

DM87
SCHEDULING,
TIMETABLING AND ROUTING

Lecture 2
Complexity hierarchies, PERT,
Mathematical programming

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Outline

1. Resume
2. Complexity Hierarchy
3. CPM/PERT
4. Mathematical Programming

2

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3

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4

Complexity Hierarchy

A problem \mathcal{A} is **reducible** to \mathcal{B} if a procedure for \mathcal{B} can be used also for \mathcal{A} .

Ex: $1 || \sum C_j \propto 1 || \sum w_j C_j$

Complexity hierarchy describes relationships between different scheduling problems.

Interest in characterizing the borderline: polynomial vs NP-hard problems

Problems Involving Numbers

Partition

- **Input:** finite set A and a size $s(a) \in \mathbf{Z}^+$ for each $a \in A$
- **Question:** is there a subset $A' \subseteq A$ such that

$$\sum_{a \in A'} s(a) = \sum_{a \in A - A'} s(a)?$$

3-Partition

- **Input:** set A of $3m$ elements, a bound $B \in \mathbf{Z}^+$, and a size $s(a) \in \mathbf{Z}^+$ for each $a \in A$ such that $B/4 < s(a) < B/2$ and such that $\sum_{a \in A} s(a) = mB$
- **Question:** can A be partitioned into m disjoint sets A_1, \dots, A_m such that for $1 \leq i \leq m$, $\sum_{a \in A_i} s(a) = B$ (note that each A_i must therefore contain exactly three elements from A)?

Complexity Hierarchy of Problems

TABLE D.1 POLYNOMIAL TIME SOLVABLE PROBLEMS

Single machine	Parallel machines	Shops
$1 r_j, p_j = 1, prec \sum C_j$	$P2 p_j = 1, prec L_{max}$	$O2 C_{max}$
$1 r_j, prmp \sum C_j$	$P2 p_j = 1, prec \sum C_j$	$Om r_j, prmp L_{max}$
$1 tree \sum w_j C_j$	$Pm p_j = 1, tree C_{max}$	$F2 block C_{max}$
$1 prec L_{max}$	$Pm prmp, tree C_{max}$	$F2 nwt C_{max}$
$1 r_j, prmp, prec L_{max}$	$Pm p_j = 1, outtree \sum C_j$	$Fm p_{ij} = p_j \sum C_j$
$1 \sum U_j$	$Pm p_j = 1,intree L_{max}$	$Fm p_{ij} = p_j L_{max}$
$1 r_j, prmp \sum U_j$	$Pm prmp,intree L_{max}$	$Fm p_{ij} = p_j \sum U_j$
$1 r_j, p_j = 1 \sum w_j U_j$	$Q2 prmp, prec C_{max}$	$J2 C_{max}$
$1 r_j, p_j = 1 \sum w_j T_j$	$Q2 r_j, prmp, prec L_{max}$	
	$Qm r_j, p_j = 1 C_{max}$	
	$Qm r_j, p_j = 1 \sum C_j$	
	$Qm prmp \sum C_j$	
	$Qm p_j = 1 \sum w_j C_j$	
	$Qm p_j = 1 L_{max}$	
	$Qm prmp \sum U_j$	
	$Qm p_j = 1 \sum w_j U_j$	
	$Qm p_j = 1 \sum w_j T_j$	
	$Rm \sum C_j$	
	$Rm r_j, prmp L_{max}$	

TABLE D.2 NP-HARD PROBLEMS IN THE ORDINARY SENSE

Single machine	Parallel machines	Shops
$1 \sum w_j U_j (*)$	$P2 C_{max} (*)$	$O2 prmp \sum C_j$
$1 r_j, prmp \sum w_j U_j (*)$	$P2 r_j, prmp \sum C_j$	$O3 C_{max}$
	$P2 \sum w_j C_j (*)$	$O3 prmp \sum w_j U_j$
$1 \sum T_j (*)$	$P2 r_j, prmp \sum U_j$	
	$Pm prmp \sum w_j C_j$	
	$Qm \sum w_j C_j (*)$	
	$Rm r_j C_{max} (*)$	
	$Rm \sum w_j U_j (*)$	
	$Rm prmp \sum w_j U_j$	

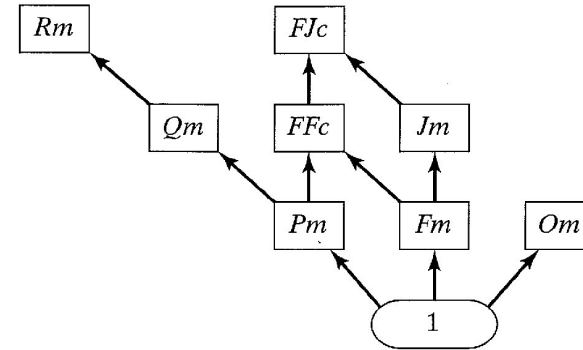
TABLE D.3 STRONGLY NP-HARD PROBLEMS

Single machine	Parallel machines	Shops
$1 s_{jk} C_{max}$	$P2 chains C_{max}$	$F2 r_j C_{max}$
$1 r_j \sum C_j$	$P2 chains \sum C_j$	$F2 r_j, prmp C_{max}$
$1 prec \sum C_j$	$P2 prmp, chains \sum C_j$	$F2 \sum C_j$
$1 r_j, prmp, tree \sum C_j$	$P2 p_j = 1, tree \sum w_j C_j$	$F2 prmp \sum C_j$
$1 r_j, prmp \sum w_j C_j$	$R2 prmp, chains C_{max}$	$F2 L_{max}$
$1 r_j, p_j = 1, tree \sum w_j C_j$		$F2 prmp L_{max}$
$1 p_j = 1, prec \sum w_j C_j$		$F3 C_{max}$
		$F3 prmp C_{max}$
		$F3 nwt C_{max}$
$1 r_j L_{max}$		$O2 r_j C_{max}$
$1 r_j \sum U_j$		$O2 \sum C_j$
$1 p_j = 1, chains \sum U_j$		$O2 prmp \sum w_j C_j$
$1 r_j \sum T_j$		$O2 L_{max}$
$1 p_j = 1, chains \sum T_j$		$O3 prmp \sum C_j$
$*1 \sum w_j T_j$		$J2 recrc C_{max}$
		$J3 p_j = 1, recrc C_{max}$

<http://www.mathematik.uni-osnabrueck.de/research/OR/class/>

Complexity Hierarchy

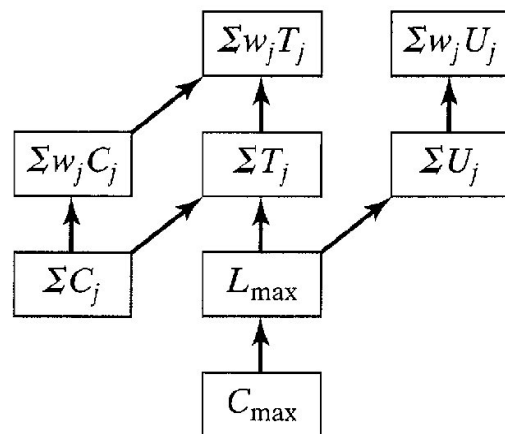
Elementary reductions for machine environment



10

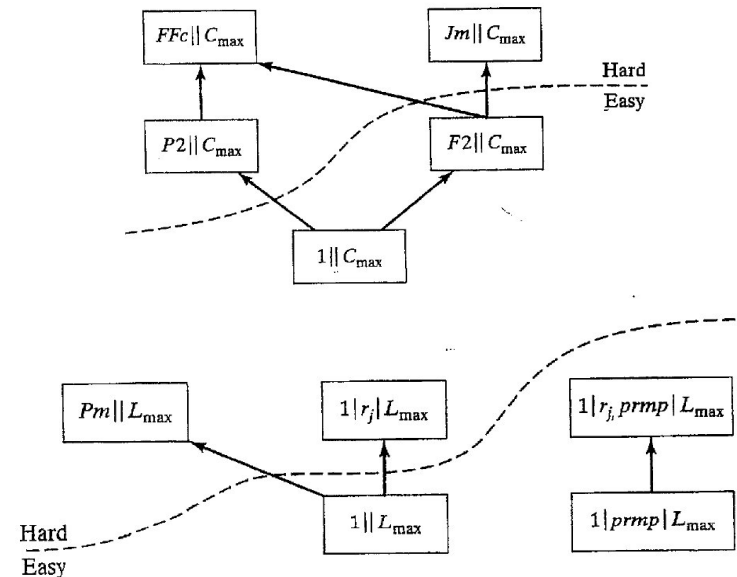
Complexity Hierarchy

Elementary reductions for regular objective functions



11

Complexity Hierarchy of Problems



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13

Project Planning

Milwaukee General Hospital Project

Activity	Description	Immediate Predecessor	Duration
A	Build internal components	-	2
B	Modify roof and floor	-	3
C	Construct collection stack	A	2
D	Pour concrete and install frame	A,B	4
E	Build high-temperature burner	C	4
F	Install pollution control system	C	3
G	Install air pollution device	D,E	5
H	Inspect and test	F,G	2

14

Project Planning

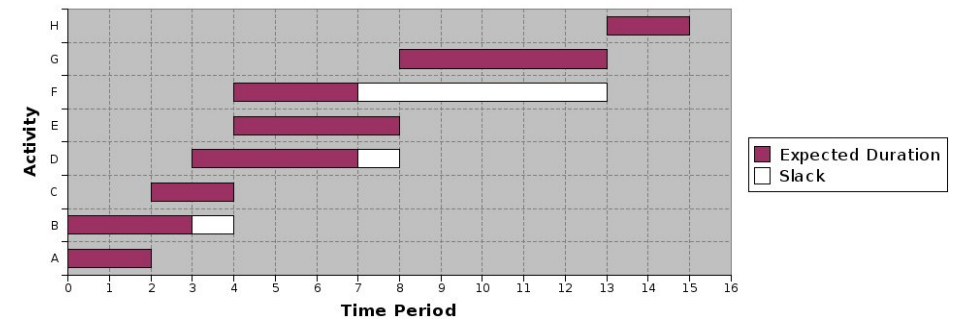
Milwaukee General Hospital Project

Activity	Description	Immediate Predecessor	Duration	EST	EFT	LST	LFT	Slack
A	Build internal components	-	2	0	2	0	2	0
B	Modify roof and floor	-	3	0	3	1	4	1
C	Construct collection stack	A	2	2	4	2	4	0
D	Pour concrete and install frame	A,B	4	3	7	6	10	3
E	Build high-temperature burner	C	4	4	8	6	10	2
F	Install pollution control system	C	3	4	7	10	13	6
G	Install air pollution device	D,E	5	8	13	8	13	0
H	Inspect and test	F,G	2	13	15	13	15	0
<i>Expected project duration</i>				15				

14

Project Planning

Gantt Chart



14

Project Planning

Activity	Description	Immediate Predecessor	Expected					Time Estimates			Activity Variance		
			$(a+m+b)/3$	EST	EFT	LST	LFT	Slack	a	m	b	$((b-a)/6)^2$	
A	Build internal components	-	2	0	2	0	2	0	1	2	3	0.1111	
B	Modify roof and floor	-	3	0	3	1	4	1	2	3	4	0.1111	
C	Construct collection stack	A	2	2	4	2	4	0	1	2	3	0.1111	
D	Pour concrete and install frame	A,B	4	3	7	4	8	1	2	4	6	0.4444	
E	Build high-temperature burner	C	4	4	8	4	8	0	1	4	7	1.0000	
F	Install pollution control system	C	3	4	7	10	13	6	1	2	9	1.7778	
G	Install air pollution device	D,E	5	8	13	8	13	0	3	4	11	1.7778	
H	Inspect and test	F,G	2	13	15	13	15	0	1	2	3	0.1111	
				Expected project duration		15		Variance of project duration					3.1111

14

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15

Linear, Integer, Nonlinear Programming

program = optimization problem

$$\begin{aligned} \min \quad & f(x) \\ & g_i(x) = 0, \quad i = 1, 2, \dots, k \\ & h_j(x) \leq 0, \quad j = 1, 2, \dots, m \\ & x \in \mathbf{R}^n \end{aligned}$$

general (nonlinear) program (NLP)

$$\begin{aligned} \min \quad & c^T x \\ & Ax = a \\ & Bx \leq b \\ & x \geq 0 \\ & (x \in \mathbf{R}^n) \end{aligned}$$

linear program (LP)

$$\begin{aligned} \min \quad & c^T x \\ & Ax = a \\ & Bx \leq b \\ & x \geq 0 \\ & (x \in \mathbf{Z}^n) \\ & (x \in \{0, 1\}^n) \end{aligned}$$

integer (linear) program (IP, MIP)

16

Linear Programming

Linear Program in standard form

$$\begin{aligned} \min \quad & c_1 x_1 + c_2 x_2 + \dots + c_n x_n \\ \text{s.t.} \quad & a_{11} x_1 + a_{12} x_2 + \dots + a_{1n} x_n = b_1 \\ & a_{21} x_1 + a_{22} x_2 + \dots + a_{2n} x_n = b_2 \\ & \vdots \\ & a_{m1} x_1 + a_{m2} x_2 + \dots + a_{mn} x_n = b_m \\ & x_1, x_2, \dots, x_n \geq 0 \end{aligned}$$

$$\begin{aligned} \min \quad & c^T x \\ & Ax = b \\ & x \geq 0 \end{aligned}$$

17

Historic Roots

- ▶ 1939 L. V. Kantorovitch: Foundations of linear programming (Nobel Prize 1975)
- ▶ George J. Stigler's 1945 (Nobel Prize 1982) "Diet Problem": "the first linear program"
find the cheapest combination of foods that will satisfy the daily requirements of a person
Army's problem had 77 unknowns and 9 constraints.
<http://www.mcs.anl.gov/home/otc/Guide/CaseStudies/diet/index.h>
- ▶ 1947 G. B. Dantzig: Invention of the simplex algorithm
- ▶ Founding fathers:
 - ▶ 1950s Dantzig: Linear Programming 1954, the Beginning of IP G. Dantzig, D.R. Fulkerson, S. Johnson TSP with 49 cities
 - ▶ 1960s Gomory: Integer Programming

18

LP Theory

▶ Max-Flow Min-Cut Theorem

The maximal (s,t)-flow in a capacitated network is equal to the minimal capacity of an (s,t)-cut

▶ The Duality Theorem of Linear Programming

$$\begin{array}{ll} \max & c^T x \\ & Ax \leq b \\ & x \geq 0 \end{array} \qquad \begin{array}{ll} \min & y^T b \\ & y^T A \geq c^T \\ & y \geq 0 \end{array}$$

If feasible solutions to both the primal and the dual problem in a pair of dual LP problems exist, then there is an optimum solution to both systems and the optimal values are equal.

19

LP Theory

▶ Max-Flow Min-Cut Theorem

does not hold if several source-sink relations are given (multicommodity flow)

▶ The Duality Theorem of Integer Programming

$$\begin{array}{ll} \max & c^T x \\ & Ax \leq b \\ & x \geq 0 \\ & x \in \mathbf{Z}^n \end{array} \leq \begin{array}{ll} \min & y^T b \\ & y^T A \geq c^T \\ & y \geq 0 \\ & y \in \mathbf{Z}^n \end{array}$$

20

LP Solvability

- ▶ Linear programs can be solved in polynomial time with the Ellipsoid Method (Khachiyan, 1979)
Interior Point Methods (Karmarkar, 1984, and others)
- ▶ **Open:** is there a strongly polynomial time algorithm for the solution of LPs?
- ▶ Certain variants of the Simplex Algorithm run - under certain conditions - in expected polynomial time (Borgwardt, 1977...)
- ▶ **Open:** Is there a polynomial time variant of the Simplex Algorithm?

21

IP Solvability

- ▶ **Theorem**
Integer, 0/1, and mixed integer programming are NP-hard.
- ▶ Consequence
 - ▶ special cases
 - ▶ special purposes
 - ▶ heuristics

22

- ▶ Algorithms for the solution of nonlinear programs
- ▶ Algorithms for the solution of linear programs
 - ▶ 1) Fourier-Motzkin Elimination (hopeless)
 - ▶ 2) The Simplex Method (good, above all with duality)
 - ▶ 3) The Ellipsoid Method (total failure)
 - ▶ 4) Interior-Point/Barrier Methods (good)
- ▶ Algorithms for the solution of integer programs
 - ▶ 1) Branch & Bound
 - ▶ 2) Cutting Planes

23

Algorithms for nonlinear programming

- ▶ Iterative methods that solve the equation and inequality systems representing the necessary local optimality conditions.
- ▶ Steepest descent (Kuhn-Tucker sufficient conditions)
- ▶ Newton method
- ▶ Subgradient method

24

Algorithms for linear programming

The Simplex Method

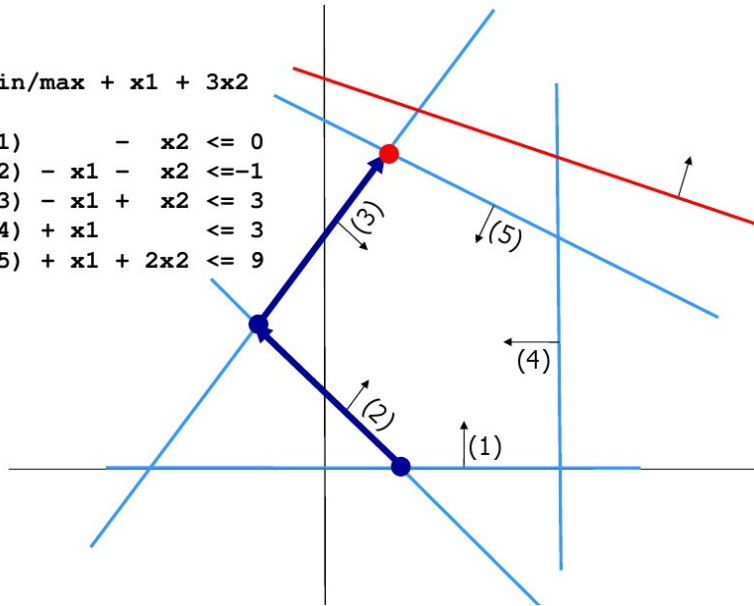
- ▶ Dantzig, 1947: primal Simplex Method
- ▶ Lemke, 1954; Beale, 1954: dual Simplex Method
- ▶ Dantzig, 1953: revised Simplex Method
- ▶
- ▶ Underlying Idea: Find a vertex of the set of feasible LP solutions (polyhedron) and move to a better neighbouring vertex, if possible.

25

The simplex method

min/max $+ x_1 + 3x_2$

- (1) $- x_2 \leq 0$
- (2) $- x_1 - x_2 \leq -1$
- (3) $- x_1 + x_2 \leq 3$
- (4) $+ x_1 \leq 3$
- (5) $+ x_1 + 2x_2 \leq 9$

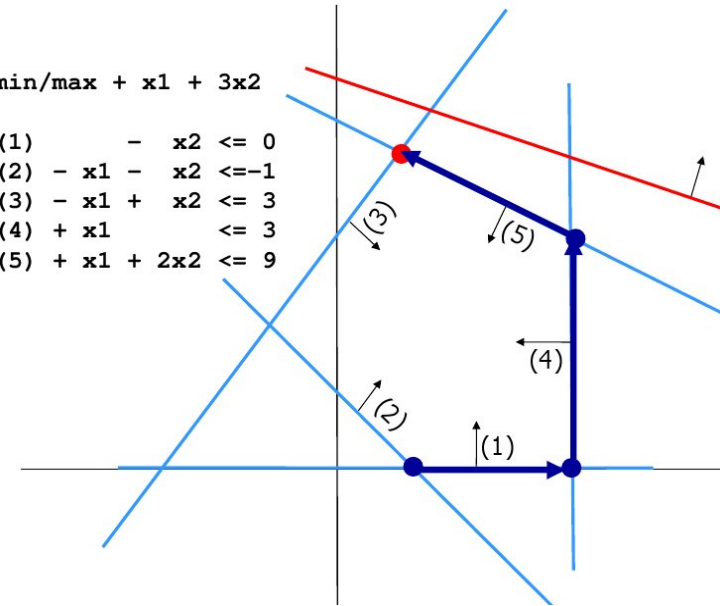


26

The simplex method

min/max $+ x_1 + 3x_2$

- (1) $- x_2 \leq 0$
- (2) $- x_1 - x_2 \leq -1$
- (3) $- x_1 + x_2 \leq 3$
- (4) $+ x_1 \leq 3$
- (5) $+ x_1 + 2x_2 \leq 9$



26

The simplex method

Hirsch Conjecture

If P is a polytope of dimension n with m facets then every vertex of P can be reached from any other vertex of P on a path of length at most $m-n$.

In the example before: $m=5$, $n=2$ and $m-n=3$, conjecture is true.

At present, not even a polynomial bound on the path length is known.

Best upper bound: Kalai, Kleitman (1992): The diameter of the graph of an n -dimensional polyhedron with m facets is at most $m(\log n + 1)$.

Lower bound: Holt, Klee (1997): at least $m-n$ (m , n large enough).

27

Algorithms for Integer Programming

special „simple" combinatorial optimization problems Finding a:

- ▶ minimum spanning tree
- ▶ shortest path
- ▶ maximum matching
- ▶ maximal flow through a network
- ▶ cost-minimal flow
- ▶ ...

solvable in polynomial time by special purpose algorithms

28

Algorithms for Integer Programs

special „hard“ combinatorial optimization problems

- ▶ traveling salesman problem
- ▶ location and routing
- ▶ set-packing, partitioning, -covering
- ▶ max-cut
- ▶ linear ordering
- ▶ scheduling (with a few exceptions)
- ▶ node and edge colouring
- ▶ ...

NP-hard (in the sense of complexity theory)

The most successful solution techniques employ linear programming.

29

Algorithms for Integer Programs

- ▶ 1) Branch & Bound
- ▶ 2) Cutting Planes

Branch & cut, Branch & Price (column generation), Branch & Cut & Price

30

Summary

- ▶ We can solve today **explicit LPs** with
 - ▶ up to 500,000 of variables and
 - ▶ up to 5,000,000 of constraints routinelyin relatively short running times.
- ▶ We can solve today structured **implicit LPs** (employing column generation and cutting plane techniques) in special cases with hundreds of million (and more) variables and almost infinitely many constraints in acceptable running times. (Examples: TSP, bus circulation in Berlin)

[Martin Grötschel, Block Course at TU Berlin,
“Combinatorial Optimization at Work”, 2005
<http://co-at-work.zib.de/berlin/>]

31