Totally unimodular matrices and network flows

Totally unimodular matrices

Introduction to integer programming III: Network Flow, Interval Scheduling, and Vehicle Routing Problems

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COMPUTATIONAL ASPECTS OF OPTIMIZATION

Definition

A matrix A is totally unimodular (TU) iff every square submatrix of A has determinant +1, -1, or 0.

The linear program has an integral optimal solution for all integer r.h.s. b if and only if A is TU.

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Totally unimodular matrices

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 \ldots based on Laplace expansion for the determinant of a basic matrix and the Cramer rule.

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Totally unimodular matrices

A set of sufficient conditions:

- $a_{ij} \in \{-1, 0, 1\}$ for all i, j
- Each column contains at most two nonzero coefficients, i.e. $\sum_{i=1}^{m} |a_{ij}| \le 2$,
- There exists a partitioning $M_1 \cap M_2 = \emptyset$ of the rows $1, \ldots, m$ such that each column *j* containing two nonzero coefficients satisfies

$$\sum_{i\in M_1}a_{ij}=\sum_{i\in M_2}a_{ij}.$$

If A is TU, then A^T and (A|I) are TU.

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Minimum cost network flow problem

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- G = (V, A) graph with vertices V and (oriented) arcs A
- *h_{ij}* arc capacity
- c_{ij} flow cost
- b_i demand, ASS. $\sum_i b_i = 0$
- $V^+(i) = \{k : (i,k) \in A\}$ successors of i
- $V^{-}(i) = \{k : (k, i) \in A\}$ predecessors of i

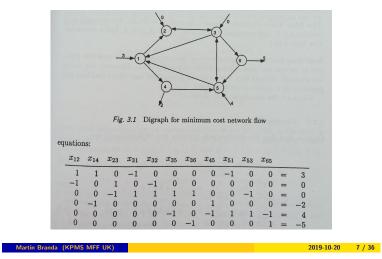
$$\begin{split} \min_{x_{ij}} & \sum_{(i,j)\in A} c_{ij} x_{ij} \\ \text{s.t.} & \sum_{k\in V^+(i)} x_{ik} - \sum_{k\in V^-(i)} x_{ki} = b_i, \ i\in V, \\ & 0 \leq x_{ij} \leq h_{ij}, \ (i,j) \in A. \end{split}$$

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Wolsey (1998), Ex. 3.1 ($M_1 = \{1, \ldots, m\}, M_2 = \emptyset$)



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Special cases

- Shortest path problem
- Critical (longest time) path problem in project scheduling (PERT = Program Evaluation and Review Technique)
- Fixed interval scheduling
- Transportation problem

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Shortest path problem

Find a minimum cost s - t path given nonnegative arc costs c_{ij} , set

•
$$b_i = 1$$
 if $i = s_i$

• $b_i = -1$ if i = t,

• $b_i = 0$ otherwise.

Then the problem can be formulated as

$$\begin{split} \min_{x_{ij}} & \sum_{(i,j) \in A} c_{ij} x_{ij} \\ \text{s.t.} & \sum_{k \in V^+(i)} x_{ik} - \sum_{k \in V^-(i)} x_{ki} = 1, \ i = s, \\ & \sum_{k \in V^+(i)} x_{ik} - \sum_{k \in V^-(i)} x_{ki} = 0, \ i \in V \setminus \{s, t\} \\ & \sum_{k \in V^+(i)} x_{ik} - \sum_{k \in V^-(i)} x_{ki} = -1, \ i = t, \\ & 0 \le x_{ij} \le 1, \ (i,j) \in A. \end{split}$$

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 $\hat{x}_{ij} = 1$ identifies the shortest path.

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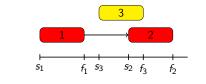
Fixed interval scheduling

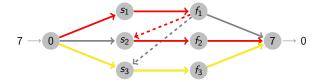
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Basic **Fixed interval scheduling** (FIS) problem: given J jobs with prescribed starting s_j and finishing f_j times, find a minimal number of identical machines that can process all jobs such that no processing intervals intersect.

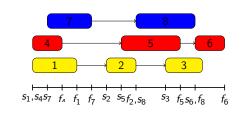
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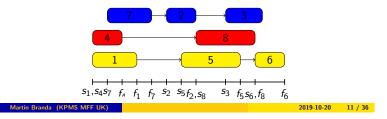
Totally unimodular matrices and network flows FIS – network flow reformulation





Totally unimodular matrices and network flows Fixed interval scheduling





Totally unimodular matrices and network flows FIS – network flow reformulation

Network structure:

- 2J + 2 vertices \mathcal{V} : $\{0, s_1, f_1, \dots, s_J, f_J, 2J + 1\}$; vertices 0, 2J + 1 correspond to the source and sink,
- **2** oriented edges $E: \{0, s_j\}, \{s_j, f_j\}, j \in \mathcal{J}, \{f_i, s_j\} \text{ if } f_i \leq s_j, \{f_i, 2J + 1\}, j \in \mathcal{J}, (2J + 1, 0)$
- **3** demands: $d_0 = d_{2J+1} = 0$, $d_{s_i} = -1$, $d_{f_i} = 1$, $j \in \mathcal{J}$,
- **3** return edge (2J + 1, 0): capacity $u_{2J+1,0} = M$, $c_{2J+1,0} = 1$,

③ edge capacities $u_{uv} = 1$, and costs $c_{uv} = 0$, $(u, v) \in E \setminus (2J + 1, 0)$. Solve the min-cost network flow problem.

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Traveling salesman problem

Traveling salesman problem

Assignment problem

Traveling salesman problem

• Consider n towns and in one of them there is a traveling salesman.

- Traveling salesman must visit all towns and return back.
- For each pair of towns the traveling costs are known and the traveling salesman is looking for the cheapest route.
- = Finding a Hamilton cycle in a graph with edge prices.

$$\min\sum_{i=1}^{n}\sum_{j=1}^{n}c_{ij}x_{ij}$$

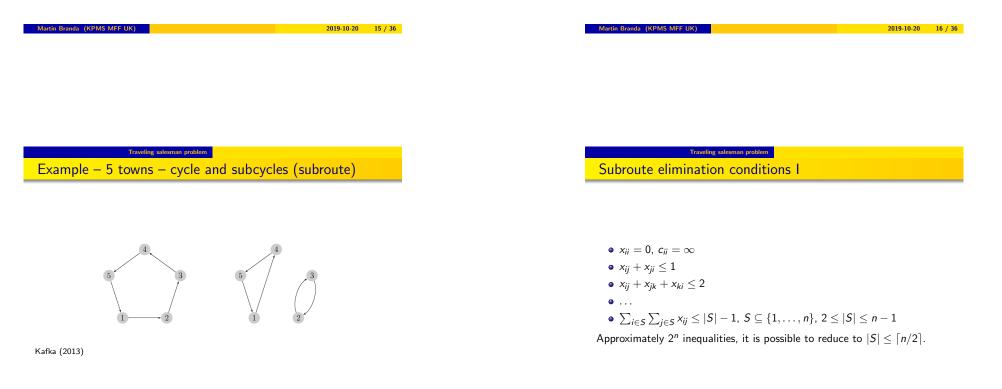
$$\tag{1}$$

$$\sum_{i=1}^{n} x_{ij} = 1, \ j = 1, \dots, n,$$
(2)

$$\sum_{j=1}^{n} x_{ij} = 1, \ i = 1, \dots, n,$$
(3)

$$x_{ij} \in \{0,1\}.$$
 (4)

We minimize the traveling costs, we arrive to j from exactly one i, we leave i to exactly one j.



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Traveling salesman problem

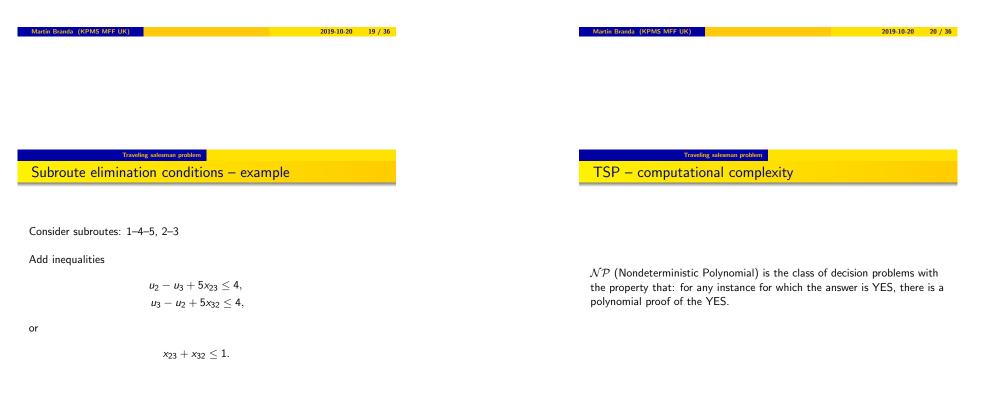
Other valid inequalities (using additional real decision variables u_i):

$$u_i-u_j+nx_{ij}\leq n-1, i,j=2,\ldots,n.$$

Eliminate subroutes: There is at least one route which does not go through vertex 1, denote this route by *C* and the number of edges by |E(C)|. If we sum all these inequalities over all edges $\{i, j\}$, which are in *C*, i.e. the corresponding variables $x_{ii} = 1$, we obtain

$$|E(C)| \le (n-1)|E(C)|,$$
 (5)

which is a contradiction.



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Traveling salesman problem

$$u_i-u_j+nx_{ij}\leq n-1, i,j=2,\ldots,n.$$

Hamilton cycle is feasible: let the vertices be ordered as $v_1 = 1, v_2, ..., v_n$. We set $u_i = l$, if $v_l = i$, i.e. u_i represent the order. For each edge of the cycle $\{i, j\}$ it holds $u_i - u_i = -1$, i.e.

$$u_i - u_i + nx_{ii} = -1 + n \le n - 1.$$
(6)

For edges, which are not in the cycle, the inequality holds too: $u_i - u_i \le n - 1$ and $x_{ij} = 0$.

Traveling Salesman Problem with Time Windows

Traveling salesman problem

- t_i time when customer i is visited
- T_{ij} time necessary to reach j from i
- I_i , u_i lower and upper bound (time window) for visiting customer i
- M a large constant

$$\min_{x_{ij},t_i} \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} x_{ij}$$
(7)

$$\sum_{i=1}^{n} x_{ij} = 1, \ j = 1, \dots, n,$$
(8)

$$\sum_{j=1} x_{ij} = 1, \ i = 1, \dots, n, \tag{9}$$
$$t_i + T_{ii} - t_i < M(1 - x_{ii}) \ i, j = 1, \dots, n, \tag{10}$$

$$\begin{array}{rcl} l_{ij} = l_{ij} & \geq & m(1 - x_{ij}) \ , \ , \ j = 1, \dots, n, \\ l_i \leq t_i & \leq & u_i, \ i = 1, \dots, n, \\ x_{ij} & \in & \{0, 1\}. \end{array}$$

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Capacitated Vehicle Routing Problem

Traveling salesman problem

Parameters

- *n* number of customers
- 0 depo (starting and finishing point of each vehicle)
- *K* number of vehicles (homogeneous)
- $d_i \ge 0$ customer demand, for depo $d_0 = 0$
- Q > 0 vehicle capacity ($KQ \ge \sum_{j=1}^{n} d_j$)
- c_{ij} transportation costs from *i* to *j* (usually $c_{ii} = 0$)

Decision variables

- x_{ii} equal to 1, if j follows after i on the route, 0 otherwise
- u_j upper bound on transported amount after visiting customer j

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Capacitated Vehicle Routing Problem

Traveling salesman problem

$$\min_{x_{ij}, u_j} \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij} x_{ij}$$
(12)

$$\sum_{i=0}^{n} x_{ij} = 1, j = 1, \dots, n,$$
(13)

$$\sum_{j=0}^{n} x_{ij} = 1, i = 1, \dots, n,$$
(14)

$$\sum_{i=1}^{n} x_{i0} = K,$$
(15)

$$\sum_{i=1}^{n} x_{0i} = K,$$
(16)

$$u_i - u_j + d_j \leq Q(1 - x_{ij}) \ i, j = 1, \dots, n,$$
(17)

$$d_i \leq u_i \leq Q, \ i = 1, \dots, n,$$
(18)

$$x_{ij} \in \{0, 1\}.$$
(12)

Capacitated Vehicle Routing Problem

Traveling salesman problem

- (12) minimization of transportation costs
- (13) exactly one vehicle arrives to customer j
- (14) exactly one vehicle leaves customer i
- (15) exactly K vehicles return to depot 0
- (16) exactly K vehicles leave depot 0
- (17) balance conditions of transported amount (serve also as subroute elimination conditions)
- (18) bounds on the vehicle capacity
- (All vehicles are employed.)

Greedy heuristic

Start with an empty set (solution) and choose the item with **the best immediate reward** at each step.

Heuristic algorithms

 $\mathsf{Example:}\xspace$ Traveling Salesman Problem with the (symmetric) distance matrix

 $\left(\begin{array}{cccccccc} -&9&2&8&12&11\\ &-&7&19&10&32\\ &&-&29&18&6\\ &&&-&24&3\\ &&&&-&19\\ &&&&&-\end{array}\right)$

Greedy steps: 1-3 (2), 3-6 (6), 6-4 (3), 4-2 (19), 2-5 (10), 5-1 (12), i.e. the route length is 52.

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Basic heuristics for VRP

Insertion heuristic:

- Start with empty routes.
- FOR all customers DO: Insert the customer to the place in a route where it causes the lowest increase of the traveled distance.

Clustering:

- Cluster the customers according to their geographic positions ("angles").
- Solve¹ the traveling salesman problem in each cluster.

Heuristic algorithms

Possible difficulties: time windows, vehicle capacities, ...

Local search heuristic

Choose an initial solution x and search its neighborhood U(x). Repeat until you are able to find a better solution, i.e. if $y \in U(x)$, f(y) < f(x), set x = y.

Example: Traveling Salesman Problem, define the neighborhood U(x) as **2-exchange**, i.e. if $S = \{(i,j) \in A : x_{ij} = 1\}$ is a feasible solution, then

$$U(x) = \{S': |S \cap S'| = n-2\},\$$

in other words: **replace edges** (i, j), (i', j') by (i, i'), (j, j').

Heuristic algorithms

Greedy steps: 1–3 (2), 3–6 (6), 6–4 (3), 4–2 (19), 2–5 (10), 5–1 (12), i.e. the route length is 52.

2-exchange: 1-3 (2), 3-4 (29), 4-6 (3), 6-2 (32), 2-5 (10), 5-1 (12), i.e. the route length is 88.

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Tabu search for VRP

For a given number of iteration, run the following steps:

Heuristic algorithms

- Find the best solution in a *neighborhood* of the current solution. Such solution can be worse than the current one or even infeasible (use a penalty function).
- Forbid moving back for a random number of steps by actualizing the **tabu list**.
- Remember the best solution.

The tabu search algorithm enables moving from local solutions (compared with a simple "hill climbing alg.").

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Genetic algorithms

Iterative procedure:

Population – finite set of individuals with genes

Heuristic algorithms

- Generation
- Evaluation fitness
- Parent selection
- Crossover produces one or two new solutions (offspring).
- Mutation
- Population selection

Real VRP

Rich Vehicle Routing Problems

- Goal maximization of the ship *filling rate* (operational planning), optimization of fleet composition, i.e. number and capacity of the ships (strategic planning)
- Rich Vehicle Routing Problem
 - time windows
 - heterogeneous fleet (vehicles with different capacities and speed)
 - several depots with inter-depot trips
 - several routes during the planning horizon
 - non-Euclidean distances (fjords)
- Mixed-integer programming :-(, constructive heuristics for getting an initial feasible solution and tabu search
- M. Branda, K. Haugen, J. Novotný, A. Olstad, Downstream logistics optimization at EWOS Norway. Research report.

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Rich Vehicle Routing Problems

Our approach

- Mathematical formulation
- GAMS implementation
- Heuristic (insertion heuristic, tabu search) implementation
- Decision Support System (DSS)

Real VRP

- M. Branda, J. Novotný, A. Olstad: Fixed interval scheduling under uncertainty

 a tabu search algorithm for an extended robust coloring formulation.
 Computers & Industrial Engineering 93, 45–54.
- M. Branda, K. Haugen, J. Novotný, A. Olstad: Downstream logistic optimization at EWOS Norway. Mathematics for Applications 6 (2), 127-141.
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