: $\ell(e_i) = 0$;
cost: $c(e) = 0$

slow edges:
upper bound: $u(e_i) = \infty$;
lower bound: $\ell(e_i) = 0$;
cost: $c(e) = s$

fast edges:
upper bound: $u(e_i) = \infty$;
lower bound: $\ell(e_i) = 0$;
cost: $c(e) = f$

trash edges:
upper bound: $u(e_i) = \infty$;
lower bound: $\ell(e_i) = 0$;
cost: $c(e) = 0$
Residual Graph

Version A:
The residual graph $G'$ for a mincost flow is just a copy of the graph $G$.

If we send $f(e)$ along an edge, the corresponding edge $e'$ in the residual graph has its lower and upper bound changed to
$\ell(e') = \ell(e) - f(e)$ and $u(e') = u(e) - f(e)$.

Version B:
The residual graph for a mincost flow is exactly defined as the residual graph for standard flows, with the only exception that one needs to define a cost for the residual edge.

For a flow of $z$ from $u$ to $v$ the residual edge $(v,u)$ has capacity $z$ and a cost of $-c((u,v))$.

Lemma 87
A given flow is a mincost-flow if and only if the corresponding residual graph $G_f$ does not have a feasible circulation of negative cost.

$\Rightarrow$ Suppose that $g$ is a feasible circulation of negative cost in the residual graph.

Then $f + g$ is a feasible flow with cost $\text{cost}(f) + \text{cost}(g) < \text{cost}(f)$. Hence, $f$ is not minimum cost.

$\Leftarrow$ Let $f$ be a non-mincost flow, and let $f^*$ be a min-cost flow.

We need to show that the residual graph has a feasible circulation with negative cost.

Clearly $f^* - f$ is a circulation of negative cost. One can also easily see that it is feasible for the residual graph. (after sending $-f$ in the residual graph (pushing all flow back) we arrive at the original graph; for this $f^*$ is clearly feasible)
14 Mincost Flow

Lemma 88
A graph (without zero-capacity edges) has a feasible circulation of negative cost if and only if it has a negative cycle w.r.t. edge-weights \( c : E \rightarrow \mathbb{R} \).

Proof.
- Suppose that we have a negative cost circulation.
- Find directed path only using edges that have non-zero flow.
- If this path has negative cost you are done.
- Otherwise send flow in opposite direction along the cycle until the bottleneck edge(s) does not carry any flow.
- You still have a circulation with negative cost.
- Repeat.

Algorithm 22 CycleCanceling(\( G = (V,E), c, u, b \))
1: establish a feasible flow \( f \) in \( G \)
2: while \( G_f \) contains negative cycle do
3: use Bellman-Ford to find a negative circuit \( Z \)
4: \( \delta \leftarrow \min \{ u_f(e) \mid e \in Z \} \)
5: augment \( \delta \) units along \( Z \) and update \( G_f \)

How do we find the initial feasible flow?
- Connect new node \( s \) to all nodes with negative \( b(v) \)-value.
- Connect nodes with positive \( b(v) \)-value to a new node \( t \).
- There exist a feasible flow in the original graph iff in the resulting graph there exists an \( s-t \) flow of value
  \[
  \sum_{v:b(v)<0} (-b(v)) = \sum_{v:b(v)>0} b(v)
  \]
14 Mincost Flow

Ernst Mayr, Harald Räcke
A *general mincost flow problem* is of the following form:

$$\begin{align*}
\min & \quad \sum_{e} c(e) f(e) \\
\text{s.t.} & \quad \forall e \in E : \ell(e) \leq f(e) \leq u(e) \\
& \quad \forall v \in V : a(v) \leq f(v) \leq b(v)
\end{align*}$$

where $a : V \to \mathbb{R}, b : V \to \mathbb{R}; \ell : E \to \mathbb{R} \cup \{-\infty\}, u : E \to \mathbb{R} \cup \{\infty\}$

$c : E \to \mathbb{R}$;

**Lemma 90 (without proof)**

A general mincost flow problem can be solved in polynomial time.

---

**15 Global Mincut**

Given an *undirected, capacitated graph* $G = (V, E, c)$ find a partition of $V$ into two non-empty sets $S, V \setminus S$ s.t. the capacity of edges between both sets is minimized.
We can solve this problem using standard maxflow/mincut.

- Construct a directed graph $G' = (V, E')$ that has edges $(u, v)$ and $(v, u)$ for every edge $\{u, v\} \in E$.
- Fix an arbitrary node $s \in V$ as source. Compute a minimum $s$-$t$ cut for all possible choices $t \in V, t \neq s$. (Time: $O(n^4)$)
- Let $(S, V \setminus S)$ be a minimum global mincut. The above algorithm will output a cut of capacity $\text{cap}(S, V \setminus S)$ whenever $|\{s, t\} \cap S| = 1$.

We can perform an edge-contraction in time $O(n)$.

Algorithm 23 KargerMincut($G = (V, E, c)$)
1: for $i = 1 \rightarrow n - 2$ do
2: choose $e \in E$ randomly with probability $c(e)/c(E)$
3: $G \leftarrow G/e$
4: return only cut in $G$

Let $G_t$ denote the graph after the $(n - t)$-th iteration, when $t$ nodes are left.
- Note that the final graph $G_2$ only contains a single edge.
- The cut in $G_2$ corresponds to a cut in the original graph $G$ with the same capacity.
- What is the probability that this algorithm returns a mincut?
Example: Randomized Mincut Algorithm

Animation only available in the lecture version of the slides.

---

Analysis

What is the probability that a given mincut \( A \) is still possible after round \( i \)?

- It is still possible to obtain cut \( A \) in the end if so far no edge in \( (A, V \setminus A) \) has been contracted.

---

Analysis

What is the probability that we select an edge from \( A \) in iteration \( i \)?

- Let \( \text{min} = \text{cap}(A, V \setminus A) \) denote the capacity of a mincut.
- Let \( \text{cap}(v) \) be capacity of edges incident to vertex \( v \in V_{n-i+1} \).
- Clearly, \( \text{cap}(v) \geq \text{min} \).
- Summing \( \text{cap}(v) \) over all edges gives

\[
2c(E) = 2 \sum_{e \in E} c(e) = \sum_{v \in V} \text{cap}(v) \geq (n - i + 1) \cdot \text{min}
\]

- Hence, the probability of choosing an edge from the cut is

\[
\frac{\text{min}}{c(E)} \leq \frac{2}{n - i + 1}.
\]

---

Analysis

The probability that we do not choose an edge from the cut in iteration \( i \) is

\[
1 - \frac{2}{n - i + 1} = \frac{n - i - 1}{n - i + 1}.
\]

The probability that the cut is alive after iteration \( n - t \) (after which \( t \) nodes are left) is

\[
\prod_{i=1}^{n-t} \frac{n - i - 1}{n - i + 1} = \frac{t(t - 1)}{n(n - 1)}.
\]

Choosing \( t = 2 \) gives that with probability \( 1/(n^2) \) the algorithm computes a mincut.
Analysis

Repeating the algorithm $c \ln n \left(\frac{n}{2}\right)$ times gives that the probability that we are never successful is

$$\left(1 - \frac{1}{e}\right)^{(t/2)c \ln n} \leq \left(e^{-1/(t^2)}\right)^{(t/2)c \ln n} \leq n^{-c},$$

where we used $1 - x \leq e^{-x}$.

**Theorem 92**

The randomized mincut algorithm computes an optimal cut with high probability. The total running time is $O(n^4 \log n)$.

---

Probability of Success

The probability of contracting an edge from the mincut during one iteration through the for-loop is only

$$\frac{t(t-1)}{n(n-1)} \leq \frac{t^2}{n^2} = \frac{1}{2},$$

as $t = \frac{n}{\sqrt{2}}$.

---

Improved Algorithm

**Algorithm 24 RecursiveMincut** ($G = (V, E, c)$)

1: for $i = 1 \rightarrow n - n/\sqrt{2}$ do
2: choose $e \in E$ randomly with probability $c(e)/c(E)$
3: $G \leftarrow G/e$
4: if $|V| = 2$ return cut-value;
5: $cuta \leftarrow$ RecursiveMincut($G$);
6: $cutb \leftarrow$ RecursiveMincut($G$);
7: return $\min\{cuta, cutb\}$

**Running time:**

- $T(n) = 2T\left(\frac{n}{\sqrt{2}}\right) + O(n^2)$
- This gives $T(n) = O(n^2 \log n)$.
Probability of Success

Let for an edge \( e \) in the recursion tree, \( h(e) \) denote the height (distance to leaf level) of the parent-node of \( e \) (end-point that is higher up in the tree). Let \( h \) denote the height of the root node.

Call an edge \( e \) alive if there exists a path from the parent-node of \( e \) to a descendant leaf, after we randomly deleted edges. Note that an edge can only be alive if it hasn’t been deleted.

Lemma 93

The probability that an edge \( e \) is alive is at least \( \frac{1}{h(e)+1} \).

Proof.

▶ An edge \( e \) with \( h(e) = 1 \) is alive if and only if it is not deleted. Hence, it is alive with probability at least \( \frac{1}{2} \).

▶ Let \( p_d \) be the probability that an edge \( e \) with \( h(e) = d \) is alive. For \( d > 1 \) this happens for edge \( e = \{c, p\} \) if it is not deleted and if one of the child-edges connecting to \( c \) is alive.

▶ This happens with probability

\[
 p_d = \frac{1}{2} \left( 2p_{d-1} - p_{2d-1}^2 \right) \geq p_{d-1} - \frac{p_{d-1}^2}{2} \geq 1 - \frac{1}{d} - \frac{1}{2d^2} \geq 1 - \frac{1}{d(d+1)} = \frac{1}{d+1}.
\]

15 Global Mincut

Lemma 94

One run of the algorithm can be performed in time \( \mathcal{O}(n^2 \log n) \) and has a success probability of \( \Omega\left(\frac{1}{\log n}\right) \).

Doing \( \Theta(\log^2 n) \) runs gives that the algorithm succeeds with high probability. The total running time is \( \mathcal{O}(n^2 \log^3 n) \).

16 Gomory Hu Trees

Given an undirected, weighted graph \( G = (V, E, c) \) a cut-tree \( T = (V, F, w) \) is a tree with edge-set \( F \) and capacities \( w \) that fulfills the following properties.

1. **Equivalent Flow Tree:** For any pair of vertices \( s,t \in V \), \( f(s, t) \) in \( G \) is equal to \( f_T(s, t) \).

2. **Cut Property:** A minimum \( s-t \) cut in \( T \) is also a minimum cut in \( G \).

Here, \( f(s, t) \) is the value of a maximum \( s-t \) flow in \( G \), and \( f_T(s, t) \) is the corresponding value in \( T \).
Overview of the Algorithm

The algorithm maintains a partition of $V$, (sets $S_1, \ldots, S_t$), and a spanning tree $T$ on the vertex set $\{S_1, \ldots, S_t\}$.

Initially, there exists only the set $S_1 = V$.

Then the algorithm performs $n - 1$ split-operations:

- In each such split-operation it chooses a set $S_i$ with $|S_i| \geq 2$ and splits this set into two non-empty parts $X$ and $Y$.
- $S_i$ is then removed from $T$ and replaced by $X$ and $Y$.
- $X$ and $Y$ are connected by an edge, and the edges that before the split were incident to $S_i$ are attached to either $X$ or $Y$.

In the end this gives a tree on the vertex set $V$.

Details of the Split-operation

- Select $S_i$ that contains at least two nodes $a$ and $b$.
- Compute the connected components of the forest obtained from the current tree $T$ after deleting $S_i$. Each of these components corresponds to a set of vertices from $V$.
- Consider the graph $H$ obtained from $G$ by contracting these connected components into single nodes.
- Compute a minimum $a$-$b$ cut in $H$. Let $A$, and $B$ denote the two sides of this cut.
- Split $S_i$ in $T$ into two sets/nodes $S^a_i = S_i \cap A$ and $S^b_i = S_i \cap B$ and add edge $\{S^a_i, S^b_i\}$ with capacity $f_H(a, b)$.
- Replace an edge $\{S_i, S_x\}$ by $\{S^a_i, S_x\}$ if $S_x \subset A$ and by $\{S^b_i, S_x\}$ if $S_x \subset B$.

Example: Gomory-Hu Construction

Analysis

Lemma 95

For nodes $s, t, x \in V$ we have $f(s, t) \geq \min\{f(s, x), f(x, t)\}$

Lemma 96

For nodes $s, t, x_1, \ldots, x_k \in V$ we have

$f(s, t) \geq \min\{f(s, x_1), f(x_1, x_2), \ldots, f(x_{k-1}, x_k), f(x_k, t)\}$
Lemma 97
Let $S$ be some minimum $r$-$s$ cut for some nodes $r, s \in V$ ($s \in S$), and let $v, w \in S$. Then there is a minimum $v$-$w$-cut $T$ with $T \subseteq S$.

Proof: Let $X$ be a minimum $v$-$w$ cut with $X \cap S \neq \emptyset$ and $X \cap (V \setminus S) \neq \emptyset$. Note that $S \setminus X$ and $S \cap X$ are $v$-$w$ cuts inside $S$.

We may assume w.l.o.g. $s \in X$.

First case $r \in X$.
- $\text{cap}(X \setminus S) + \text{cap}(S \setminus X) \leq \text{cap}(S) + \text{cap}(X)$.
- $\text{cap}(X \setminus S) \geq \text{cap}(S)$ because $X \setminus S$ is an $r$-$s$ cut.
- This gives $\text{cap}(S \setminus X) \leq \text{cap}(X)$.

Second case $r \notin X$.
- $\text{cap}(X \cup S) + \text{cap}(S \cap X) \leq \text{cap}(S) + \text{cap}(X)$.
- $\text{cap}(X \cup S) \geq \text{cap}(S)$ because $X \cup S$ is an $r$-$s$ cut.
- This gives $\text{cap}(S \cap X) \leq \text{cap}(X)$.

Analysis

Lemma 97 tells us that if we have a graph $G = (V, E)$ and we contract a subset $X \subseteq V$ that corresponds to some mincut, then the value of $f(s,t)$ does not change for two nodes $s,t \notin X$.

We will show (later) that the connected components that we contract during a split-operation each correspond to some mincut and, hence, $f_H(s,t) = f(s,t)$, where $f_H(s,t)$ is the value of a minimum $s$-$t$ mincut in graph $H$. 
Analysis

Invariant [existence of representatives]:
For any edge \{S_i, S_j\} in T, there are vertices \(a \in S_i\) and \(b \in S_j\) such that \(w(S_i, S_j) = f(a, b)\) and the cut defined by edge \{S_i, S_j\} is a minimum \(a\)-\(b\) cut in \(G\).

Analysis

We first show that the invariant implies that at the end of the algorithm \(T\) is indeed a cut-tree.

▶ Let \(s = x_0, x_1, \ldots, x_k-1, x_k = t\) be the unique simple path from \(s\) to \(t\) in the final tree \(T\). From the invariant we get that \(f(x_i, x_{i+1}) = w(x_i, x_{i+1})\) for all \(j\).

▶ Then
\[
f_T(s, t) = \min_{i \in \{0, \ldots, k-1\}} \{w(x_i, x_{i+1})\}
= \min_{i \in \{0, \ldots, k-1\}} \{f(x_i, x_{i+1})\} \leq f(s, t).
\]

▶ Let \(\{x_j, x_{j+1}\}\) be the edge with minimum weight on the path.

▶ Since by the invariant this edge induces an \(s\)-\(t\) cut with capacity \(f(x_j, x_{j+1})\) we get \(f(s, t) \leq f(x_j, x_{j+1}) = f_T(s, t)\).

▶ Hence, \(f_T(s, t) = f(s, t)\) (flow equivalence).

▶ The edge \(\{x_j, x_{j+1}\}\) is a mincut between \(s\) and \(t\) in \(T\).

▶ By invariant, it forms a cut with capacity \(f(x_j, x_{j+1})\) in \(G\) (which separates \(s\) and \(t\)).

▶ Since, we can send a flow of value \(f(x_j, x_{j+1})\) btw. \(s\) and \(t\), this is an \(s\)-\(t\) mincut (cut property).

Proof of Invariant

The invariant obviously holds at the beginning of the algorithm.

Now, we show that it holds after a split-operation provided that it was true before the operation.

Let \(S_i\) denote our selected cluster with nodes \(a\) and \(b\). Because of the invariant all edges leaving \(\{S_i\}\) in \(T\) correspond to some mincuts.

Therefore, contracting the connected components does not change the mincut btw. \(a\) and \(b\) due to Lemma 97.

After the split we have to choose representatives for all edges. For the new edge \(\{S_i^a, S_i^b\}\) with capacity \(w(S_i^a, S_i^b) = f_H(a, b)\) we can simply choose \(a\) and \(b\) as representatives.
Proof of Invariant

For edges that are not incident to \( S_i \) we do not need to change representatives as the neighbouring sets do not change.

Consider an edge \( \{X, S_i\} \), and suppose that before the split it used representatives \( x \in X \), and \( s \in S_i \). Assume that this edge is replaced by \( \{X, S_a^i\} \) in the new tree (the case when it is replaced by \( \{X, S_b^i\} \) is analogous).

If \( s \in S_a^i \) we can keep \( x \) and \( s \) as representatives.

Otherwise, we choose \( x \) and \( a \) as representatives. We need to show that \( f(x, a) = f(x, s) \).

Proof of Invariant

Because the invariant was true before the split we know that the edge \( \{X, S_i\} \) induces a cut in \( G \) of capacity \( f(x, s) \). Since, \( x \) and \( a \) are on opposite sides of this cut, we know that \( f(x, a) \leq f(x, s) \).

The set \( B \) forms a mincut separating \( a \) from \( b \). Contracting all nodes in this set gives a new graph \( G' \) where the set \( B \) is represented by node \( v_B \). Because of Lemma 97 we know that \( f'(x, a) = f(x, a) \) as \( x, a \notin B \).

We further have \( f'(x, a) \geq \min\{f'(x, v_B), f'(v_B, a)\} \).

Since \( s \in B \) we have \( f'(v_B, x) \geq f(s, x) \).

Also, \( f'(a, v_B) \geq f(a, b) \geq f(x, s) \) since the \( a-b \) cut that splits \( S_i \) into \( S_a^i \) and \( S_b^i \) also separates \( s \) and \( x \).
Matching
- Input: undirected graph $G = (V, E)$.
- $M \subseteq E$ is a matching if each node appears in at most one edge in $M$.
- Maximum Matching: find a matching of maximum cardinality

18 Bipartite Matching via Flows

Which flow algorithm to use?
- Generic augmenting path: $O(m \text{val}(f^*)) = O(mn)$.
- Capacity scaling: $O(m^2 \log C) = O(m^2)$.
- Shortest augmenting path: $O(mn^2)$.

For unit capacity simple graphs shortest augmenting path can be implemented in time $O(m\sqrt{n})$.

19 Augmenting Paths for Matchings

Definitions.
- Given a matching $M$ in a graph $G$, a vertex that is not incident to any edge of $M$ is called a **free vertex w.r.t.** $M$.
- For a matching $M$ a path $P$ in $G$ is called an **alternating path** if edges in $M$ alternate with edges not in $M$.
- An alternating path is called an **augmenting path** for matching $M$ if it ends at distinct free vertices.

**Theorem 98**
A matching $M$ is a maximum matching if and only if there is no augmenting path w.r.t. $M$. 

Augmenting Paths in Action
Augmenting Paths in Action

19 Augmenting Paths for Matchings

Proof.
⇒ If $M$ is maximum there is no augmenting path $P$, because we could switch matching and non-matching edges along $P$. This gives matching $M' = M \oplus P$ with larger cardinality.

⇐ Suppose there is a matching $M'$ with larger cardinality. Consider the graph $H$ with edge-set $M' \oplus M$ (i.e., only edges that are in either $M$ or $M'$ but not in both).

Each vertex can be incident to at most two edges (one from $M$ and one from $M'$). Hence, the connected components are alternating cycles or alternating path.

As $|M'| > |M|$ there is one connected component that is a path $P$ for which both endpoints are incident to edges from $M'$. $P$ is an alternating path.

19 Augmenting Paths for Matchings

Algorithmic idea:
As long as you find an augmenting path augment your matching using this path. When you arrive at a matching for which no augmenting path exists you have a maximum matching.

Theorem 99
Let $G$ be a graph, $M$ a matching in $G$, and let $u$ be a free vertex w.r.t. $M$. Further let $P$ denote an augmenting path w.r.t. $M$ and let $M' = M \oplus P$ denote the matching resulting from augmenting $M$ with $P$. If there was no augmenting path starting at $u$ in $M$ then there is no augmenting path starting at $u$ in $M'$.

The above theorem allows for an easier implementation of an augmenting path algorithm. Once we checked for augmenting paths starting from $u$ we don’t have to check for such paths in future rounds.

Proof
Arrow A
Assume there is an augmenting path $P'$ w.r.t. $M'$ starting at $u$.

Arrow A
If $P'$ and $P$ are node-disjoint, $P'$ is also augmenting path w.r.t. $M$ ($f$).

Let $u'$ be the first node on $P'$ that is in $P$, and let $e$ be the matching edge from $M'$ incident to $u'$.

$u'$ splits $P$ into two parts one of which does not contain $e$. Call this part $P_1$. Denote the sub-path of $P'$ from $u$ to $u'$ with $P_1'$.

$P_1 \circ P_1'$ is augmenting path in $M$ ($f$).
How to find an augmenting path?

Construct an alternating tree.

**even nodes**

**odd nodes**

**Case 1:**

\( y \) is free vertex not contained in \( T \)
you found alternating path

**Case 2:**

\( y \) is matched vertex not in \( T \); then
\( \text{mate}[y] \in T \)
grow the tree

**Case 3:**

\( y \) is already contained in \( T \) as an odd vertex
ignore successor \( y \)

**Case 4:**

\( y \) is already contained in \( T \) as an even vertex
can't ignore \( y \)
does not happen in bipartite graphs
 Algorithm 25 BiMatch(G, match)
1: for \( x \in V \) do mate\([x]\) \( \leftarrow 0 \);
2: \( r \leftarrow 0 \); free \( \leftarrow n \);
3: while free \( \geq 1 \) and \( r < n \) do
4: \( r \leftarrow r + 1 \)
5: if mate\([r]\) = 0 then
6: for \( i = 1 \) to \( n \) do parent\([i']\) \( \leftarrow 0 \);
7: \( Q \leftarrow \emptyset \); Q.append\((r)\); aug \( \leftarrow \) false;
8: while aug = false and \( Q \neq \emptyset \) do
9: \( x \leftarrow Q\).dequeue();
10: for \( y \in A_x \) do
11: if mate\([y]\) = 0 then
12: augm\((\text{mate}, \text{parent}, y)\);
13: aug \( \leftarrow \) true;
14: free \( \leftarrow \) free \( - 1 \);
15: else
16: if parent\([y]\) = 0 then
17: parent\([y]\) \( \leftarrow x \);
18: Q.enqueue(mate\([y]\));

The lecture version of the slides contains a step-by-step explanation of the algorithm.

**Weighted Bipartite Matching**

**Theorem 100 (Halls Theorem)**

A bipartite graph \( G = (L \cup R, E) \) has a perfect matching if and only if for all sets \( S \subseteq L \), \( |\Gamma(S)| \geq |S| \), where \( \Gamma(S) \) denotes the set of nodes in \( R \) that have a neighbour in \( S \).
Halls Theorem

Proof:
⇐ Of course, the condition is necessary as otherwise not all nodes in $S$ could be matched to different neighbours.
⇒ For the other direction we need to argue that the minimum cut in the graph $G'$ is at least $|L|$.

- Let $S$ denote a minimum cut and let $L_S \equiv L \cap S$ and $R_S \equiv R \cap S$ denote the portion of $S$ inside $L$ and $R$, respectively.
- Clearly, all neighbours of nodes in $L_S$ have to be in $S$, as otherwise we would cut an edge of infinite capacity.
- This gives $R_S \geq |\Gamma(L_S)|$.
- The size of the cut is $|L| - |L_S| + |R_S|$.
- Using the fact that $|\Gamma(L_S)| \geq L_S$ gives that this is at least $|L|$.

Algorithm Outline

Idea:
We introduce a node weighting $\vec{x}$. Let for a node $v \in V$, $x_v \in \mathbb{R}$ denote the weight of node $v$.

- Suppose that the node weights dominate the edge-weights in the following sense:
  $$x_u + x_v \geq w_e \text{ for every edge } e = (u,v).$$

- Let $H(\vec{x})$ denote the subgraph of $G$ that only contains edges that are tight w.r.t. the node weighting $\vec{x}$, i.e. edges $e = (u,v)$ for which $w_e = x_u + x_v$.

- Try to compute a perfect matching in the subgraph $H(\vec{x})$. If you are successful you found an optimal matching.

Algorithm Outline

Reason:
The weight of your matching $M^*$ is
$$\sum_{(u,v) \in M^*} w_{(u,v)} = \sum_{(u,v) \in M^*} (x_u + x_v) = \sum_{v} x_v .$$

Any other perfect matching $M$ (in $G$, not necessarily in $H(\vec{x})$) has
$$\sum_{(u,v) \in M} w_{(u,v)} \leq \sum_{(u,v) \in M} (x_u + x_v) = \sum_{v} x_v .$$

Algorithm Outline

What if you don’t find a perfect matching?
Then, Halls theorem guarantees you that there is a set $S \subseteq L$, with $|\Gamma(S)| < |S|$, where $\Gamma$ denotes the neighbourhood w.r.t. the subgraph $H(\vec{x})$.

Idea: reweight such that:
- the total weight assigned to nodes decreases
- the weight function still dominates the edge-weights

If we can do this we have an algorithm that terminates with an optimal solution (we analyze the running time later).
Changing Node Weights

Increase node-weights in $\Gamma(S)$ by $+\delta$, and decrease the node-weights in $S$ by $-\delta$.

- Total node-weight decreases.
- Only edges from $S$ to $R - \Gamma(S)$ decrease in their weight.
- Since, none of these edges is tight (otw. the edge would be contained in $H(\vec{x})$, and hence would go between $S$ and $\Gamma(S)$) we can do this decrement for small enough $\delta > 0$ until a new edge gets tight.

Weighted Bipartite Matching

Edges not drawn have weight $0$.

$\delta = 1 \; \delta = 1$

Analysis

How many iterations do we need?

- One reweighting step increases the number of edges out of $S$ by at least one.
- Assume that we have a maximum matching that saturates the set $\Gamma(S)$, in the sense that every node in $\Gamma(S)$ is matched to a node in $S$ (we will show that we can always find $S$ and a matching such that this holds).
- This matching is still contained in the new graph, because all its edges either go between $\Gamma(S)$ and $S$ or between $L - S$ and $R - \Gamma(S)$.
- Hence, reweighting does not decrease the size of a maximum matching in the tight sub-graph.

Analysis

- We will show that after at most $n$ reweighting steps the size of the maximum matching can be increased by finding an augmenting path.
- This gives a polynomial running time.
How to find an augmenting path?

Construct an alternating tree.

Analysis

How do we find \( S \)?

- Start on the left and compute an alternating tree, starting at any free node \( u \).
- If this construction stops, there is no perfect matching in the tight subgraph (because for a perfect matching we need to find an augmenting path starting at \( u \)).
- The set of even vertices is on the left and the set of odd vertices is on the right and contains all neighbours of even nodes.
- All odd vertices are matched to even vertices. Furthermore, the even vertices additionally contain the free vertex \( u \).

Hence, \( |V_{\text{odd}}| = |\Gamma(V_{\text{even}})| < |V_{\text{even}}| \), and all odd vertices are saturated in the current matching.

Analysis

- The current matching does not have any edges from \( V_{\text{odd}} \) to \( L \setminus V_{\text{even}} \) (edges that may possibly be deleted by changing weights).
- After changing weights, there is at least one more edge connecting \( V_{\text{even}} \) to a node outside of \( V_{\text{odd}} \). After at most \( n \) reweights we can do an augmentation.
- A reweighting can be trivially performed in time \( O(n^2) \) (keeping track of the tight edges).
- An augmentation takes at most \( O(n) \) time.
- In total we obtain a running time of \( O(n^4) \).
- A more careful implementation of the algorithm obtains a running time of \( O(n^3) \).

How to find an augmenting path?

Construct an alternating tree.

Case 4:

\( y \) is already contained in \( T \) as an even vertex can't ignore \( y \)

The cycle \( w \rightarrow y \rightarrow x \rightarrow w \) is called a blossom. \( w \) is called the base of the blossom (even node!!!). The path \( u \rightarrow w \) is called the stem of the blossom.
**Flowers and Blossoms**

**Definition 101**
A flower in a graph \( G = (V, E) \) w.r.t. a matching \( M \) and a (free) root node \( r \), is a subgraph with two components:

- A stem is an even length alternating path that starts at the root node \( r \) and terminates at some node \( w \). We permit the possibility that \( r = w \) (empty stem).
- A blossom is an odd length alternating cycle that starts and terminates at the terminal node \( w \) of a stem and has no other node in common with the stem. \( w \) is called the base of the blossom.

**Properties:**
1. A stem spans \( 2\ell + 1 \) nodes and contains \( \ell \) matched edges for some integer \( \ell \geq 0 \).
2. A blossom spans \( 2k + 1 \) nodes and contains \( k \) matched edges for some integer \( k \geq 1 \). The matched edges match all nodes of the blossom except the base.
3. The base of a blossom is an even node (if the stem is part of an alternating tree starting at \( r \)).
4. Every node \( x \) in the blossom (except its base) is reachable from the root (or from the base of the blossom) through two distinct alternating paths; one with even and one with odd length.
5. The even alternating path to \( x \) terminates with a matched edge and the odd path with an unmatched edge.
When during the alternating tree construction we discover a blossom $B$ we replace the graph $G$ by $G' = G/B$, which is obtained from $G$ by contracting the blossom $B$.

- Delete all vertices in $B$ (and its incident edges) from $G$.
- Add a new (pseudo-)vertex $b$. The new vertex $b$ is connected to all vertices in $V \setminus B$ that had at least one edge to a vertex from $B$.

Edges of $T$ that connect a node $u$ not in $B$ to a node in $B$ become tree edges in $T'$ connecting $u$ to $b$.

Matching edges (there is at most one) that connect a node $u$ not in $B$ to a node in $B$ become matching edges in $M'$.

Nodes that are connected in $G$ to at least one node in $B$ become connected to $b$ in $G'$. 

Edges of $T$ that connect a node $u$ not in $B$ to a node in $B$ become tree edges in $T'$ connecting $u$ to $b$.

Matching edges (there is at most one) that connect a node $u$ not in $B$ to a node in $B$ become matching edges in $M'$.

Nodes that are connected in $G$ to at least one node in $B$ become connected to $b$ in $G'$. 

Example: Blossom Algorithm

Animation of Blossom Shrinking algorithm is only available in the lecture version of the slides.

Correctness

Proof.

If $P'$ does not contain $b$ it is also an augmenting path in $G$.

Case 1: non-empty stem

Next suppose that the stem is non-empty.

After the expansion $\ell$ must be incident to some node in the blossom. Let this node be $k$.

If $k \neq w$ there is an alternating path $P_2$ from $w$ to $k$ that ends in a matching edge.

$P_1 \circ (i, w) \circ P_2 \circ (k, \ell) \circ P_3$ is an alternating path.

If $k = w$ then $P_1 \circ (i, w) \circ (w, \ell) \circ P_3$ is an alternating path.
Proof.

Case 2: empty stem
- If the stem is empty then after expanding the blossom, \( w = r \).

The path \( r \circ P_2 \circ (k, \ell) \circ P_3 \) is an alternating path.

Correctness

Illustration for Case 1:

Lemma 103
If \( G \) contains an augmenting path \( P \) from \( r \) to \( q \) w.r.t. matching \( M \) then \( G' \) contains an augmenting path from \( r \) (or the pseudo-node containing \( r \)) to \( q \) w.r.t. \( M' \).
Correctness

Case 2: non-empty stem

Let $P_3$ be alternating path from $r$ to $w$; this exists because $r$ and $w$ are root and base of a blossom. Define $M_+ = M \oplus P_3$.

In $M_+$, $r$ is matched and $w$ is unmatched.

$G$ must contain an augmenting path w.r.t. matching $M_+$, since $M$ and $M_+$ have same cardinality.

This path must go between $w$ and $q$ as these are the only unmatched vertices w.r.t. $M_+$.

For $M'_+$, the blossom has an empty stem. Case 1 applies.

$G'$ has an augmenting path w.r.t. $M'_+$. It must also have an augmenting path w.r.t. $M'$, as both matchings have the same cardinality.

This path must go between $r$ and $q$.

Algorithm 26 search($r$, $found$)
1: set $\bar{A}(i) \leftarrow A(i)$ for all nodes $i$
2: $found \leftarrow$ false
3: unlabel all nodes;
4: give an even label to $r$ and initialize list $\leftarrow \{r\}$
5: while list $\neq \emptyset$ do
6: delete a node $i$ from list
7: examine($i$, $found$)
8: if $found = true$ then return

Search for an augmenting path starting at $r$.

Algorithm 27 examine($i$, $found$)
1: for all $j \in \bar{A}(i)$ do
2: if $j$ is even then contract($i$, $j$) and return
3: if $j$ is unmatched then
4: $q \leftarrow j$;
5: pred($q$) $\leftarrow i$;
6: $found \leftarrow true$;
7: return
8: if $j$ is matched and unlabeled then
9: pred($j$) $\leftarrow i$;
10: pred(mate($j$)) $\leftarrow j$;
11: add mate($j$) to list

Examine the neighbours of a node $i$.

Algorithm 28 contract($i$, $j$)
1: trace pred-indices of $i$ and $j$ to identify a blossom $B$
2: create new node $b$ and set $\bar{A}(b) \leftarrow \cup x \in B \bar{A}(x)$
3: label $b$ even and add to list
4: update $\bar{A}(j) \leftarrow \bar{A}(j) \cup \{b\}$ for each $j \in \bar{A}(b)$
5: form a circular double linked list of nodes in $B$
6: delete nodes in $B$ from the graph

Contract blossom identified by nodes $i$ and $j$. 
Algorithm 28 contract\((i, j)\)

1: trace pred-indices of \(i\) and \(j\) to identify a blossom \(B\)
2: create new node \(b\) and set \(\tilde{A}(b) = \bigcup_{x \in B} \tilde{A}(x)\)
3: label \(b\) even and add to list
4: update \(\tilde{A}(j) = \tilde{A}(j) \cup \{b\}\) for each \(j \in \tilde{A}(b)\)
5: form a circular double linked list of nodes in \(B\)
6: delete nodes in \(B\) from the graph

Get all nodes of the blossom.
Time: \(O(m)\)

Identify all neighbours of \(b\).
Time: \(O(m)\) (how?)

\(b\) will be an even node, and it has unexamined neighbours.

Every node that was adjacent to a node in \(B\) is now adjacent to \(b\).
Algorithm 28 contract\((i, j)\)

1. trace pred-indices of \(i\) and \(j\) to identify a blossom \(B\)
2. create new node \(b\) and set \(\tilde{A}(b) = \cup_{x \in B} \tilde{A}(x)\)
3. label \(b\) even and add to list
4. update \(\tilde{A}(j) = \tilde{A}(j) \cup \{b\}\) for each \(j \in \tilde{A}(b)\)
5. form a circular double linked list of nodes in \(B\)
6. delete nodes in \(B\) from the graph

Only for making a blossom expansion easier.

Analysis

- A contraction operation can be performed in time \(O(m)\).
  Note, that any graph created will have at most \(m\) edges.
- The time between two contraction-operation is basically a
  BFS/DFS on a graph. Hence takes time \(O(m)\).
- There are at most \(n\) contractions as each contraction reduces
  the number of vertices.
- The expansion can trivially be done in the same time as needed
  for all contractions.
- An augmentation requires time \(O(n)\). There are at most \(n\)
  of them.
- In total the running time is at most
  \[n \cdot (O(mn) + O(n)) = O(mn^2)\].

Example: Blossom Algorithm

Animation of Blossom Shrinking
algorithm is only available in the
lecture version of the slides.
A Fast Matching Algorithm

Algorithm 29 Bimatch-Hopcroft-Karp(G)

1: \( M \leftarrow \emptyset \)
2: repeat
3: let \( P = \{P_1, \ldots, P_k\} \) be maximal set of
4: vertex-disjoint, shortest augmenting path w.r.t. \( M \).
5: \( M \leftarrow M \oplus (P_1 \cup \cdots \cup P_k) \)
6: until \( P = \emptyset \)
7: return \( M \)

We call one iteration of the repeat-loop a phase of the algorithm.

Analysis Hopcroft-Karp

Lemma 104
Given a matching \( M \) and a maximal matching \( M^* \) there exist \( |M^*| - |M| \) vertex-disjoint augmenting path w.r.t. \( M \).

Proof:
- Similar to the proof that a matching is optimal iff it does not contain an augmenting path.
- Consider the graph \( G = (V, M \oplus M^*) \), and mark edges in this graph blue if they are in \( M \) and red if they are in \( M^* \).
- The connected components of \( G \) are cycles and paths.
- The graph contains \( k \leq |M^*| - |M| \) more red edges than blue edges.
- Hence, there are at least \( k \) components that form a path starting and ending with a red edge. These are augmenting paths w.r.t. \( M \).

Let \( P_1, \ldots, P_k \) be a maximal collection of vertex-disjoint, shortest augmenting paths w.r.t. \( M \) (let \( \ell = |P_i| \)).

\( M' \equiv M \oplus (P_1 \cup \cdots \cup P_k) = M \oplus P_1 \oplus \cdots \oplus P_k \).

Let \( P \) be an augmenting path in \( M' \).

Lemma 105
The set \( A \equiv M \oplus (M' \oplus P) = (P_1 \cup \cdots \cup P_k) \oplus P \) contains at least \((k + 1)\ell\) edges.
The Hopcroft-Karp algorithm requires at most $2\sqrt{|V|}$ phases.

Proof.
- After iteration $\lfloor\sqrt{|V|}\rfloor$ the length of a shortest augmenting path must be at least $\lfloor\sqrt{|V|}\rfloor + 1 \geq \sqrt{|V|}$.
- Hence, there can be at most $|V|/(\sqrt{|V|} + 1) \leq \sqrt{|V|}$ additional augmentations.
Analysis Hopcroft-Karp

- a shortest augmenting path must go from Level 0 to the last layer constructed
- it can only use edges between layers
- construct a maximal set of vertex disjoint augmenting path connecting the layers
- for this, go forward until you either reach a free vertex or you reach a "dead end" $v$
- if you reach a free vertex delete the augmenting path and all incident edges from the graph
- if you reach a dead end backtrack and delete $v$ together with its incident edges

Analysis: Shortest Augmenting Path for Flows

cost for searches during a phase is $O(mn)$

- a search (successful or unsuccessful) takes time $O(n)$
- a search deletes at least one edge from the level graph

there are at most $n$ phases

Time: $O(mn^2)$.

Analysis for Unit-capacity Simple Networks

cost for searches during a phase is $O(m)$

- an edge/vertex is traversed at most twice

need at most $O(\sqrt{n})$ phases

- after $\sqrt{n}$ phases there is a cut of size at most $\sqrt{n}$ in the residual graph
- hence at most $\sqrt{n}$ additional augmentations required

Time: $O(m\sqrt{n})$. 