

# COSC1285/2123: Algorithms & Analysis

## Iterative Improvement

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Lecture 11

## Levitin – The design and analysis of algorithms

This week we will be covering the material from Chapters 10.

Learning outcomes:

- Understand the paradigm of iterative improvement
- Understand and apply examples of iterative improvement:
  - Maximum-flow problem
  - Stable marriage problem (Gale-Shapeley algorithm)

# Outline

- 1 Overview
- 2 Maximum-flow Problem
- 3 Stable Marriage Problem
- 4 Summary

# Overview

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# Iterative Improvement

Previously, we looked at greedy approaches to solving optimisation problems. It constructs a solution piece by piece, in a greedy fashion.

In contrast, **iterative improvement** starts with a feasible solution (one that satisfies all constraints), then proceed to improve it by repeated application of simple steps.

# Overview

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- 2 Maximum-flow Problem**
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# Maximum-Flow Problem

Imagine you are given this problem:

## Problem

Yarra Valley Waters needs to move water from a dam to a local water reservoir. There is a network of pipes and junctions that they can transport water over. Assume there is no loss within the network. How do we maximise the amount of water transported each day?



# Maximum-Flow Problem

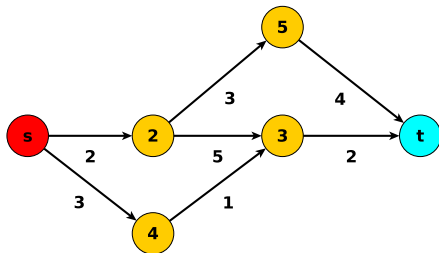
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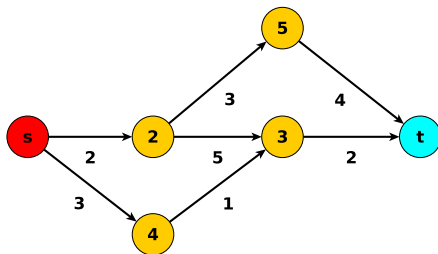
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This is an instance of a **maximum-flow** problem.

# Flow Network

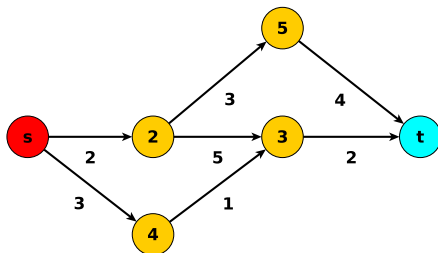


# Flow Network



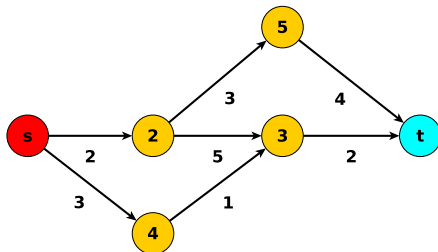
- **Source**: vertex which has no incoming edges.

# Flow Network



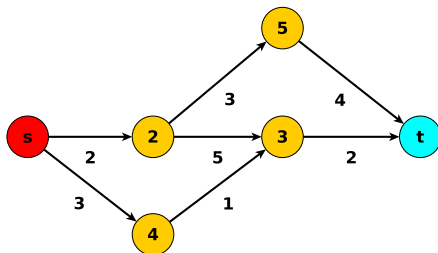
- **Source**: vertex which has no incoming edges.
- **Sink**: vertex with no outgoing edges.

# Flow Network



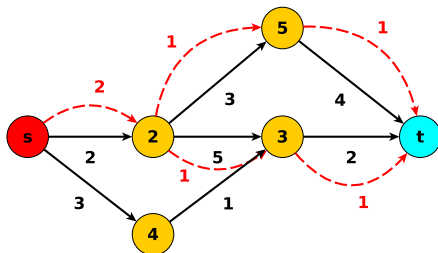
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- **Sink**: vertex with no outgoing edges.
- Edge has a weight representing its **capacity**.

# Flow Network



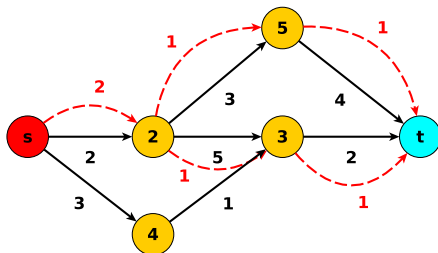
- **Source**: vertex which has no incoming edges.
- **Sink**: vertex with no outgoing edges.
- Edge has a weight representing its **capacity**.
- Graphs satisfying above properties called **flow network**.

# Maximum-Flow Problem



- **Source** is the origin of all “material” into the flow network.

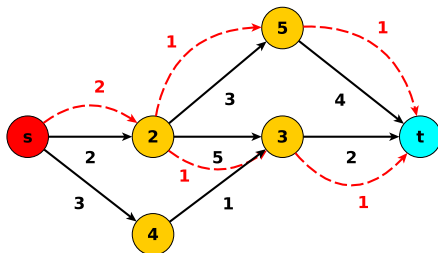
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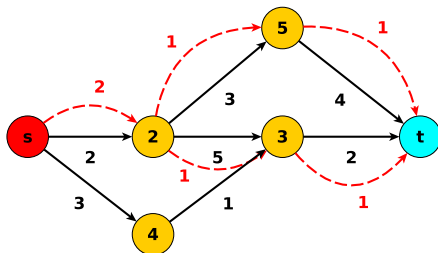


# Maximum-Flow Problem



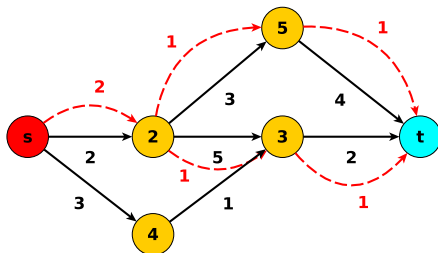
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# Maximum-Flow Problem



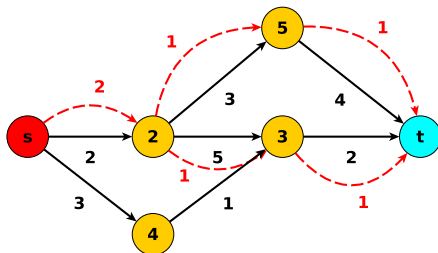
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# Maximum-Flow Problem



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- Total material leaving source = total material flowing into sink; called **value** of the flow.

# Maximum-Flow Problem



## Problem

Given a flow network, the *maximum-flow problem* is find a flow of maximum *value*, subject to (edge) capacity constraints and flow-conservation.

# Ford Fulkerson Method – Sketch

## Idea:

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# Ford Fulkerson Method – Sketch

## Idea:

- Given an initial flow network, find an initial **feasible** flow.
- Find a path from source to sink that can increase the total flow.
- Increase the flow along that path.
- Repeat until no more such paths.



# Preliminaries: Residual Network

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For each edge  $(u,v)$  in flow network, we have two edges in the residual network with following residual capacity:

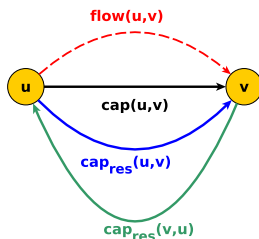
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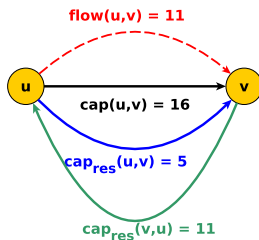
$\text{cap}_{\text{res}}(u,v) = \text{cap}(u,v) - \text{flow}(u,v)$ ,  $\text{cap}_{\text{res}}(u,v) > 0$  (**forward edge**)

$\text{cap}_{\text{res}}(v,u) = \text{flow}(u,v)$ ,  $\text{cap}_{\text{res}}(v,u) > 0$  (**backward edge**)



# Preliminaries: Residual Network

**Example:**  $\text{cap}(u,v) = 16$ ,  $\text{flow}(u,v) = 11$ , then can still increase the flow by  $\text{cap}_{\text{res}}(u,v) = 5$  in the  $(u,v)$  direction, but can also send up to  $\text{cap}_{\text{res}}(v,u) = 11$  units in the other  $(v,u)$  direction to cancel out  $\text{flow}(u,v)$ .



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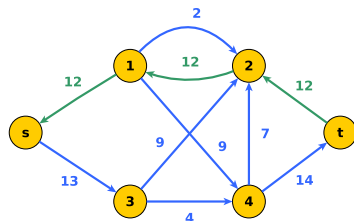
This path basically tells us which individual flows to **increase** (when traversing forward edge), and which to **decrease** (when traversing backward edge) to increase the total flow/value, while satisfying capacity and flow conservation constraints.

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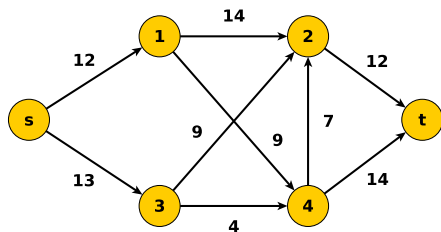
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\* There are generally many possible augmenting path. We select the shortest one (in terms of number of edges) for step 3.

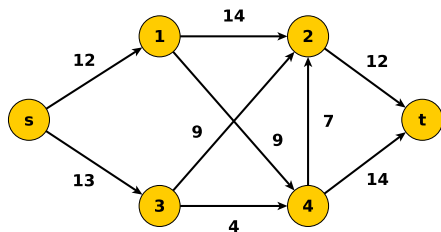


# Ford-Fulkerson Method – Example

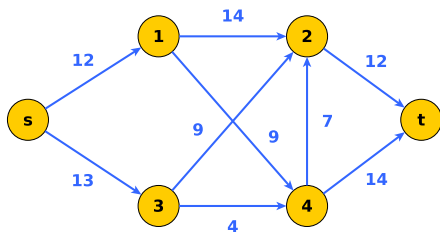


(a) Flow network

# Ford-Fulkerson Method – Example

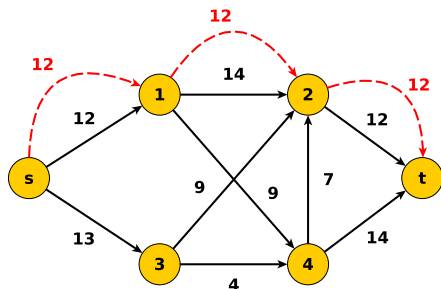


(c) Flow network



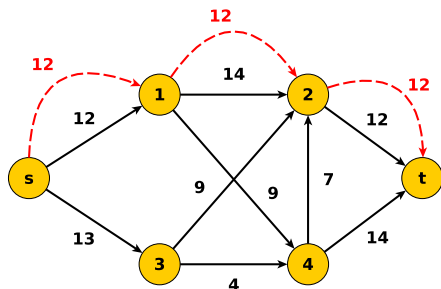
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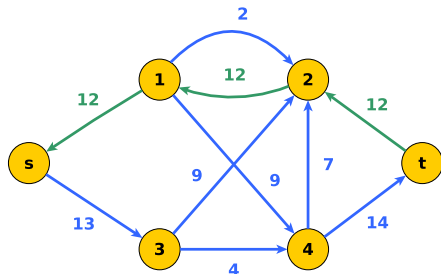


(e) Flow network

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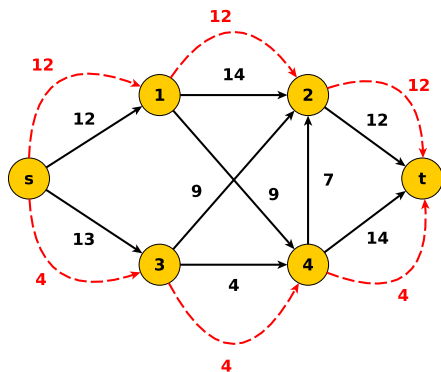


(g) Flow network



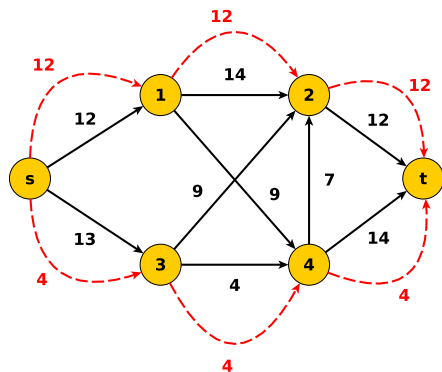
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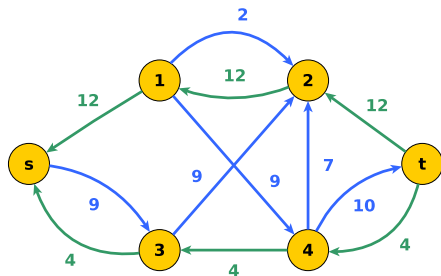


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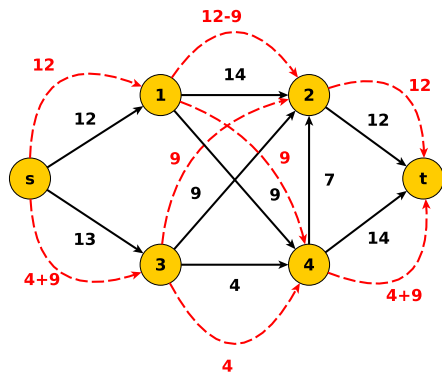


(k) Flow network



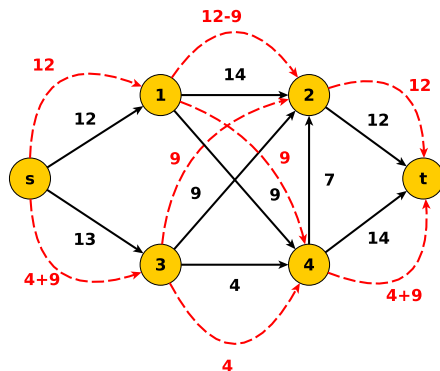
(l) Residual network

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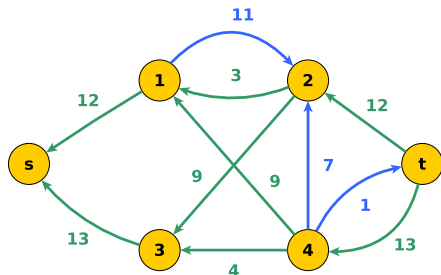


(m) Flow network

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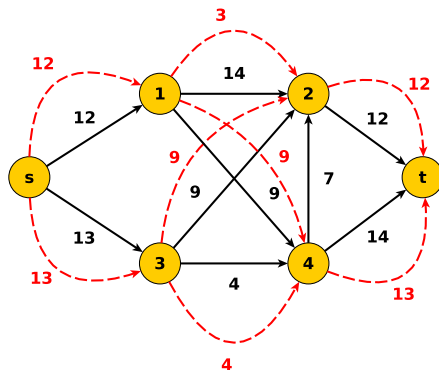
(o) Flow network



(p) Residual network



# Ford-Fulkerson Method – Example



Value of flow?

# Maximum-Flow Problem

Applications of maximum-flow problem:

<https://www.youtube.com/watch?v=D36MJCXT4Qk>

# Overview

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# Stable Marriage Problem



(q) Males and Females.

# Stable Marriage Problem

  
Danny

  
Anita

  
Chris

  
Sarah

  
John

  
Barbie

  
Ken

  
Michelle

(s) Males and Females.

  
Danny

  
Anita

  
Chris

  
Sarah

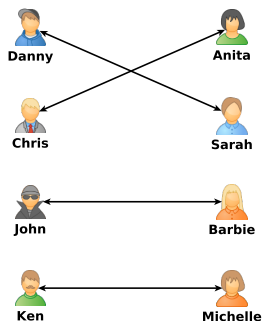
  
John

  
Barbie

  
Ken

  
Michelle

(t) Matched couples!



# Stable Marriage Problem

## Stable Marriage Problem

Given a set of  $n$  men and  $n$  women, who has a list of preferences to the other sex (in terms of a ranking), the problem is how to find a matching between them such that the matching is *stable*?

A matching is stable if:

- No matched pair of man and woman can find other partners and **both** do better, i.e., both man and woman prefer other partners over their existing match.

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Is a stable marriage (matching) always possible?

- Yes, if equal number of men and women.

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- 3 This continues until all females (and males) are matched.

# Gale-Shapley Algorithm

Female Proposing variant:

- 1 Round 1: Each female **proposes** to their **first** male preferences. Each male receives 0 or more proposals. They reply “maybe” to the female they **most prefer** and “no” to all other proposals. For each “maybe” reply, the corresponding female-male are **tentatively** matched.

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- 2 Round 2: Each **unmatched** female proposes to their **next** preferred male (2nd ranked), even if the male is tentatively matched already. Each male evaluates their proposals, and again reply “maybe” to the female they most prefer (this can be their existing matched partner) and “no” to all other proposals. For each “maybe” reply, the corresponding female-male are **tentatively** matched.

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- 3 Round 3 onwards: We continue with this process until all females and males are matched.

# Gale-Shapley Algorithm Example



# Gale-Shapley Algorithm Example

<b>Anita</b>	<b>Sarah</b>	<b>Barbie</b>	<b>Michelle</b>
Chris	Chris	Ken	Chris
Ken	Ken	Danny	Ken
Danny	Danny	John	Danny
John	John	Chris	John

Table: Female preferences

<b>Danny</b>	<b>Chris</b>	<b>John</b>	<b>Ken</b>
Michelle	Anita	Barbie	Michelle
Sarah	Sarah	Anita	Barbie
Barbie	Michelle	Michelle	Sarah
Anita	Barbie	Sarah	Anita

Table: Male preferences

# Gale-Shapley Algorithm Example

Round 1 (proposing):

<b>Anita</b>	<b>Sarah</b>	<b>Barbie</b>	<b>Michelle</b>
Chris	Chris	Ken	Chris

Table: Female preferences

<b>Danny</b>	<b>Chris</b>	<b>John</b>	<b>Ken</b>
Michelle	Anita	Barbie	Michelle
Sarah	Sarah	Anita	Barbie
Barbie	Michelle	Michelle	Sarah
Anita	Barbie	Sarah	Anita

Table: Male preferences



# Gale-Shapley Algorithm Example

Round 1 (end):

<b>Anita</b>	<b>Sarah</b>	<b>Barbie</b>	<b>Michelle</b>
Chris	Chris	Ken	Chris

Table: Female preferences

<b>Danny</b>	<b>Chris</b>	<b>John</b>	<b>Ken</b>
Michelle	Anita	Barbie	Michelle
Sarah	Sarah	Anita	Barbie
Barbie	Michelle	Michelle	Sarah
Anita	Barbie	Sarah	Anita

Table: Male preferences

# Gale-Shapley Algorithm Example

Round 2 (proposing):

<b>Anita</b>	<b>Sarah</b>	<b>Barbie</b>	<b>Michelle</b>
Chris	Chris Ken	Ken	Chris Ken

Table: Female preferences

<b>Danny</b>	<b>Chris</b>	<b>John</b>	<b>Ken</b>
Michelle Sarah Barbie Anita	Anita Sarah Michelle Barbie	Barbie Anita Michelle Sarah	Michelle Barbie Sarah Anita

Table: Male preferences

# Gale-Shapley Algorithm Example

Round 2 (end):

Anita	Sarah	Barbie	Michelle
Chris	Chris Ken	Ken	Chris Ken

Table: Female preferences

Danny	Chris	John	Ken
Michelle Sarah Barbie Anita	Anita Sarah Michelle Barbie	Barbie Anita Michelle Sarah	Michelle Barbie Sarah Anita

Table: Male preferences

# Gale-Shapley Algorithm Example

Round 3 (proposing):

<b>Anita</b>	<b>Sarah</b>	<b>Barbie</b>	<b>Michelle</b>
Chris	Chris Ken Danny	Ken Danny	Chris Ken

Table: Female preferences

<b>Danny</b>	<b>Chris</b>	<b>John</b>	<b>Ken</b>
Michelle Sarah Barbie Anita	Anita Sarah Michelle Barbie	Barbie Anita Michelle Sarah	Michelle Barbie Sarah Anita

Table: Male preferences

# Gale-Shapley Algorithm Example

Round 3 (end):

Anita	Sarah	Barbie	Michelle
Chris	Chris Ken Danny	Ken Danny	Chris Ken

Table: Female preferences

Danny	Chris	John	Ken
Michelle Sarah Barbie Anita	Anita Sarah Michelle Barbie	Barbie Anita Michelle Sarah	Michelle Barbie Sarah Anita

Table: Male preferences

# Gale-Shapley Algorithm Example

Round 4 (proposing):

Anita	Sarah	Barbie	Michelle
Chris	Chris Ken Danny	Ken Danny John	Chris Ken

Table: Female preferences

Danny	Chris	John	Ken
Michelle Sarah Barbie Anita	Anita Sarah Michelle Barbie	Barbie Anita Michelle Sarah	Michelle Barbie Sarah Anita

Table: Male preferences

# Gale-Shapley Algorithm Example

Round 4 (end):

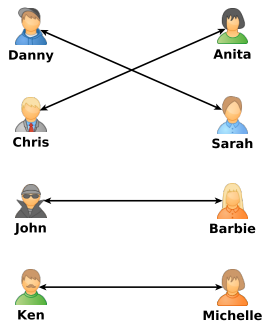
Anita	Sarah	Barbie	Michelle
Chris	Chris Ken Danny	Ken Danny John	Chris Ken

Table: Female preferences

Danny	Chris	John	Ken
Michelle Sarah Barbie Anita	Anita Sarah Michelle Barbie	Barbie Anita Michelle Sarah	Michelle Barbie Sarah Anita

Table: Male preferences

# Gale-Shapley Algorithm Example





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Time complexity?

# Stable Marriage Video

<https://www.youtube.com/watch?v=fudb8DuzQlM>

# Overview

- 1 Overview
- 2 Maximum-flow Problem
- 3 Stable Marriage Problem
- 4 Summary

# Summary

- Maximum flow problem (Ford-Fulkerson method)
- Stable marriage problem (Gale-Shapley algorithm)