

# Algorithms, Matching

## Part 1. Networks and Matchings

B9 - Algorithms Matching

M-ALG-102

# Overview of the module

Day 1 Networks, the matching problem and the maximum flow problem

Day 2 Data clustering and representation

## Organisation of the module

- ▶ Course and exercises in python 3
- ▶ Small coding exercises, also paper + pen
- ▶ Project : explained tomorrow
- ▶ Please clone the following repository  
<https://github.com/nlehkir/ALG02>

## Introductory example 1 : Max Flow

*Le réseau national  
après déclassement*

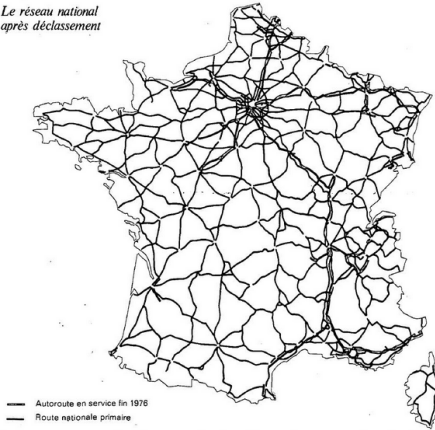
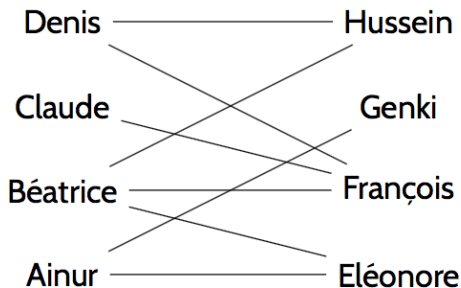


Figure: Problem 1 : transporting merchandise through a network

## Introductory example 2 : Optimal allocation



**Figure:** Problem 2 : Building the largest possible number of teams of 2 persons.

## Introductory example 2

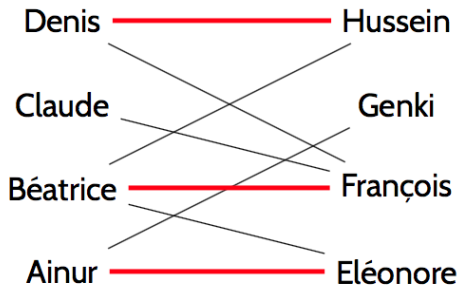


Figure: Problem 2 : not optimal allocation

## Introductory example 2

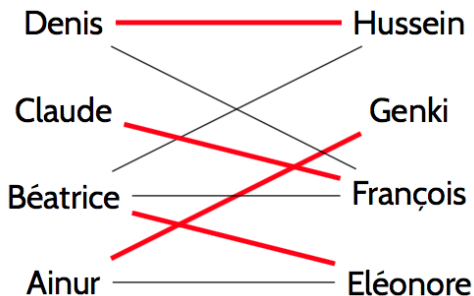


Figure: Problem 2 : optimal allocation

## Introductory example 2 : allocation

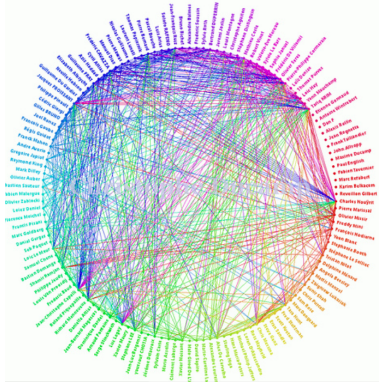


Figure: Problem 2 : not that easy if the dataset is big !



## Other examples

- ▶ Assigning students to internships

## Other examples

- ▶ Assigning students to internships
- ▶ Assigning machines to a task (no analogy intended !)

# Introduction

We will see that these problems (flow and allocation) are **related**,  
and under some restrictions, **equivalent** !

# Day 1

## The matching problem

- Definition of the problem

- Experimental solutions

- Greedy algorithm

## The Maximum flow problem

- Presentation of the problem

- Solution with the Ford-Fulkerson algorithm

- Connection with the matching problem

- More results on the two problems

## Reminders on graphs

- ▶ A graph is defined by ?

## Reminders on graphs

- ▶ A graph is defined by set of vertices  $V$  and a set of edges  $E$ .

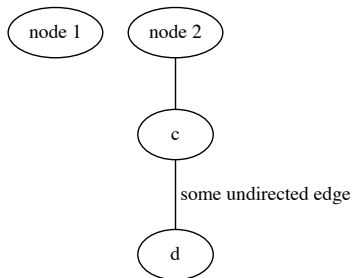


Figure: Simple graph (graphviz demo)

## Reminders on graphs

- It can be **undirected**, as this one :

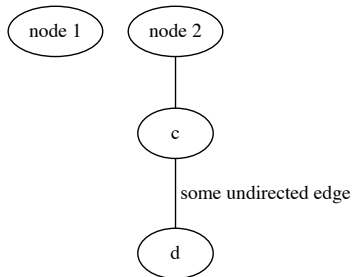
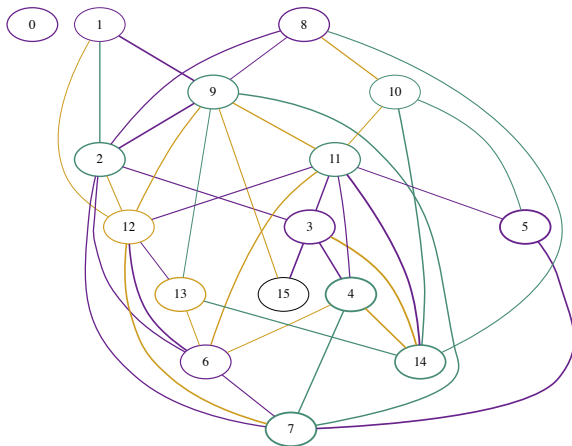


Figure: Simple graph (graphviz demo)

## Reminders on graphs

### Undirected graph





## Reminders on graphs

- Or **directed**, as this one. (it is then called a **digraph**)

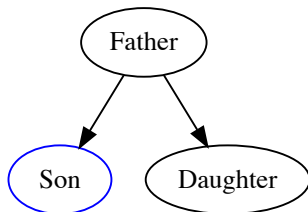
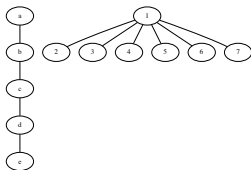


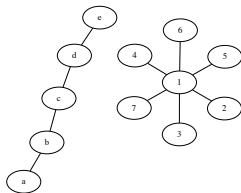
Figure: Digraph (graphviz demo)

## Useful tool : graphviz

- ▶ A tool to visualize graphs
- ▶ Several **generator programs** : dot, neato



(a) Image generated with **dot**



(b) Image generated with **neato**

## Warm up question

Given an **unoriented** graph with  $n$  nodes, how many edges can we build ?

Notation of a graph :  $G(V, E)$

- ▶  $V$  : set of  $n$  vertices
- ▶  $E$  : set of edges

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Notation of a graph :  $G(V, E)$

- ▶  $V$  : set of  $n$  vertices
- ▶  $E$  : set of edges, maximum size :  $\frac{n(n-1)}{2} = \binom{n}{2} = \frac{n!}{2!(n-2)!}$

## Back to our problem

Given a graph  $G = (V, E)$ , we want a **matching**  $M$ , which means:

- ▶ A subset of edges  $M \subset E$

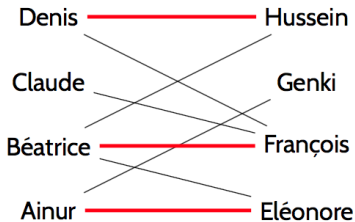


Figure: Non optimal allocation

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- ▶ Such that no pairs of edges of  $M$  are incident
- ▶ Equivalently, each node in the graph has **at most** one edge connected

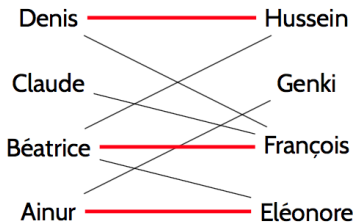


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Given a graph  $G = (V, E)$ , we want a **matching**, which means:

- ▶ A subset of edges  $M \subset E$
- ▶ Equivalently, each node in the graph has **at most** one edge connected
- ▶ Such that no pairs of edges of  $M$  are incident
- ▶ Of **Maximum size** (maximum number of edges)

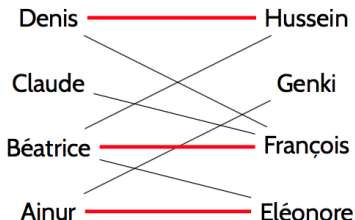


Figure: snippet

## Example 1

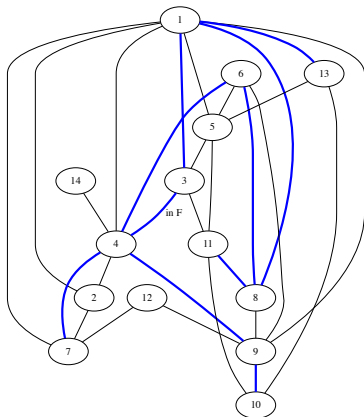


Figure: Is this a matching ?



## Example 2

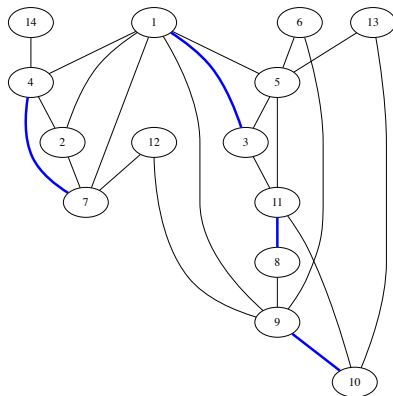


Figure: Is this a matching ?

## Example 3

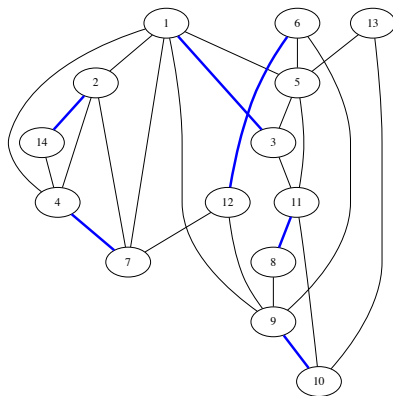


Figure: Is this an optimal matching ?

## Example 4

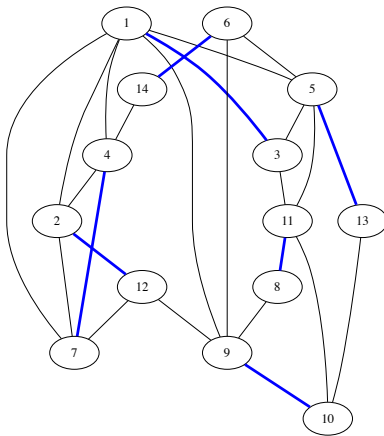


Figure: Is this an optimal matching ?

## Example 5

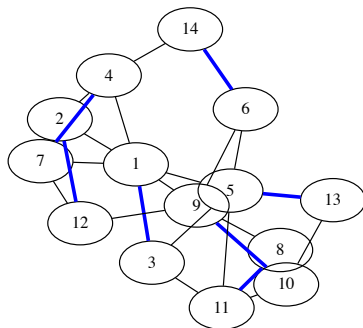


Figure: With neato

# Experiments

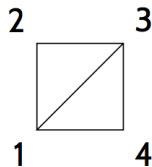
How would you code a graph ?

# Experiments

How would you code a graph ?

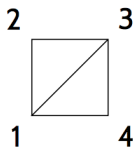
- ▶ list of sets of size 2 (for an undirected graph)
- ▶ a dictionary of successors

## Coding a graph : as a list



```
g1 = [{1,2},{1,3},{2,3},{3,4},{1,4}]
```

## Coding a graph : as a dictionary



$g1 = \{ 1:\{2,3,4\}, 2:\{1,3\}, 3:\{1,2,4\}, 4:\{1,3\} \}$



## Exercise 1

- ▶ **cd other\_graphs** and please use **random\_graph** to build a graph with 20 vertices and 50 edges.
- ▶ You will need to install **graphviz**

## Exercise 2

- ▶ **cd other\_graphs** and please use **random\_graph** to build a graph with 20 vertices and 50 edges.
- ▶ You will need to install **graphviz**
- ▶ Please manually find an **optimal matching in your graph**

# Algorithms

- ▶ We now have an idea of what the problem is.
- ▶ When the size of the problem is large, is it possible to find an optimal matching manually ?

# Algorithms

- ▶ We now have an idea of what the problem is.
- ▶ When the size of the problem is large, is it possible to find an optimal matching manually ?
- ▶ When the size of the problem is large, is it possible to find an optimal matching by trying all possible matching ?

## Exercise 3

- ▶ What would be the necessary time to enumerate all possible matchings ?
- ▶ Formally : if the graph has  $n$  nodes, what is the worst case **complexity** of the exhaustive search ?

# Algorithms

- ▶ To find an optimal solution, we want to have an algorithm.
- ▶ Thus, let us introduce some theoretical notions.

## Notion of maximal and maximum matching

We will say that a matching  $M$  of cardinality  $|M|$  is:

- ▶ **Maximum** if it has the maximum possible number of edges (it is thus optimal)

## Notion of maximal and maximum matching

We will say that a matching  $M$  of cardinality  $|M|$  is:

- ▶ **Maximum** if it has the maximum possible number of edges (is thus optimal)
- ▶ **Maximal** if the set of edges obtained by adding any edge to it is **not a matching**. This means that  $M \cup \{e\}$  is not a matching for any  $e \notin M$ .



## Question

Exercise : is being **Maximal** the same thing as being **Maximum** ?

## Maximum implies maximal

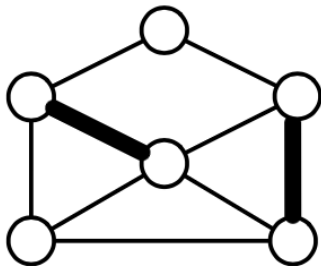
Let us show that a maximum matching is maximal.

## Counter Example

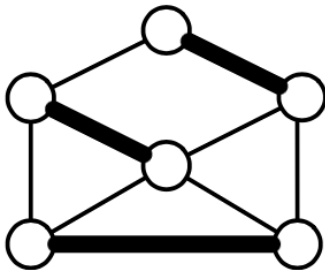
However, a matching that is maximal is **not necessary Maximum**.

## Counter Example

However, a matching that is maximal is **not necessary Maximum**.  
Can you find an example ?



(a) A maximal matching not maximum



(b) A maximum matching

## Greedy algorithm

Can you propose a greedy algorithm to address the maximum matching problem ?

## Greedy algorithm

**Result:** Matching  $M$

$M \leftarrow \emptyset;$

**for**  $e \in E$  **do**

**if**  $M \cup \{e\}$  *is a matching* **then**

$M \leftarrow M \cup \{e\}$

**end**

**end**

return  $M$

**Algorithm 0:** Greedy algorithm to find a matching

## Greedy algorithm

- ▶ What is the type of matching algorithm returned by this algorithm ?
- ▶ What is the complexity of this algorithm ?



## Greedy algorithm

- ▶ The greedy algorithm returns a **maximal** matching (proof)
- ▶ Its complexity is  $\mathcal{O}(n^2)$

## Greedy algorithm

- ▶ We will implement the greedy algorithm to find a maximal matching.

## Exercise 4

- ▶ **cd matching\_greedy** and use **generate\_graph** to build a graph with a least 30 nodes.

## Exercise 5

- ▶ We will use the functions written in **matching\_functions** from the file **match\_graphs**
- ▶ edit the lines below "CHANGE HERE" to perform the greedy algorithm.

## Exercise 6

- ▶ Can you think of an example where the greedy algorithm gives a matching of the size **half** the size of an optimal matching ?

## Changing the problem (for now)

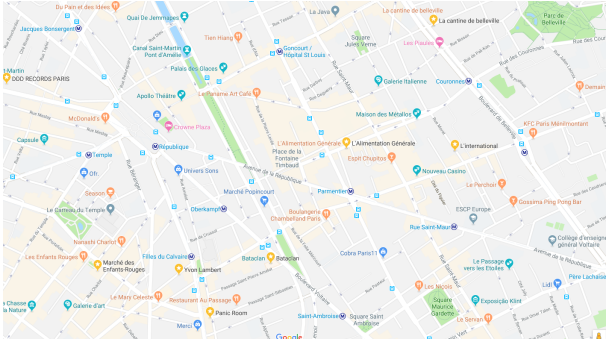
We temporarily leave the maximum matching problem to focus on another problem : the **Maximum flow problem**

## Max flow



**Figure:** Optimizing the quantity of something transported from one place to another, under constraints

## Example



**Figure:** Optimizing the quantity of something transported from one place to another, under constraints



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- ▶ We define two special nodes : a **source**  $s$  and a **sink**  $t$ .

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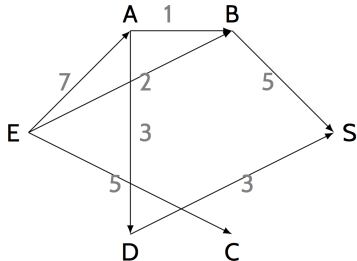


Figure: A **transport graph** with a capacities

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- ▶ A flow  $f$  is a function  $f(u, v) \leq c(u, v)$  (+ additional constraints)

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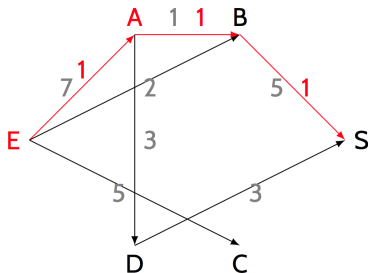


Figure: A non optimal flow

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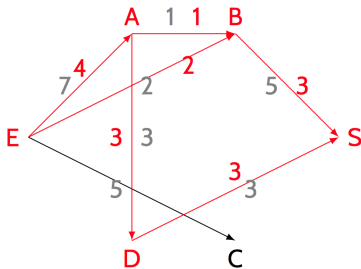


Figure: An optimal flow



## Conservation of the flow

We must have :

- ▶ antisymetry :  $f(v, u) = -f(u, v)$
- ▶ flow conservation :  $\sum_{w \in V} f(u, w) = 0$  for  $u \notin \{E, S\}$   
(somme des flux entrant et sortant est nulle)
- ▶ equivalently :  $\sum_{v \in V} f(v, u) = \sum_{w \in V} f(u, w)$

## Maximum flow

- ▶ The **value of the flow**, noted  $|f|$ , is  $\sum_{v \in S} f(E, v)$
- ▶ The problem is that of finding a flow with **maximum value**

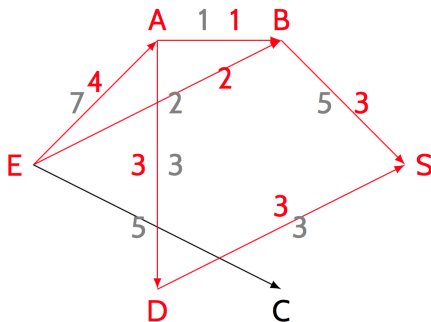


Figure: Max flow

## Solution

- ▶ How would you solve this with an algorithm ?

# Ford Fulkerson algorithm

We will introduce an algorithm to solve the problem. This algorithm :

- ▶ terminates
- ▶ is correct
- ▶ is polynomial

## Ford Fulkerson algorithm

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- ▶ is correct
- ▶ is polynomial

So it's great.

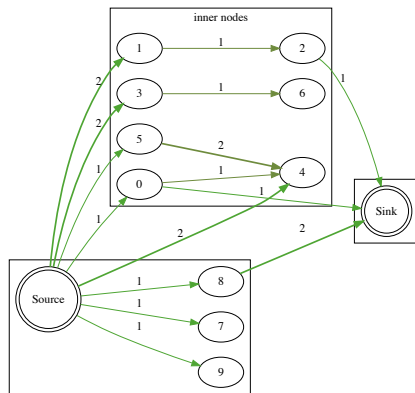
## Residual graph

- ▶ Given a graph with capacities  $c(u, v)$  and a flow  $f(u, v)$ , we will define its **residual graph** that has a capacity  $c_r(u, v)$  :

$$c_r(u, v) = c(u, v) - f(u, v) \quad (1)$$

- ...
- └ The Maximum flow problem
  - └ Solution with the Ford-Fulkerson algorithm

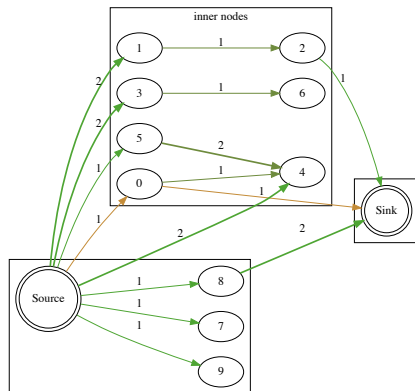
## Example of residual graph



Initial Flow network

- ...
  - └ The Maximum flow problem
    - └ Solution with the Ford-Fulkerson algorithm

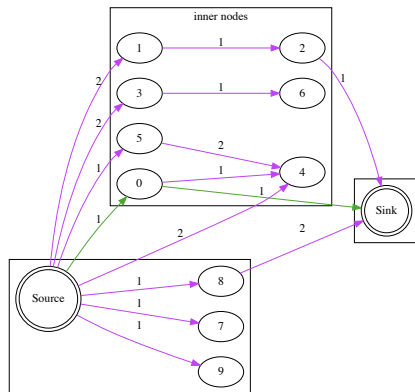
## Example of residual graph



Flow  
Algorithm step: 1  
flow value: 1



## Example of residual graph



Residual graph  
Algorithm step: 2

## Residual graph

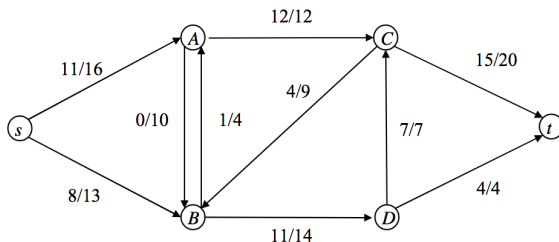


Figure: A transport graph with a flow

## Residual graph

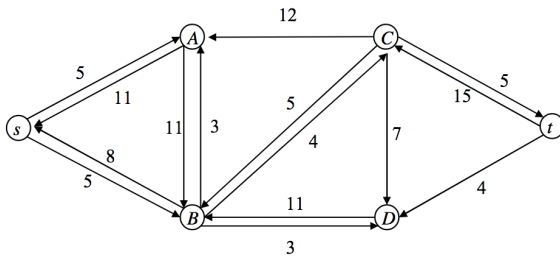
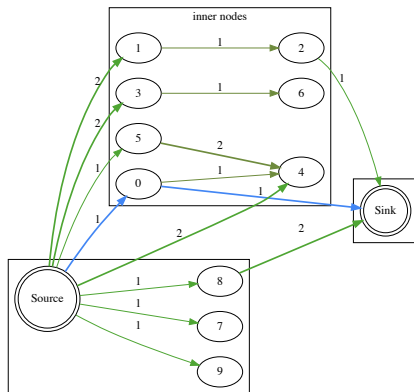


Figure: Residual graph

## Augmenting path

An augmenting path is a path in the **residual graph** from the source to the sink with capacities  $> 0$ .

## Augmenting path



augmenting path: [0, 1, 11]

Algorithm step: 1

path capacity: 1.0

## Augmenting path

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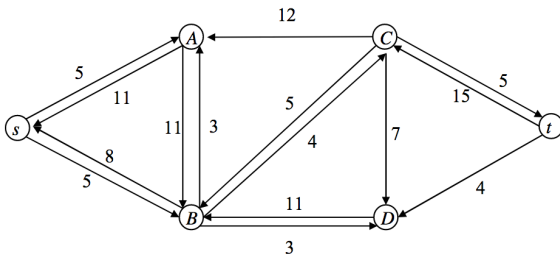


Figure: Residual graph

## Augmenting path

An augmenting path is a path from the source to the sink with capacities  $> 0$ .

The Ford-Fulkerson algorithm uses augmenting paths until there are no more augmenting paths.

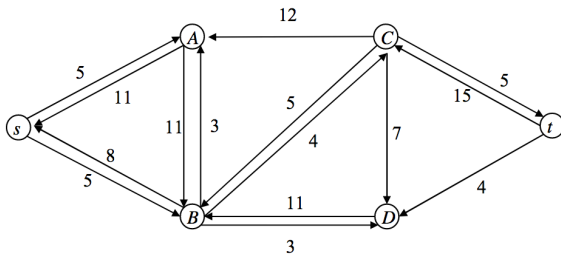


Figure: Residual graph

## Ford Fulkerson algorithm

Can you deduce the algorithm from the previous remarks ?



## Ford Fulkerson algorithm

```
Result: Flow  $f$   
for  $(u, v) \in E$  do  
  |  $f(u, v) = 0$   
end  
while  $\exists \rho$  augmenting path do  
  | augment  $g$  with  $\rho$   
end  
return  $f$ 
```

**Algorithm 1:** Ford Fulkerson algorithm

- ...
- └ The Maximum flow problem
  - └ Solution with the Ford-Fulkerson algorithm

# Ford

Let's do an example

# Ford Fulkerson algorithm

- ▶ We will implement the Ford Fulkerson algorithm (1956)

## Exercise 5

- ▶ We will implement the Ford Fulkerson algorithm (1956)
- ▶ **cd ford\_fulkerson** and edit **generate\_flow\_network** to generate a flow network.

# Algorithm

- ▶ We will now use the functions contained in **ford\_functions** and call them from **apply\_ford\_fulkerson**
- ▶ We will do it step by step.
- ▶ Let's look at the algorithm.

## Exercise 6

- ▶ We will now use the functions contained in **ford\_functions** and call them from **apply\_ford\_fulkerson**
- ▶ We will do it step by step.
- ▶ edit the function **show\_residual** in order to plot the residual graph.

## Exercise 7

- ▶ Modify **find\_augmenting\_paths** in order to find the augmenting paths.

## Exercise 8

- ▶ now edit **augment\_flow**



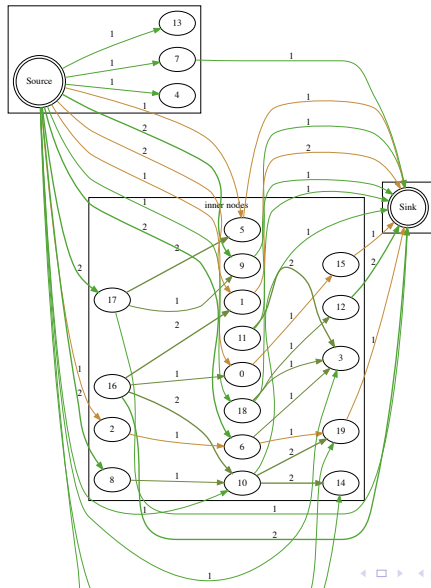
## Exercise 9

- ▶ finally, edit the computation of the value of the flow

## Exercise 10

- ▶ Now the algorithm should be able to run

- ...
  - └ The Maximum flow problem
    - └ Solution with the Ford-Fulkerson algorithm



- ...
- └ The Maximum flow problem
  - └ Solution with the Ford-Fulkerson algorithm

## Complexity

What is the complexity of Ford Fulkerson ?

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$$\mathcal{O}(|f^*| \times |E|) \quad (2)$$

## Modification of Ford Fulkerson

What would we an intuitive and potentially faster modification of the algorithm ?

## Edmonds Karp

What would we an intuitive and potentially faster modification of the algorithm ?

Use the shortest augmenting path with positive capacity.

## Termination

- ▶ When the capacities are **real numbers** or **rational numbers** Ford Fulkerson terminates.



## Termination

- ▶ When the capacities are **integer numbers** or **rational numbers** Ford Fulkerson terminates.
- ▶ However, when the capacities are general **real numbers**, the algorithm might not terminate.

## Link with the matching problem

- ▶ We now go back to the matching problem, in the case of a **bipartite graph**.
- ▶ We will show that in that case, we can connect the two problems.

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- ▶ We now go back to the matching problem, in the case of a **bipartite graph**.
- ▶ We will show that in that case, we can connect the two problems.
- ▶ how ?

## Matching problem

We now go back to the matching problem, in the case of a **bipartite graph**.

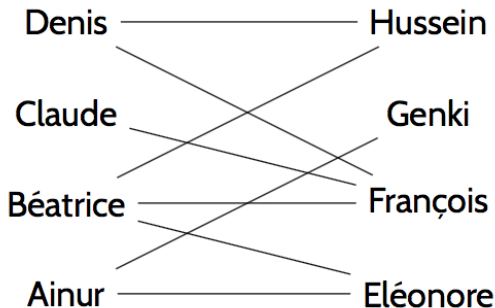
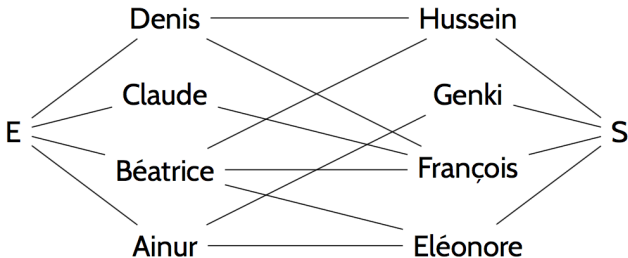


Figure: Bipartite graph

## Equivalence between matching and flow



**Figure:** Introduce two more nodes. All edges have capacity 1. We consider **flows with integer values**

## Ford Fulkerson for matching

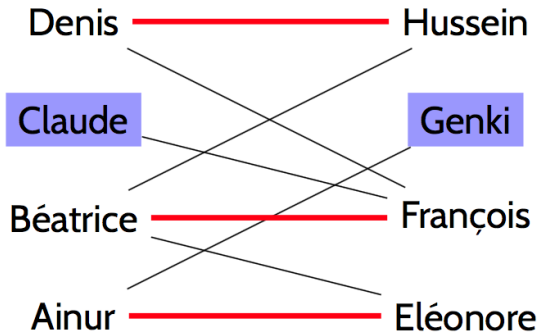


Figure: Non optimal solution

## Ford Fulkerson for matching

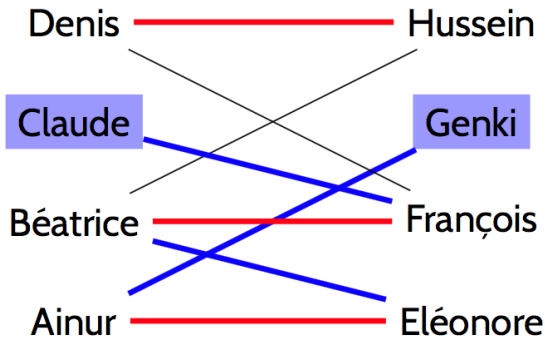


Figure: Optimal solution

## Exercise 10

- ▶ We will transpose Ford Fulkerson to a bipartite graph in order to find an optimal matching.
- ▶ **cd ford\_matching**
- ▶ edit **generate\_matching\_problem** in order to generate an instance of the problem.



## Exercise 11

- ▶ Apply the algorithm on an example generated by the previous function.
- ▶ Apply the algorithm to as an instance of your choice.

- ...
- └ The Maximum flow problem
  - └ More results on the two problems

## Famous theorem

The maximum flow theorem is equivalent to another famous problem, the **minimum cut** theorem.

## Perfect matching

In the case of a bipartite graph, what is the best matching possible?

## Perfect matching

In the case of a bipartite graph, what is the best matching possible ?

A matching where **all nodes are allocated**. It is called a **perfect** matching.

We obviously must have that the two parts of the graph are of same cardinality.

## Hall's marriage theorem

A theorem gives a condition that is necessary and sufficient for the existence of a perfect matching in a bipartite graph : the "marriage condition".

If  $G = (U, V, E)$  is bipartite, the condition means that :

$$\forall X \subset U, |N_G(X)| \geq |X| \quad (3)$$

where  $N_G(X)$  is the set of neighbors of  $X$  in  $G$ .

## Conclusion

Ford Fulkerson and its variants (Edmonds-Karp) are polynomial. As a result they can run on datasets that are way bigger than exhaustive search algorithms.

See you tomorrow