Algorithms 2023: Reduction

(Based on [Manber 1989])

Yih-Kuen Tsay

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1 Introductin

Introduction

- The basic idea of *reduction* (transformation is perhaps a better term) is to solve a problem with the solution to another "similar" problem.
- When Problem A can be reduced (transformed) to Problem B, there are two consequences:
  - A solution to Problem B may be used to solve Problem A.
  - If A is known to be "hard", then B is also necessarily "hard".

  /* A reduction involves transforming/converting the input of Problem A into an input of Problem B. The conversion should be reasonably efficient (this will be made precise in the topic of NP-completeness). Otherwise, one might be able to reduce a hard problem to a simpler one, by solving the more time-consuming part during the process of conversion and leaving the easier part to the second problem. */
- One should avoid the pitfall of reducing a problem to another that is too general or too hard.

2 Bipartite Matching

Matching

- Given an undirected graph $G = (V, E)$, a **matching** is a set of edges that do not share a common vertex.
- A **maximum** matching is one with the maximum number of edges.
- A **maximal** matching is one that cannot be extended by adding any other edge.

Bipartite Matching

- A bipartite graph $G = (V, E, U)$ is a graph with $V \cup U$ as the set of vertices and E as the set of edges such that
  - V and U are disjoint and
  - The edges in E connect vertices from V to vertices in U.

Problem 1. *Given a bipartite graph $G = (V, E, U)$, find a maximum matching in G.*

Bipartite Matching (cont.)

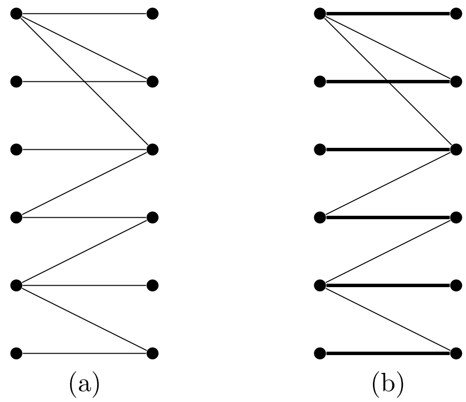

Figure: A bipartite graph and a maximum matching.

Source: adapted from [Manber 1989, Figure 7.37].

Bipartite Matching (cont.)

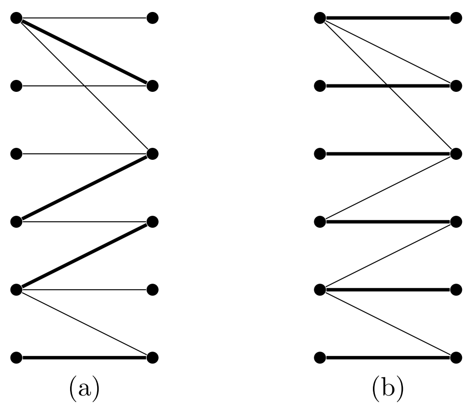

Figure: A maximal matching and a maximum matching.

Source: adapted from [Manber 1989, Figure 7.37].

3 Network Flows

Networks

- Consider a directed graph, or network, $G = (V, E)$ with two distinguished vertices: s (the source) with indegree 0 and t (the sink) with outdegree 0.
- Each edge e in E has an associated positive weight $c(e)$, called the *capacity* of e.

The Network Flow Problem

- A **flow** is a function f on E that satisfies the following two conditions:
  1. $0 \leq f(e) \leq c(e)$.
  2. $\sum_u f(u, v) = \sum_w f(v, w)$, for all $v \in V - \{s, t\}$.
- The **network flow problem** is to maximize the flow f for a given network G.

4 Bipartite Matching to Network Flow

Bipartite Matching to Network Flow

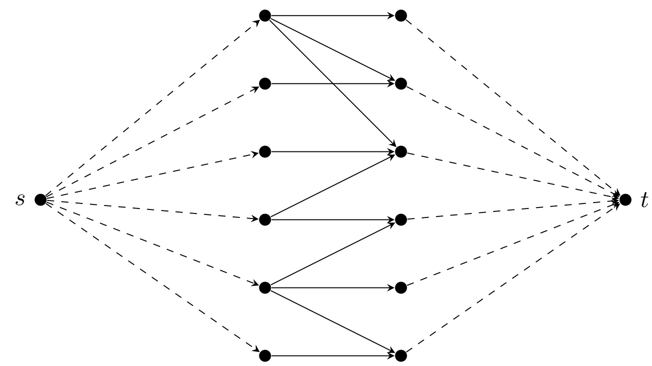

Figure: Reducing bipartite matching to network flow. Every edge has capacity 1.
Source: redrawn from [Manber 1989, Figure 7.39].

Bipartite Matching to Network Flow (cont.)

- Mapping from the input $G = (V, E, U)$ of the bipartite matching problem to the input $G' = (V', E')$ and c of the network flow problem:
  - The network is $G' = (V', E')$ where
    * $V' = \{s\} \cup V \cup U \cup \{t\}$
    * $E' = \{(s, v) \mid v \in V\} \cup E \cup \{(u, t) \mid u \in U\}$
  - The capacity for every $e \in E'$ is 1, i.e., $\forall e \in E', c(e) = 1$.
- Correspondence between the two solutions
  - A maximum flow f in G' defines a maximum matching M_f in G.
  - A maximum matching M in G induces a maximum flow f_M in G'.

5 Linear Programming

Notations

- Let $\overline{v}$ denote a vector $(v_1, v_2, \ldots, v_n)$ of n constants or n variables.
- In the following, $\overline{a}$, $\overline{b}$, $\overline{c}$, and $\overline{e}$ are vectors of n constants.
- And, $\overline{x}$ and $\overline{y}$ are vectors of n variables.
- The (inner or dot) product $\overline{a} \cdot \overline{x}$ of two vectors $\overline{a}$ and $\overline{x}$ is defined as follows:

$$\overline{a} \cdot \overline{x} = \sum_{i=1}^{n} a_i \cdot x_i$$

Linear Programming

- Objective function:
$$\overline{c} \cdot \overline{x}$$
- Equality constraints:
$$\begin{aligned} \overline{e}_1 \cdot \overline{x} &= d_1 \\ \overline{e}_2 \cdot \overline{x} &= d_2 \\ &\vdots \\ \overline{e}_m \cdot \overline{x} &= d_m \end{aligned}$$
- Inequality constraints may be turned into equality constraints by introducing *slack* variables.
- Non-negative constraints: $x_j \geq 0,$ for all j in P, where P is a subset of $\{1, 2, \ldots, n\}$.
- The goal is to *maximize* (or *minimize*) the value of the objective function, subject to the equality constraints.

6 Network Flow to Linear Programming

Network Flow to Linear Programming

- From the input $G = (V, E)$ and c of the network flow problem to the objective function and constraints of linear programming:
  - Let $x_1, x_2, \ldots, x_n$ represent the flow values of the n edges.
  - Objective function:
  $$\sum_{i \in S} x_i$$
  where S is the set of edges leaving the source.
  - Inequality constraints:
  $$x_i \leq c_i, \text{for all } i,\ 1 \leq i \leq n$$
  where c_i is the capacity of edge i.
  - Equality constraints:
  $$\sum_{i \text{ leaves } v} x_i - \sum_{j \text{ enters } v} x_j = 0, \text{ for every } v \in V \setminus \{s, t\}$$
  - Non-negative constraints: $x_i \geq 0,$ for all i, $1 \leq i \leq n$.

/* If f is a maximum flow for $G = (V, E)$ and c, then $x_i = f(i)$, for $1 \leq i \leq n$, is a solution to the resulting linear programming problem.

Conversely, if $x_i = v_i$, for $1 \leq i \leq n$, is a solution to the resulting linear programming problem, then f with $f(i) = v_i$, for $1 \leq i \leq n$, is a maximum flow for $G = (V, E)$ and c. */