

## Example: Minimum Cost Flow Problem

**Given:** directed graph  $D = (V, A)$ , with arc capacities  $u : A \rightarrow \mathbb{R}_{\geq 0}$ , arc costs  $c : A \rightarrow \mathbb{R}$ , and node balances  $b : V \rightarrow \mathbb{R}$ .

**Interpretation:**

- ▶ nodes  $v \in V$  with  $b(v) > 0$  ( $b(v) < 0$ ) have *supply* (*demand*) and are called *sources* (*sinks*)
- ▶ the capacity  $u(a)$  of arc  $a \in A$  limits the amount of flow that can be sent through arc  $a$ .

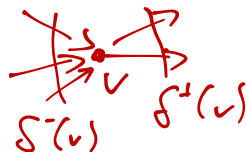
**Task:** find a flow  $x : A \rightarrow \mathbb{R}_{\geq 0}$  obeying capacities and satisfying all supplies and demands, that is,

$$0 \leq x(a) \leq u(a)$$
$$\sum_{a \in \delta^+(v)} x(a) - \sum_{a \in \delta^-(v)} x(a) = b(v)$$

for all  $a \in A$ ,

for all  $v \in V$ ,

such that  $x$  has minimum cost  $c(x) := \sum_{a \in A} c(a) \cdot x(a)$ .



# Example: Minimum Cost Flow Problem (cont.)

Formulation as a linear program (LP):

$$\text{minimize } \sum_{a \in A} c(a) \cdot x(a) \quad (1.1)$$

$$\text{subject to } \sum_{a \in \delta^+(v)} x(a) - \sum_{a \in \delta^-(v)} x(a) = b(v) \quad \text{for all } v \in V, \quad (1.2)$$

$$x(a) \leq u(a) \quad \text{for all } a \in A, \quad (1.3)$$

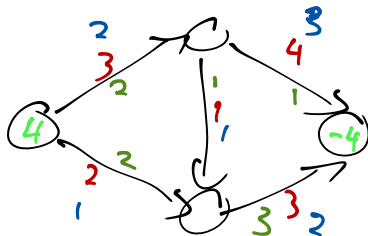
$$x(a) > 0 \quad \text{for all } a \in A. \quad (1.4)$$

Flow conservation

capacity

$x(a)$

cost( $x$ )  
= 16



$u(a)$  ... capacity of  $a$   
 $c(a)$  ... cost of shipping 1 unit over  $a$

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► Objective function given by (1.1). Set of feasible solutions:

$$X = \{x \in \mathbb{R}^A \mid x \text{ satisfies (1.2), (1.3), and (1.4)}\} .$$

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- ▶ Notice that (1.1) is a linear function of  $x$  and (1.2) – (1.4) are linear equations and linear inequalities, respectively.  $\rightarrow$  **linear program**

## Example (cont.): Adding Fixed Cost

Fixed costs  $w : A \rightarrow \mathbb{R}_{\geq 0}$ .

If arc  $a \in A$  shall be used (i. e.,  $x(a) > 0$ ), it must be bought at cost  $w(a)$ .

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This leads to the following mixed-integer linear program (MIP):

$$\begin{array}{ll} \text{minimize} & \sum_{a \in A} c(a) \cdot x(a) + \sum_{a \in A} w(a) \cdot y(a) \\ \text{subject to} & \sum_{a \in \delta^+(v)} x(a) - \sum_{a \in \delta^-(v)} x(a) = b(v) \quad \text{for all } v \in V, \\ & x(a) \leq u(a) \cdot y(a) \quad \text{for all } a \in A, \\ & x(a) \geq 0 \quad \text{for all } a \in A. \\ & y(a) \in \{0, 1\} \quad \text{for all } a \in A. \end{array}$$

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**MIP:** Linear program where some variables may only take integer values.

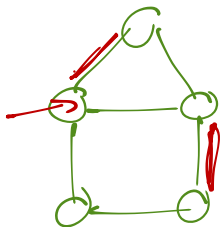


## Example: Maximum Weighted Matching Problem

**Given:** undirected graph  $G = (V, E)$ , weight function  $w : E \rightarrow \mathbb{R}$ .

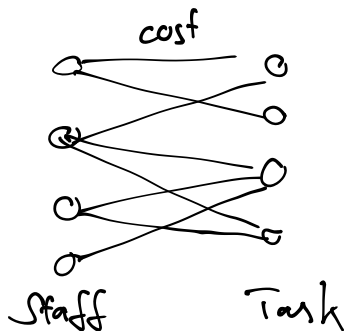
**Task:** find matching  $M \subseteq E$  with maximum total weight.

( $M \subseteq E$  is a **matching** if every node is incident to at most one edge in  $M$ .)



Application:

Task assignment



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Variables:  $x_e \in \{0, 1\}$  for  $e \in E$  with  $x_e = 1$  if and only if  $e \in M$ .

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$$\text{subject to } \sum_{e \in \delta(v)} x_e \leq 1$$

$$x_e \in \{0, 1\}$$

for all  $v \in V$ ,

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**IP:** Linear program where all variables may only take integer values.

## Example: Traveling Salesperson Problem (TSP)

**Given:** complete graph  $K_n$  on  $n$  nodes, weight function  $w : E(K_n) \rightarrow \mathbb{R}$ .

**Task:** find a Hamiltonian circuit with minimum total weight.

(A **Hamiltonian circuit** visits every node exactly once.)

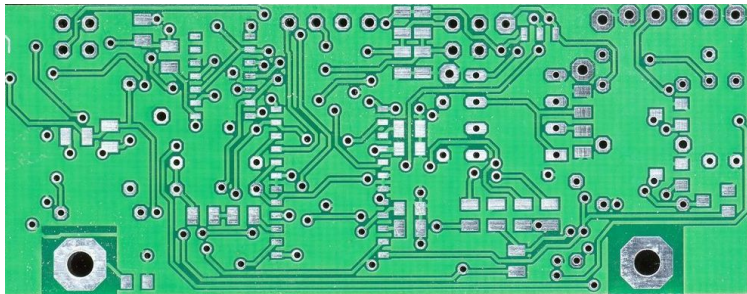
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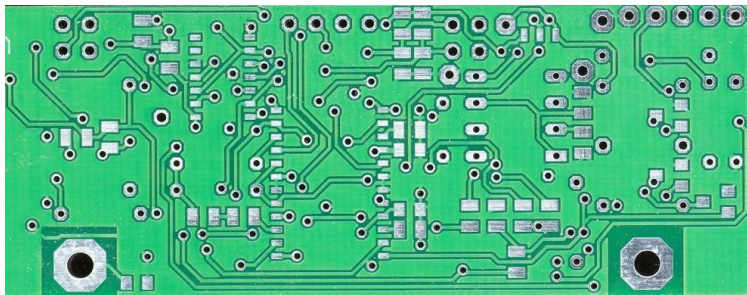
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Formulation as an integer linear program? (maybe later!)

## Example: Weighted Vertex Cover Problem

**Given:** undirected graph  $G = (V, E)$ , weight function  $w : V \rightarrow \mathbb{R}_{\geq 0}$ .

**Task:** find  $U \subseteq V$  of minimum total weight such that every edge  $e \in E$  has at least one endpoint in  $U$ .



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$$\begin{array}{ll} \text{minimize} & \sum_{v \in V} w(v) \cdot x_v \\ \text{subject to} & x_v + x_{v'} \geq 1 \quad \text{for all } e = \{v, v'\} \in E, \\ & x_v \in \{0, 1\} \quad \text{for all } v \in V. \end{array}$$

## Markowitz' Portfolio Optimisation Problem

**Given:**  $n$  different securities (stocks, bonds, etc.) with random returns, target return  $R$ , for each security  $i \in [n]$ :

- ▶ expected return  $\mu_i$ , variance  $\sigma_i$

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Formulation as a **quadratic programme (QP)**:

$$\begin{aligned} & \text{minimize} && \sum_{i,j} \rho_{ij} \sigma_i \sigma_j x_i x_j \\ & \text{subject to} && \sum_i x_i = 1 \\ & && \sum_i \mu_i x_i \geq R \\ & && x_i \geq 0, \end{aligned} \quad \text{for all } i.$$

## Typical Questions

For a given optimization problem:

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- ▶ How difficult is the problem?
- ▶ Does there exist an *efficient algorithm* with “small” worst-case running time?
- ▶ How to formulate the problem as a (mixed integer) linear program?
- ▶ Is there a useful special structure of the problem?

## Literature on Linear Optimization (not complete)

- ▶ D. Bertsimas, J. N. Tsitsiklis, *Introduction to Linear Optimization*, Athena, 1997.
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## Literature on Combinatorial Optimization (not complete)

- ▶ R. K. Ahuja, T. L. Magnanti, J. B. Orlin, *Network Flows: Theory, Algorithms, and Applications*, Prentice-Hall, 1993.
- ▶ W. J. Cook, W. H. Cunningham, W. R. Pulleyblank, A. Schrijver, *Combinatorial Optimization*, Wiley, 1998.
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- ▶ B. Korte, J. Vygen, *Combinatorial Optimization: Theory and Algorithms*, Springer, 2002.
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# Chapter 2: Linear Programming Basics

(Bertsimas & Tsitsiklis, Chapter 1)





## Example of a Linear Program

$$\begin{array}{llllll} \text{minimize} & 2x_1 & - & x_2 & + & 4x_3 \\ \text{subject to} & x_1 & + & x_2 & & + x_4 \leq 2 \\ & & & 3x_2 & - & x_3 = 5 \\ & & & & & x_3 + x_4 \geq 3 \\ & x_1 & & & & \geq 0 \\ & & & & & x_3 \leq 0 \end{array}$$

### Remarks.

- ▶ **objective function** is linear in vector of variables  $x = (x_1, x_2, x_3, x_4)^T$
- ▶ **constraints** are linear inequalities and linear equations
- ▶ last two constraints are special  
(**non-negativity** and **non-positivity constraint**, respectively)

# General Linear Program

$$\text{minimize } c^T \cdot x = c_1 x_1 + c_2 x_2 + \dots + c_n x_n$$

$$\text{subject to } a_i^T \cdot x \geq b_i \quad \text{for } i \in M_1, \quad (2.1)$$

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with  $c \in \mathbb{R}^n$ ,  $a_i \in \mathbb{R}^n$  and  $b_i \in \mathbb{R}$  for  $i \in M_1 \dot{\cup} M_2 \dot{\cup} M_3$  (finite index sets), and  $N_1, N_2 \subseteq \{1, \dots, n\}$  given.

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- ▶ linear program is **unbounded** if, for all  $k \in \mathbb{R}$ , there is a feasible solution  $x \in \mathbb{R}^n$  with  $c^T \cdot x \leq k$ .