# Graph Algorithms: Lecture 1 Introduction

Michael Lampis

August 29, 2025

# Before we begin

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- This is a **Theoretical Computer Science** course. . .
  - Focus will be on algorithms and their theoretical analysis.
  - We will discuss algorithms that solve problems on graphs.
  - Proofs will be important (just like in a math course).

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  - Focus will be on algorithms and their theoretical analysis.
  - We will discuss algorithms that solve problems on graphs.
  - Proofs will be important (just like in a math course).
- ...with a bit of an applied side
  - The course includes a (small) programming component.
  - We will be (somewhat) interested in real-world relevance (applications).

#### Administrative Stuff

- Course Instructor: Michael Lampis (michail.lampis AT dauphine.fr)
- Course Web page:

https://www.lamsade.dauphine.fr/~mlampis/GraphAlgs/

- Grade Calculation:
  - Midterm Exam: 30% of grade (date: TBD)
  - Final Exam: 70% of grade
- Material to Study:
  - Slides (posted on web page)
  - TD exercises and solutions (posted on web page)
  - Further reading material linked on web page

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- Please come to class and participate actively!
- NB: Programming component is NOT graded.

#### Motivation



#### Definition

(Informal) A graph is a mathematical object that models **identical** pair-wise symmetric relations between objects.

#### Definition

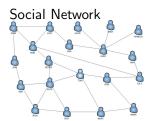
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Application Examples:

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Application Examples:

#### Telecommunication Network



#### Definition

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Application Examples:

#### Protein-Protein Interactions



#### Definition

(Informal) A graph is a mathematical object that models **identical** pair-wise symmetric relations between objects.

#### Definition

A simple graph G = (V, E) is a pair of a set of **vertices** and **edges**, with  $E \subseteq \binom{V}{2}$ .

- Pair-wise.  $e = \{u, v\}$ , for  $e \in E, u, v \in V$ . We write simply e = uv.
  - Otherwise: hypergraph
- Identical.
  - Otherwise: weighted graph, multi-graph
- Symmetric.
  - Otherwise: directed graph









Cabbage



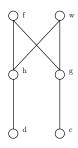


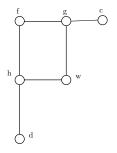


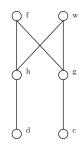








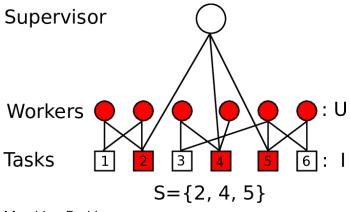




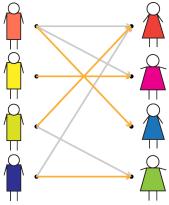
#### Mathematical definition:

- $V = \{f, w, g, h, d, c\}$
- $E = \{wg, gc, wh, fg, fh, hd\}$





Matching Problems



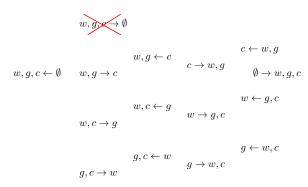
Matching Problems

$$w, g, c \leftarrow \emptyset$$

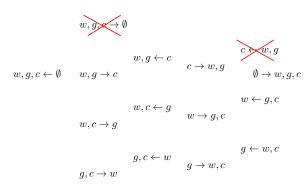
$$\emptyset \to w, g, c$$

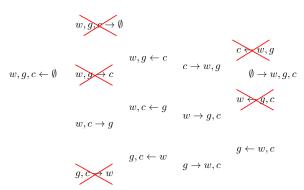


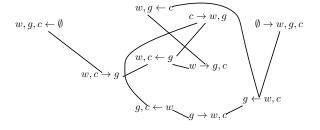




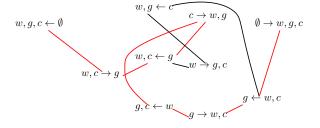






















Angela l







Angela l

Christine









Angela B

Christine

Donald











Angela Bor

Christine

Emmant

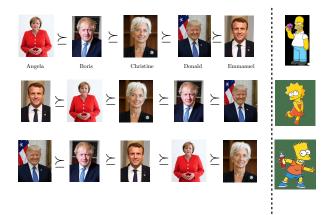




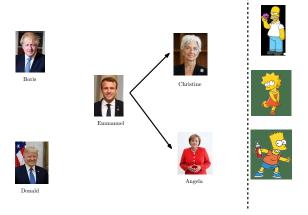


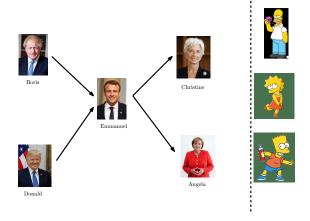


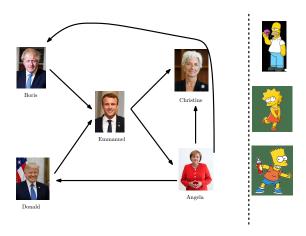


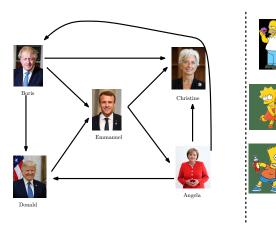


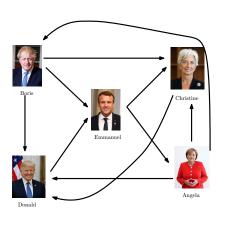








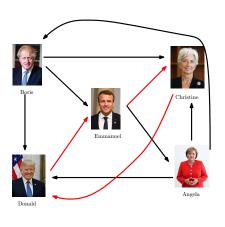








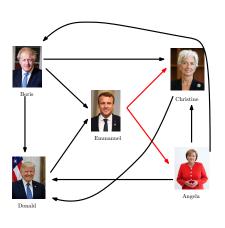








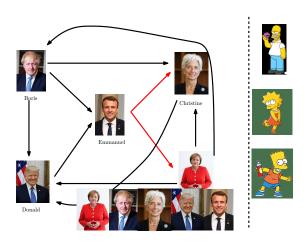


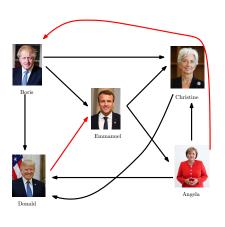








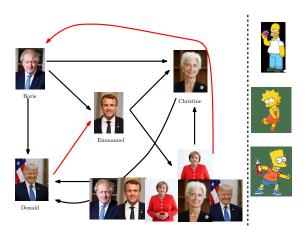




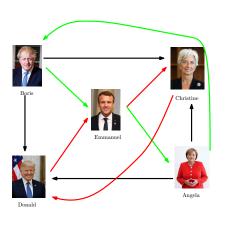


















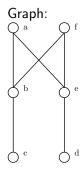
### **Basic Definitions**



Adjacency Matrix:

	a	b	С	d	е	f
а	0	1	0	0	1	0
b	1	0	1	0	0	1
С	0	1	0	0	0	0
d	0	0	0	0	1	0
е	1	0	0	1	0	1
f	0	1	0	0	1	0

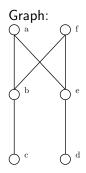
- $n \times n$  symmetric matrix
- 0 diagonal
- Number of 1's = 2m



Incidence Matrix:

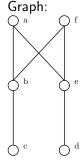
	ab	ae	bf	bc	de	ef
а	1	1	0	0	0	0
b	1	0	1	1	0	0
С	0	0	0	1	0	0
d	0	0	0	0	1	0
е	0	1	0	0	1	1
f	0	0	1	0	0	1

- $n \times m$  matrix
- Two 1's per column
- Number of 1's = 2m



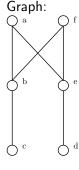
#### Adjacency Matrix:

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е	1	0	0	1	0	1
f	0	1	0	0	1	0



- Several different matrices could represent the same graph!
- Permuting rows/columns does not change the graph.

#### Adjacency lists:



A graph may also be represented by:

- n lists of neighbors
- ...or even a list of edges

Which representation is "better"?

### Algorithmic Background

### Polynomial Time

Algorithmic Efficiency: we care about

- Time/Space Complexity
- In the worst case
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- Polynomial in n is good!

### Polynomial Time

#### Algorithmic Efficiency: we care about

- Time/Space Complexity
- In the worst case
- As function of input size (n)
- Polynomial in n is good!
- And we care about which polynomial!

#### Reminder: O-notation

#### Definitions:

• 
$$f(n) = O(g(n)) \Leftrightarrow \exists C, n_0 \forall n > n_0 : f(n) \leq Cg(n)$$

• 
$$f(n) = \Omega(g(n)) \Leftrightarrow \exists C, n_0 \forall n > n_0 : f(n) \geq Cg(n)$$

• 
$$f(n) = \Theta(g(n)) \Leftrightarrow f(n) = O(g(n)) \wedge f(n) = \Omega(g(n))$$

• 
$$f(n) = o(g(n)) \Leftrightarrow \lim_{n \to \infty} \frac{f(n)}{g(n)} = 0$$

• 
$$f(n) = \omega(g(n)) \Leftrightarrow \lim_{n \to \infty} \frac{f(n)}{g(n)} = \infty$$

### Reminder: O-notation

(Slightly Inaccurate) Definitions:

• 
$$f(n) = O(g(n)) \Leftrightarrow f(n) \leq g(n)$$

• 
$$f(n) = \Omega(g(n)) \Leftrightarrow f(n) \geq g(n)$$

• 
$$f(n) = \Theta(g(n)) \Leftrightarrow f(n) \approx g(n)$$

• 
$$f(n) = o(g(n)) \Leftrightarrow f(n) << g(n)$$

• 
$$f(n) = \omega(g(n)) \Leftrightarrow f(n) >> g(n)$$

#### Reminder: O-notation

#### Intuition:

- We care what happens when n is huge ( $\rightarrow$  asymptotically):
- $n^2$  and  $3n^2 + 25n$  are "roughly" the same
- $500n^2$  is "much less" than  $\frac{n^3}{10}$
- $\log n$  is negligible compared to n which is negligible compared to  $2^n$
- (We do care about the distinction between n and  $n \log n$ )

### Reminder: Basic data structures

- Array/Matrix
  - O(1) time to access/modify an arbitrary element
  - O(n) time to add/remove an element
- Linked List
  - O(1) time to access first or last element
  - O(n) time to access arbitrary element
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Other data structures: Stack, Queue, Priority Queue...

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- In graph G with n vertices and m edges:
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- Incidence matrix size:  $\Theta(nm)$
- Adjacency lists:  $\Theta(n+m)$

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- Adjacency lists are always best!

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- Actually, adjacency lists take space  $O(m \log n)$ , because we need  $\log n$  bits to give the index of a vertex.
- But, for any reasonable input  $n < 2^{100}$ , so log n is basically a constant.
- Take home message: this is why we don't worry too much about log *n* factors. *n* factors are another story. . .

### **Notation Basics**



- n = |V|, m = |E|
- uv ∈ E ⇒ u, v are adjacent or neighbors
- N(v): set of neighbors of v
- $e = uv \in E \Rightarrow e$  is incident on u
- Degree d(v): number of edges incident on v
- Δ: maximum degree



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- Wheel  $W_n$ :  $C_n$  plus a universal vertex

# Conventions and Interesting Graphs

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Q: Is there a polynomial-time algorithm to decide if a graph belongs in one of these classes?

# Simple facts about Degrees

#### **Theorem**

For all 
$$G = (V, E)$$
 we have  $\sum_{v \in V} \deg(v) = 2|E|$ .

### **Theorem**

For all G = (V, E) the number of vertices of odd degree in G is even.

### **Theorem**

Every graph G has two vertices with the same degree.

# Degrees and Digraphs

### In directed graphs:

- e = uv is an **arc** from u to v.
- The outdegree of u,  $\deg^+(u)$ , is the number of arcs going out of u.
- The indegree of u,  $\deg^-(u)$ , is the number of arcs going into u.

### Theorem

For all digraphs 
$$G = (V, A)$$
 we have  $\sum_{v \in V} \deg^+(v) = |A| = \sum_{v \in V} \deg^-(v)$ .

### **Theorem**

In all digraphs, there exist two vertices with the same outdegree.

# Paths and Connectivity

### Definition

A path is an ordered sequence of **distinct** vertices  $v_1, v_2, \dots, v_k$  such that for all  $i \in [k-1]$  we have  $v_i v_{i+1} \in E$ .

### Definition

A graph is connected if there is a path between any two of its vertices.

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Can we decide in polynomial time if there is a path from s to  $t? \to \mathsf{Graph}$  traversal algorithms (in a bit. . . )



- Subgraph Containment
- Short-Long Paths
- Interesting Sets
- Coloring

- $G_1$  is a subgraph of  $G_2$  if it can be obtained from  $G_2$  by deleting vertices and edges.
- G<sub>1</sub> is an **induced** subgraph of
   G<sub>2</sub> if we only delete vertices.
- G<sub>1</sub> is a spanning subgraph of G<sub>2</sub> if we only delete edges.
- Typical question: does G contain a given graph H?

- Subgraph Containment
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- A Hamiltonian Path is a path that visits every vertex exactly once.
- An Fulerian Walk is a walk (path that may repeat vertices) that visits every edge exactly once.
- Typical question: find the shortest/longest path between two vertices.
- Related Is G Hamiltonian? Fulerian?

- Subgraph Containment
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- An independent set is a set of vertices inducing no edges.
- A vertex cover is a set of vertices that intersects all edges.
- A dominating set is a set of vertices that is adjacent to all vertices.
- . . . .
- Typical question: Find the smallest/largest set of vertices satisfying some property.

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- A coloring is a partitioning of a graph into independent sets.
- Typical question: How many colors do we need to color the vertices of this graph?

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Many of these questions are **Hard**! Which are easy and for which classes of graphs? This is something we will discuss...

# Examples

### **Problem**

Given graph G as an adjacency matrix, design an algorithm that finds two vertices of G with the same degree.



### **Problem**

Given graph G as an adjacency matrix, design an algorithm that finds two vertices of G with the same degree.

### Solution:

- For  $i \in \{1, ..., n\}$
- For  $j \in \{i+1, ..., n\}$ 
  - Check if deg(i) = deg(j). If yes, output (i, j).

Complexity?



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Complexity?  $O(n^3)$ , because computing deg(i) takes time O(n)

### **Problem**

Given graph G as an adjacency matrix, design an algorithm that finds two vertices of G with the same degree.

### Solution:

- For  $i \in \{1, ..., n\}$ 
  - Compute deg(i)
- Sort array of degrees D
- For  $i \in \{1, ..., n\}$  check if D[i] = D[i + 1]

Complexity?  $O(n^2)$  time.



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Complexity?  $O(n^2)$  time.

 $O(n^2)$  time is optimal (why?). However, we are now using O(n) space, whereas previously we were using O(1)...



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Given graph G as an adjacency matrix, find two vertices u, v (if they exist) which are at distance at least 3.



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- For  $i \in \{1, ..., n\}$
- For  $j \in \{i+1, ..., n\}$ 
  - if  $ij \notin E$  and  $N(i) \cap N(j) = \emptyset$  then output (i, j)
- Otherwise, Output Not Found!

### Complexity?



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Complexity?  $O(n^3)$  assuming  $N(i) \cap N(j) = \emptyset$  can be checked in O(n) (how?)Can we do it in sub-cubic time???



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Given graph G as an adjacency matrix, find two vertices u, v (if they exist) which touch all edges of G.

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### Solution:

- For  $i \in \{1, ..., n\}$
- For  $j \in \{1, ..., n\}$ 
  - Check if there is an edge not incident on either i nor j.

Complexity?



### **Problem**

Given graph G as an adjacency matrix, find two vertices u, v (if they exist) which touch all edges of G.

### Solution:

- For  $i \in \{1, ..., n\}$
- For  $j \in \{1, \dots, n\}$ 
  - Check if there is an edge not incident on either *i* nor *j*.

Complexity?

 $O(n^4)$  in the obvious implementation. Better?



#### **Problem**

Given graph G as an adjacency matrix, find two vertices u, v (if they exist) which touch all edges of G.

First, let us find is G has vertex cover of size 1 in  $O(n^2)$  (instead of  $O(n^3)$ ) Solution:

- Find an edge ij
- Check if  $\{i\}$  is a vertex cover. If yes, output i
- If not, check if  $\{j\}$  is a vertex cover. If yes, output j
- Otherwise, output No



### **Problem**

Given graph G as an adjacency matrix, find two vertices u, v (if they exist) which touch all edges of G.

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 $O(n^2)$  time



### **Problem**

Given graph G as an adjacency matrix, find two vertices u, v (if they exist) which touch all edges of G.

Now, work recursively:

### Solution:

- Find an edge ij.
- Let  $G_1$  be the graph obtained from G if we remove i. Check if  $G_1$  has a vertex cover of size 1. If yes, output  $\{i\}$  plus the vertex cover of  $G_1$ .
- If not, let  $G_2$  be the graph obtained from G if we remove j. If  $G_2$  has a vertex cover of size 1, output  $\{j\}$  plus the vertex cover of  $G_2$ .
- Otherwise, output No

Complexity:  $O(n^2)$ 



# Digraph Transpose I

### **Problem**

Given digraph G as an adjacency matrix, compute the adjacency matrix of  $G^T$ , which is the digraph where the direction of all arcs is reversed.

# Digraph Transpose I

### **Problem**

Given digraph G as an adjacency matrix, compute the adjacency matrix of  $G^T$ , which is the digraph where the direction of all arcs is reversed.

### Solution: (easy!)

• For each  $i, j \in \{1, ..., n\}$  set A'[i, j] = A[j, i], where A is the original matrix.

## Digraph Transpose II

#### **Problem**

Given digraph G as adjacency lists, compute the adjacency list representation of  $G^T$ , which is the digraph where the direction of all arcs is reversed.



# Digraph Transpose II

### **Problem**

Given digraph G as adjacency lists, compute the adjacency list representation of  $G^T$ , which is the digraph where the direction of all arcs is reversed.

Wait! What is the adjacency list representation of a digraph?

• For each  $v \in V$  we have a list  $N^+(v)$  with all the out-neighbors of v.

# Digraph Transpose II

### **Problem**

Given digraph G as adjacency lists, compute the adjacency list representation of  $G^T$ , which is the digraph where the direction of all arcs is reversed.

- Initialize with empty lists for all  $v \in V$
- For each  $v \in V$ 
  - For each  $u \in N^+(v)$  in the original graph
  - ullet ... Add v to the list of outneighbors of u in the new graph.

Complexity: O(m+n) time, but **NB** adjacency lists are not sorted (we never promised they were!)



# Digraph degree I

### **Problem**

Given digraph G in adjacency list representaion and a vertex v, compute the outdegree of v.



# Digraph degree I

### **Problem**

Given digraph G in adjacency list representation and a vertex v, compute the outdegree of v.

### Solution (easy):

• Output  $|N^+(v)|$ 

Complexity:  $O(\deg^+(v))$  or O(1) (depending on how list is stored)

# Digraph degree II

### **Problem**

Given digraph G in adjacency list representation and a vertex v, compute the indegree of v.

# Digraph degree II

### **Problem**

Given digraph G in adjacency list representation and a vertex v, compute the indegree of v.

Solution (less easy):

- c := 0
  - For each  $u \in V \setminus \{v\}$ 
    - If  $v \in N^+(u)$  then c++
  - Output c

Complexity: O(n+m), as we have to traverse all the lists (deciding if  $v \in N^+(u)$  takes time  $O(|N^+(u)|)$ ).

