Graph Theory

CE642: Social and Economic Networks
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01

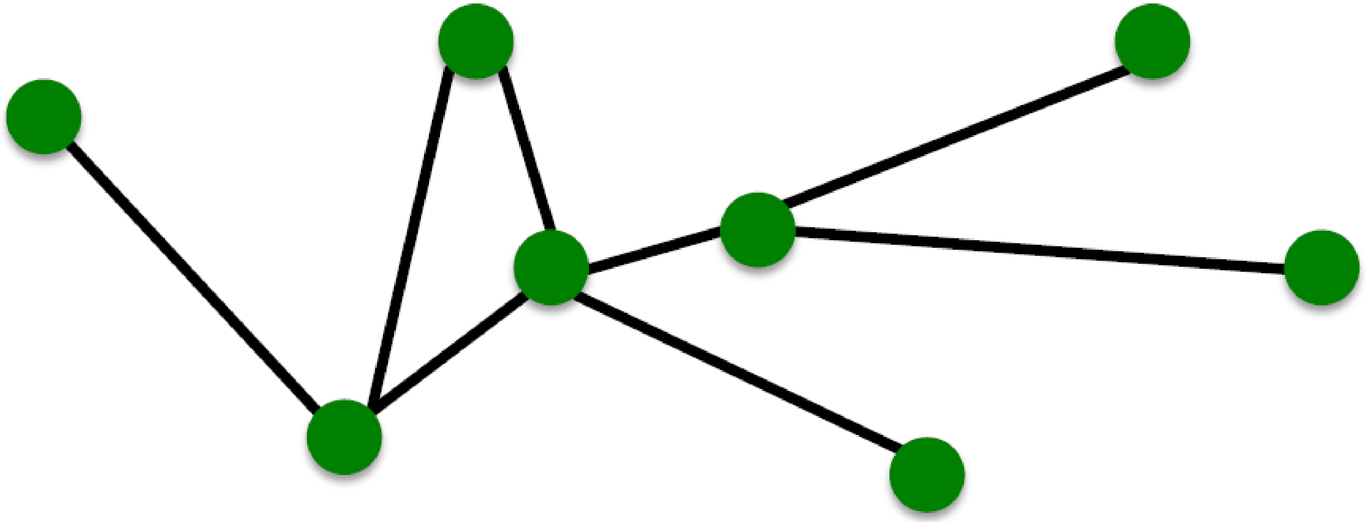
Introduction

Structure of Networks

A network is a collection of objects where some pairs of objects are connected by links

What is the structure of the network?

Components of a Network



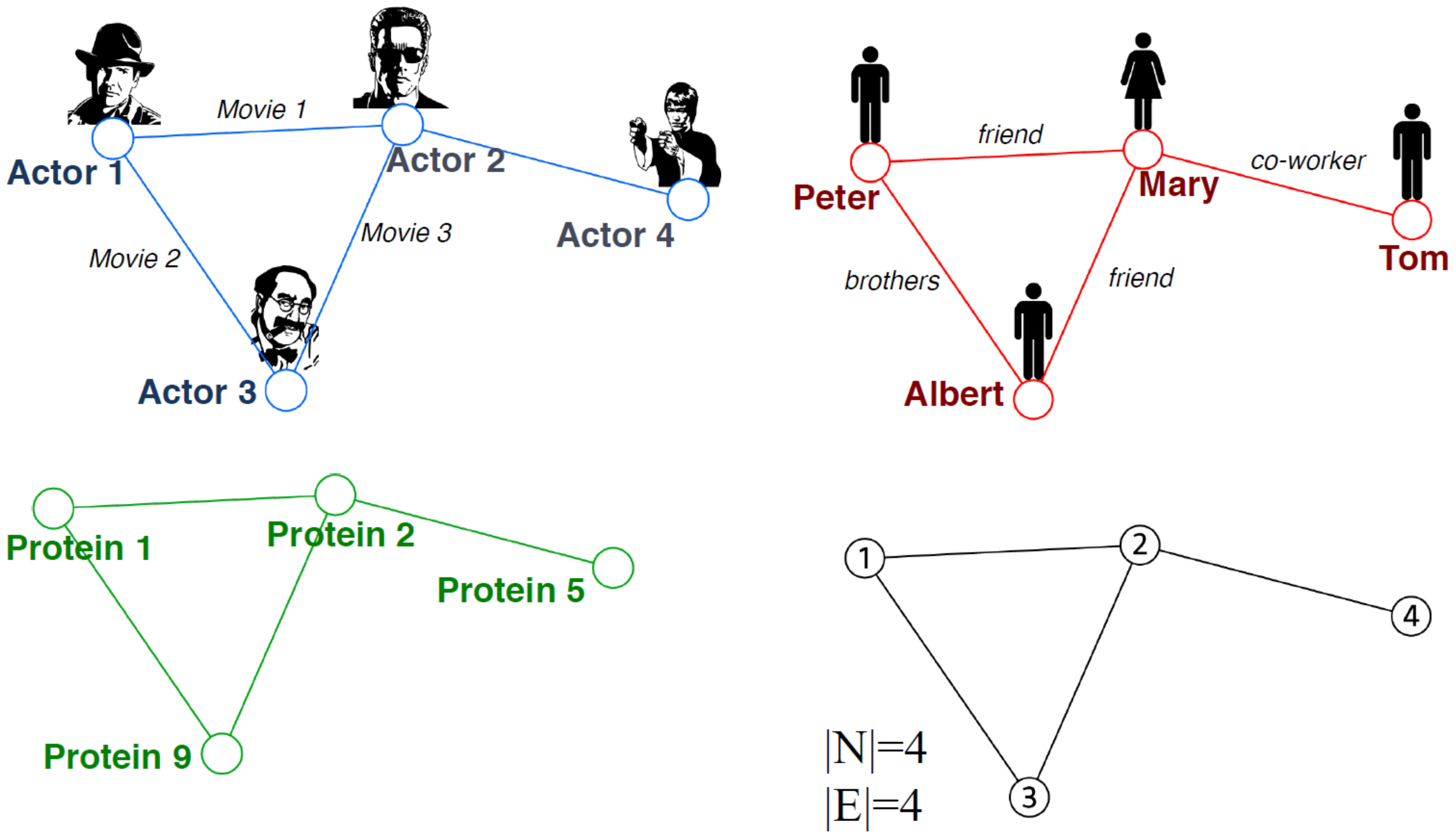
- Objects: nodes, vertices N
- Interactions: links, edges E
- System: network, graph G(N,E)

Networks or Graphs?

- Network often refers to real systems
  - Web, Social network, Metabolic network
  - Language: Network, node, link
- Graph is a mathematical representation of a network
  - Web graph, Social graph, Knowledge Graph
  - Language: Graph, vertex, edge

We will try to make this distinction whenever it is appropriate, but in most cases we will use the two terms interchangeably

Networks: Common Language



How do you define a network?

- **How to build a graph:**
  - **What are nodes?**
  - **What are edges?**
- **Choice of the proper network representation of a given domain/problem determines our ability to use networks successfully:**
  - In some cases there is a unique, unambiguous representation
  - In other cases, the representation is by no means unique
  - The way you assign links will determine the nature of the question you can study

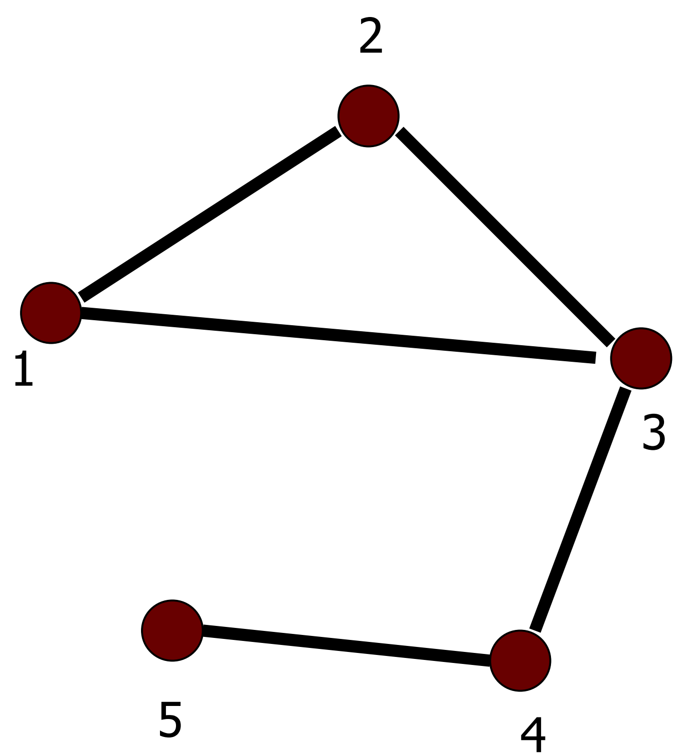
02

Types of Graphs

Undirected Graph

- Graph G=(V,E)
  - V = set of vertices
  - E = set of edges

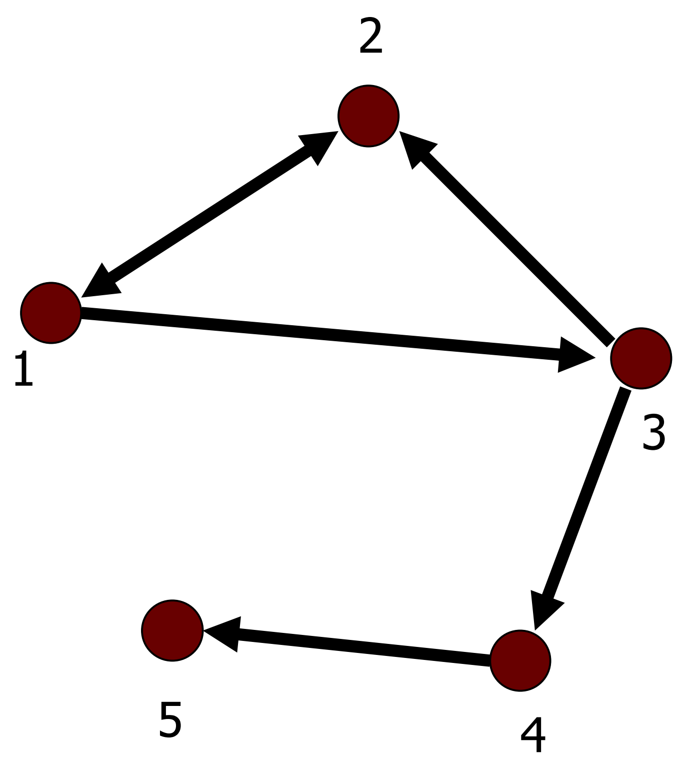
undirected graph
V = {1, 2, 3, 4, 5}
E={(1,2),(1,3),(2,3),(3,4),(4,5)}



Directed Graph

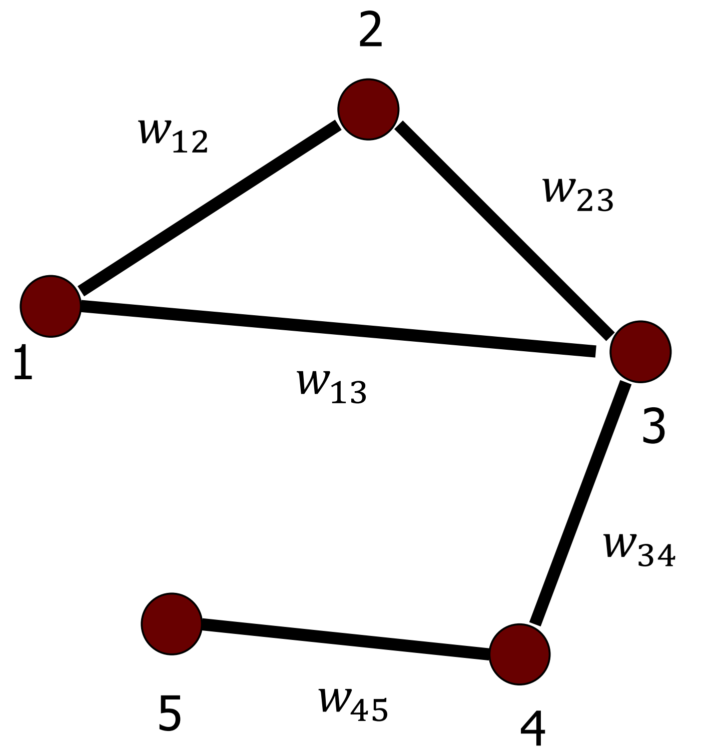
- Graph G=(V,E)
  - V = set of vertices
  - E = set of edges

directed graph
V = {1, 2, 3, 4, 5}
E={‹1,2›, ‹2,1› ‹1,3›, ‹3,2›, ‹3,4›, ‹4,5›}



Weighted Graph

- Graph G=(V,E)
  - V = set of vertices
  - E = set of edges and their weights

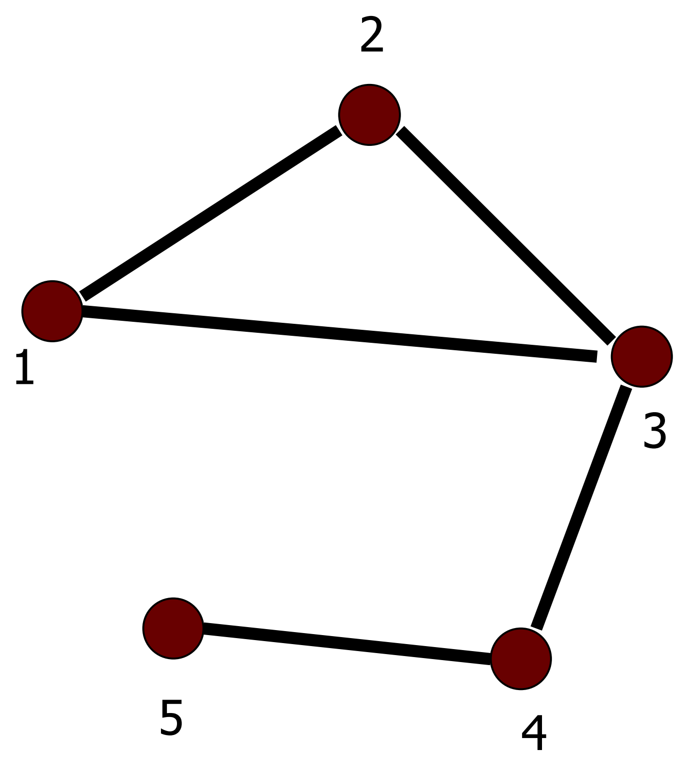


Weights can be either distances or similarities

weighted graph
V = {1, 2, 3, 4, 5}
E={(1,2,w_{12}),(1,3, w_{12}),(2,3, w_{12}),(3,4, w_{12}),(4,5, w_{12})}

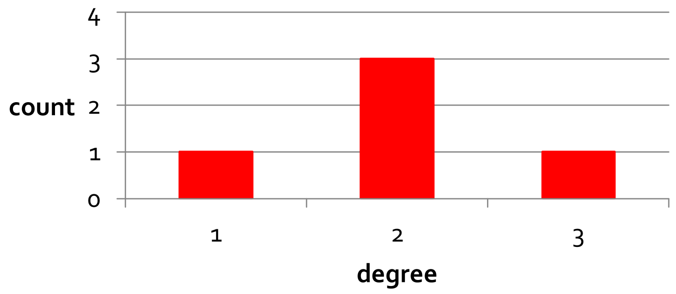
Undirected graph

- Neighborhood N(i) of node i
  - Set of nodes adjacent to i
- degree d(i) of node i
  - Size of N(i)
  - number of edges incident on i

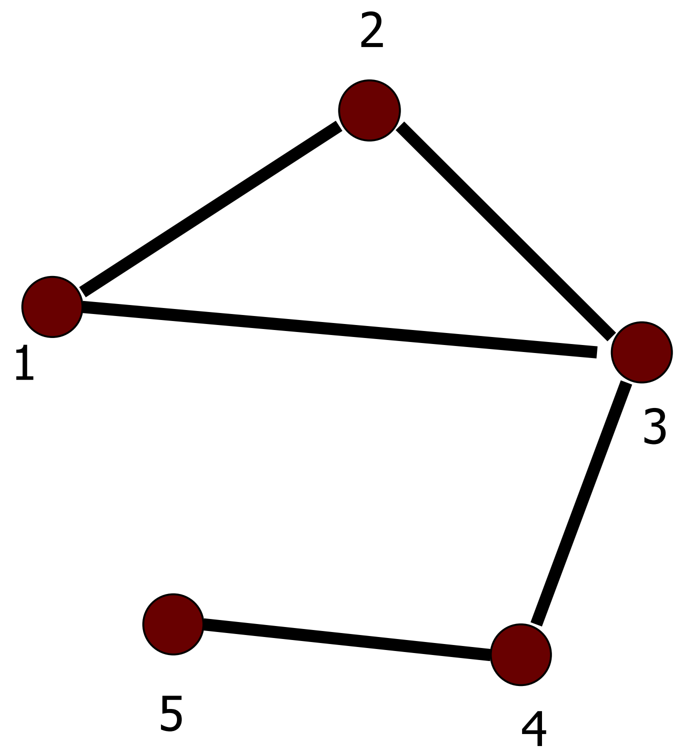


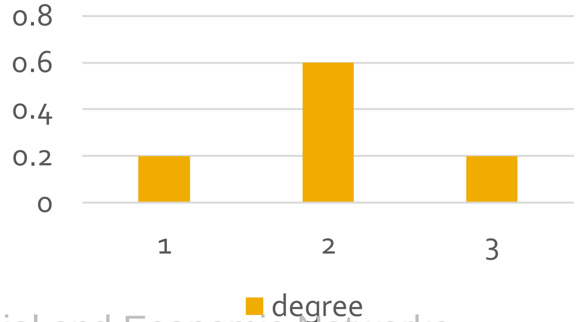
Undirected graph

- degree sequence
  - [d(1),d(2),d(3),d(4),d(5)]
  - [2,2,3,2,1]
- degree histogram
  - [(1:1),(2:3),(3,1)]



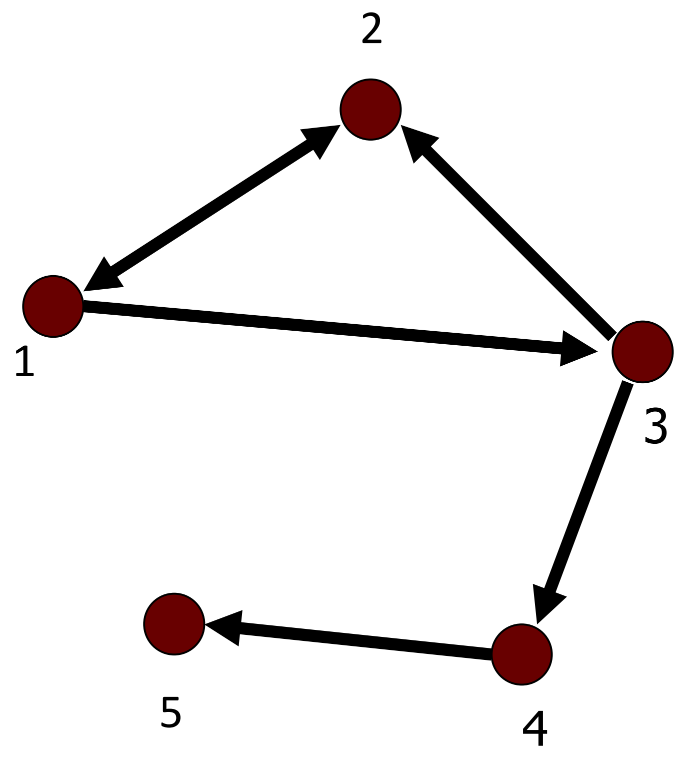
- degree distribution
  - [(1:0.2),(2:0.6),(3,0.2)]





Directed Graph

- in-degree $d_{in}(i)$ of node i
  - number of edges incoming to node i
- out-degree $d_{out}(i)$ of node i
  - number of edges leaving node i

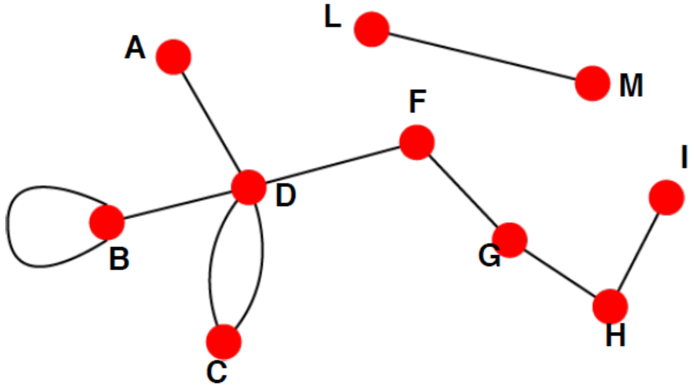


- in-degree sequence
  - [1,2,1,1,1]
- out-degree sequence
  - [2,1,2,1,0]
- in-degree histogram
  - [(1:4),(2:1)]
- out-degree histogram
  - [(0:1),(1:2),(2:2)]

Directed vs Undirected Graphs

Undirected

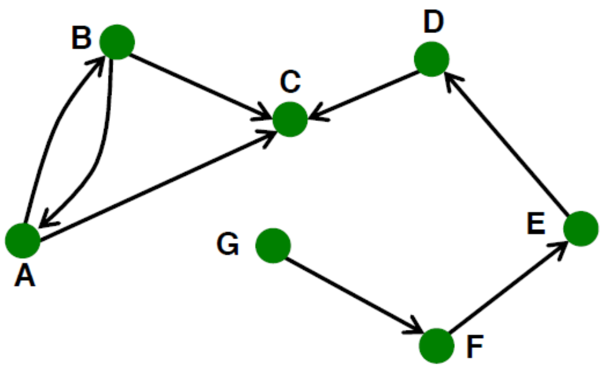
- **Links:** undirected (symmetrical, reciprocal)



- **Examples:**
  - Collaborations
  - Friendship on Facebook

Directed

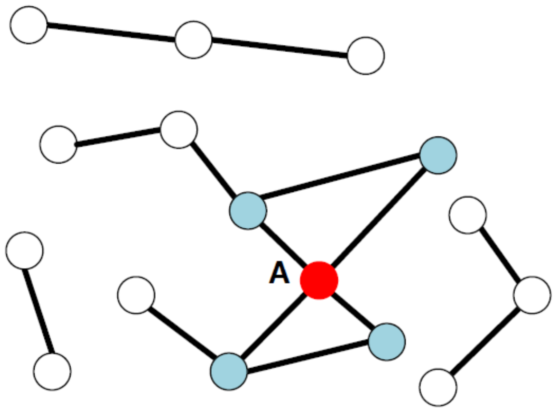
- **Links:** directed (arcs)



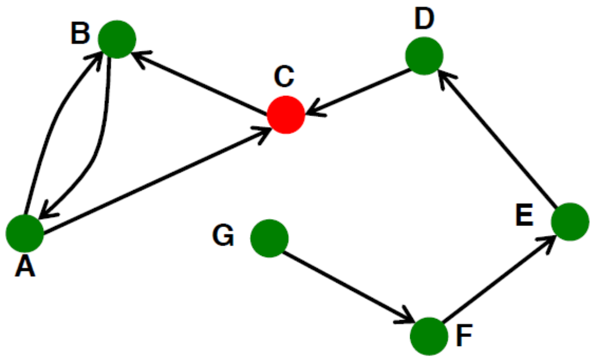
- **Examples:**
  - Phone calls
  - Following on Twitter

Node Degrees

Undirected



Directed



Source: Node with $k^{in} = 0$
Sink: Node with $k^{out} = 0$

Node degree, k_i: the number of edges adjacent to node i

$$k_A = 4$$

Avg. degree: $\bar{k} = \langle k \rangle = \frac{1}{N}\sum_{i=1}^{N} k_i = \frac{2E}{N}$

In directed networks we define an **in-degree** and **out-degree.**

The (total) degree of a node is the sum of in- and out-degrees.

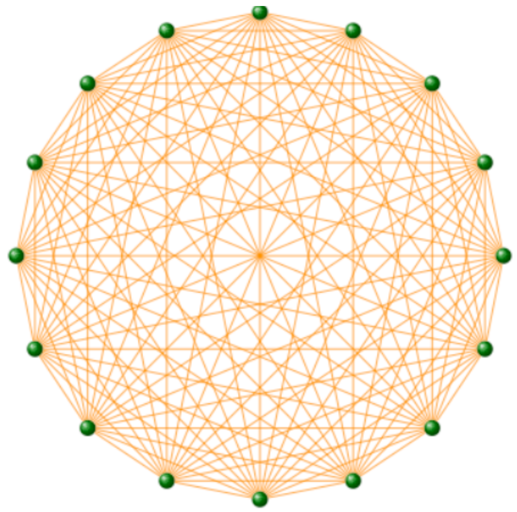
$$k_C^{in} = 2 \qquad k_C^{out} = 1 \qquad k_C = 3$$

$$\bar{k} = \frac{E}{N} \qquad \overline{k^{in}} = \overline{k^{out}}$$

Complete Graph

The **maximum number of edges** in an undirected graph on N nodes is

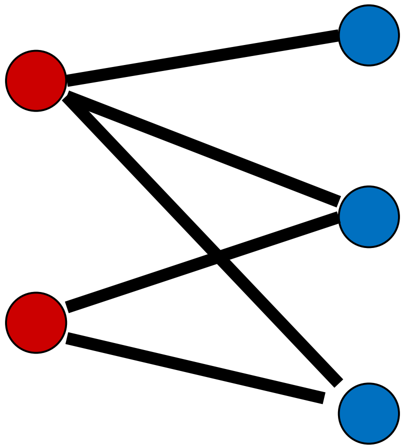
$$E_{\max} = \binom{N}{2} = \frac{N(N-1)}{2}$$

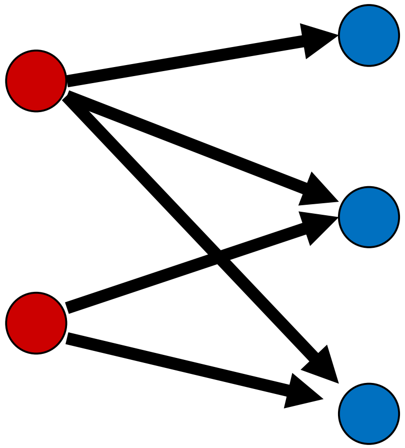


An undirected graph with the number of edges $E = E_{max}$ is called a **complete graph**, and its average degree is $N\text{-}1$

Bipartite graphs

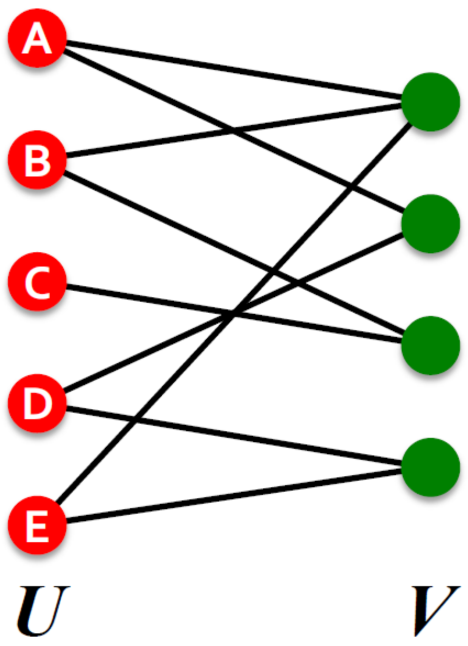
- Graphs where the set of nodes V can be partitioned into two sets L and R, such that there are edges only between nodes in L and R, and there is no edge within L or R



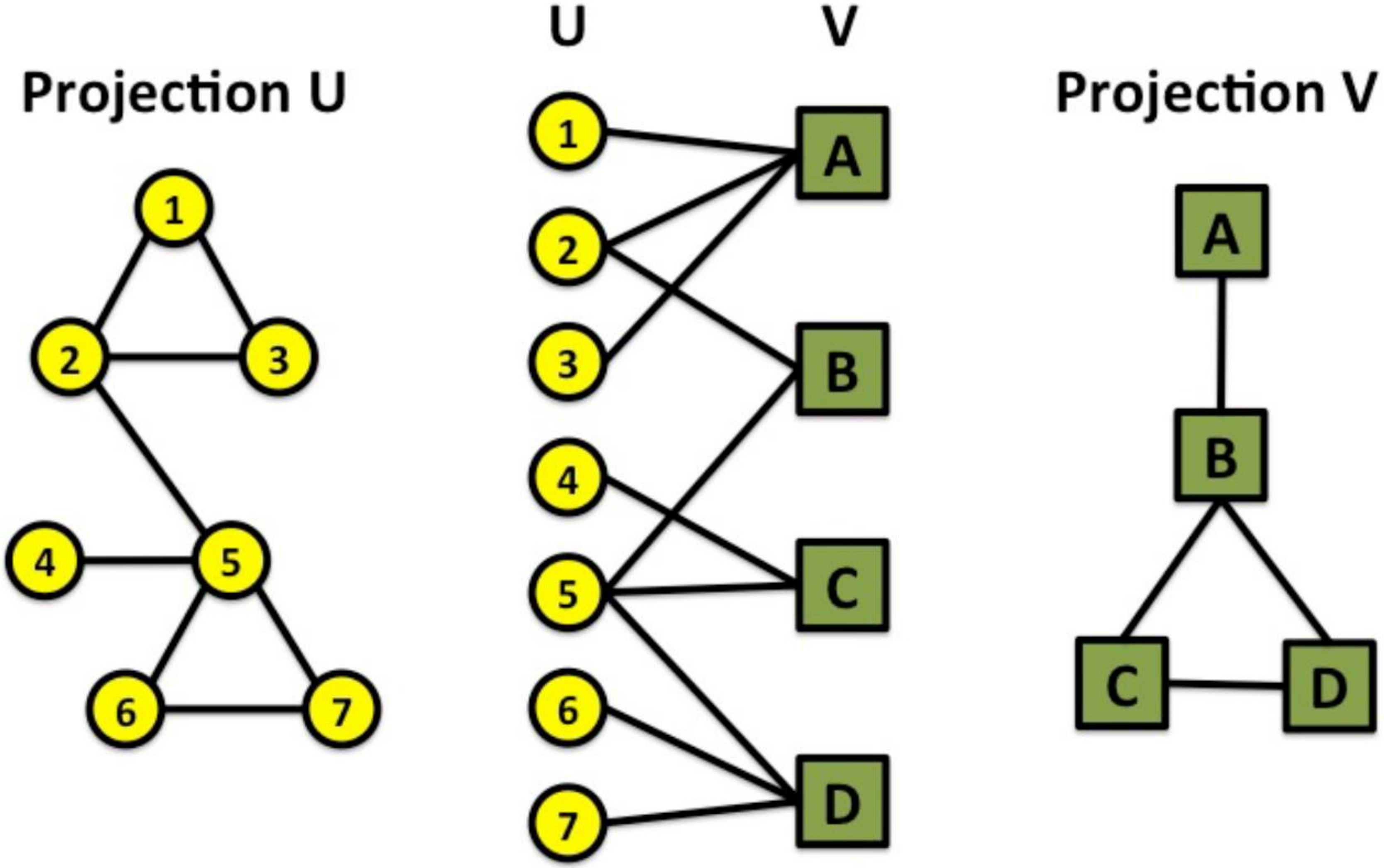


Bipartite Graph

- **Bipartite graph** is a graph whose nodes can be divided into two disjoint sets U and V such that every link connects a node in U to one in V; that is, U and V are **independent sets**
- **Examples:**
  - Authors-to-Papers (they authored)
  - Actors-to-Movies (they appeared in)
  - Users-to-Movies (they rated)
  - Recipes-to-Ingredients (they contain)
- **"Folded" networks:**
  - Author collaboration networks
  - Movie co-rating networks



Folded/Projected Bipartite Graph



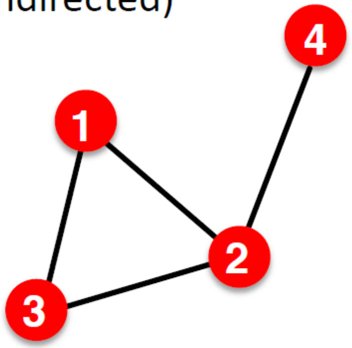
Edge Attributes

Possible options:

- Weight (e.g. frequency of communication)
- Ranking (best friend, second best friend…)
- Type (friend, relative, co-worker)
- Sign: Friend vs. Foe, Trust vs. Distrust
- Properties depending on the structure of the rest of the graph: number of common friends

More Types of Graphs

- **Unweighted**
(undirected)



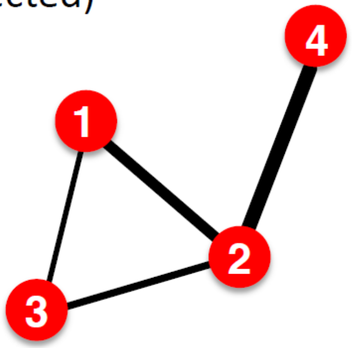
$$A_{ij} = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

$$A_{ii} = 0 \qquad A_{ij} = A_{ji}$$

$$E = \frac{1}{2}\sum_{i,j=1}^{N} A_{ij} \qquad \bar{k} = \frac{2E}{N}$$

Examples: Friendship, Hyperlink

- **Weighted**
(undirected)



$$A_{ij} = \begin{pmatrix} 0 & 2 & 0.5 & 0 \\ 2 & 0 & 1 & 4 \\ 0.5 & 1 & 0 & 0 \\ 0 & 4 & 0 & 0 \end{pmatrix}$$

$$A_{ii} = 0 \qquad A_{ij} = A_{ji}$$

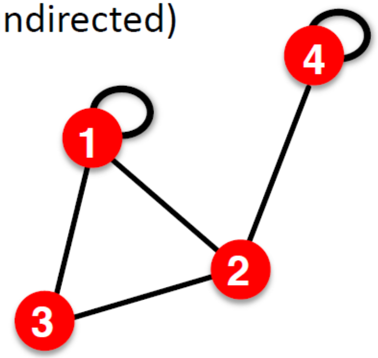
$$E = \frac{1}{2}\sum_{i,j=1}^{N} nonzero(A_{ij}) \qquad \bar{k} = \frac{2E}{N}$$

Examples: Collaboration, Internet, Roads

More Types of Graphs

- ## Self-edges (self-loops)

(undirected)



$$A_{ij} = \begin{pmatrix} 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 \end{pmatrix}$$

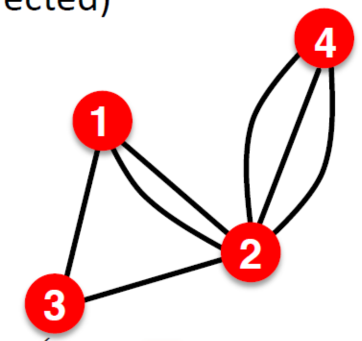
$$A_{ii} \neq 0 \qquad A_{ij} = A_{ji}$$

$$E = \frac{1}{2} \sum_{i,j=1, i \neq j}^{N} A_{ij} + \sum_{i=1}^{N} A_{ii}$$

Examples: Proteins, Hyperlinks

- ## Multigraph

(undirected)



$$A_{ij} = \begin{pmatrix} 0 & 2 & 1 & 0 \\ 2 & 0 & 1 & 3 \\ 1 & 1 & 0 & 0 \\ 0 & 3 & 0 & 0 \end{pmatrix}$$

$$A_{ii} = 0 \qquad A_{ij} = A_{ji}$$

$$E = \frac{1}{2} \sum_{i,j=1}^{N} nonzero(A_{ij}) \qquad \bar{k} = \frac{2E}{N}$$

Examples: Communication, Collaboration

03

Graph Traversals

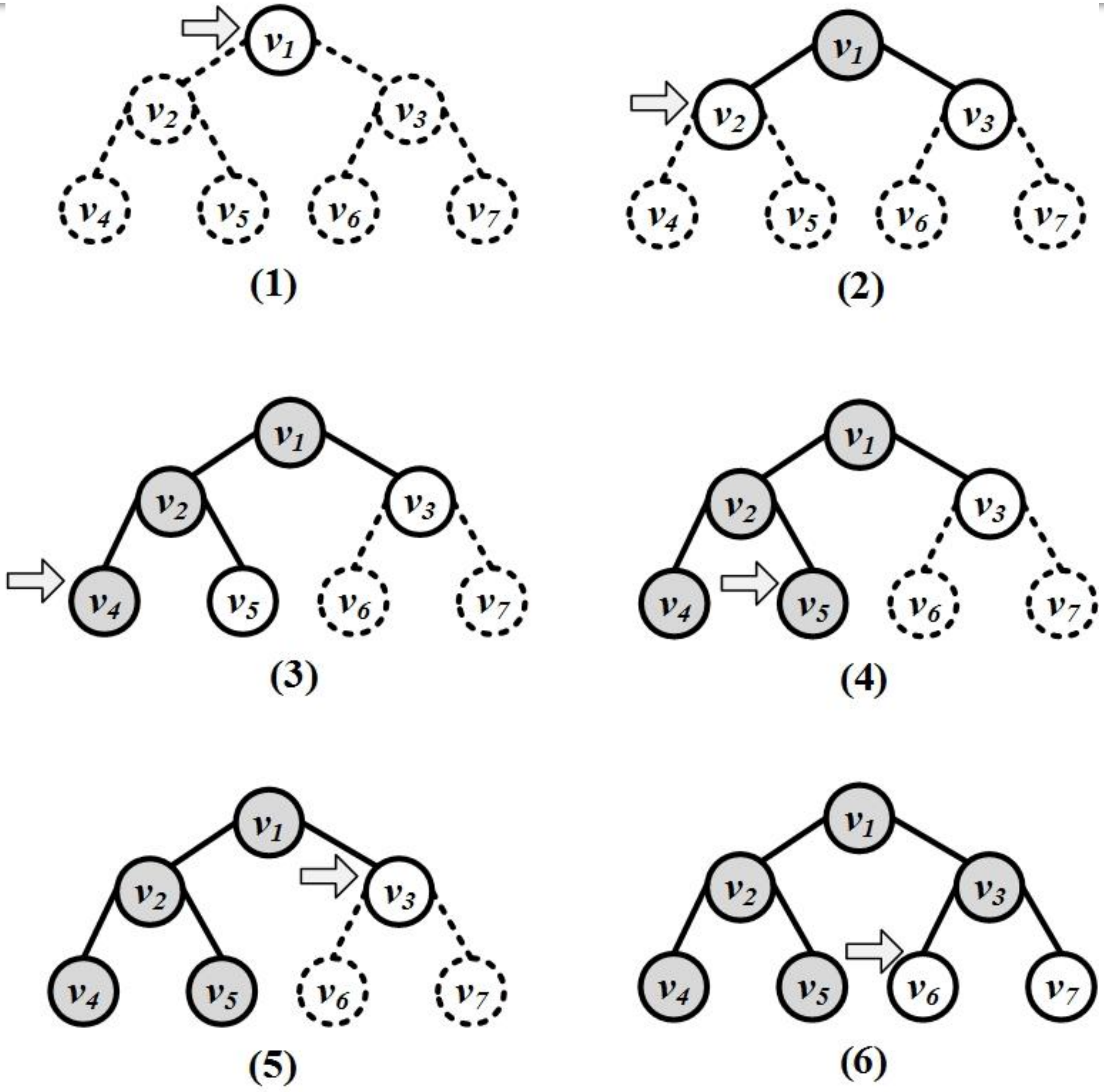
Graph Traversals

- A traversal is a procedure for visiting (going through) all the nodes in a graph:
  - Depth First Search (DFS)
  - Breadth First Search (BFS)

Depth First Search Traversal

- Depth-First Search (DFS) starts from a node i, selects one of its neighbors j from N(i) and performs Depth-First Search on j before visiting other neighbors in N(i).
  - The algorithm can be implemented using a *stack structure*

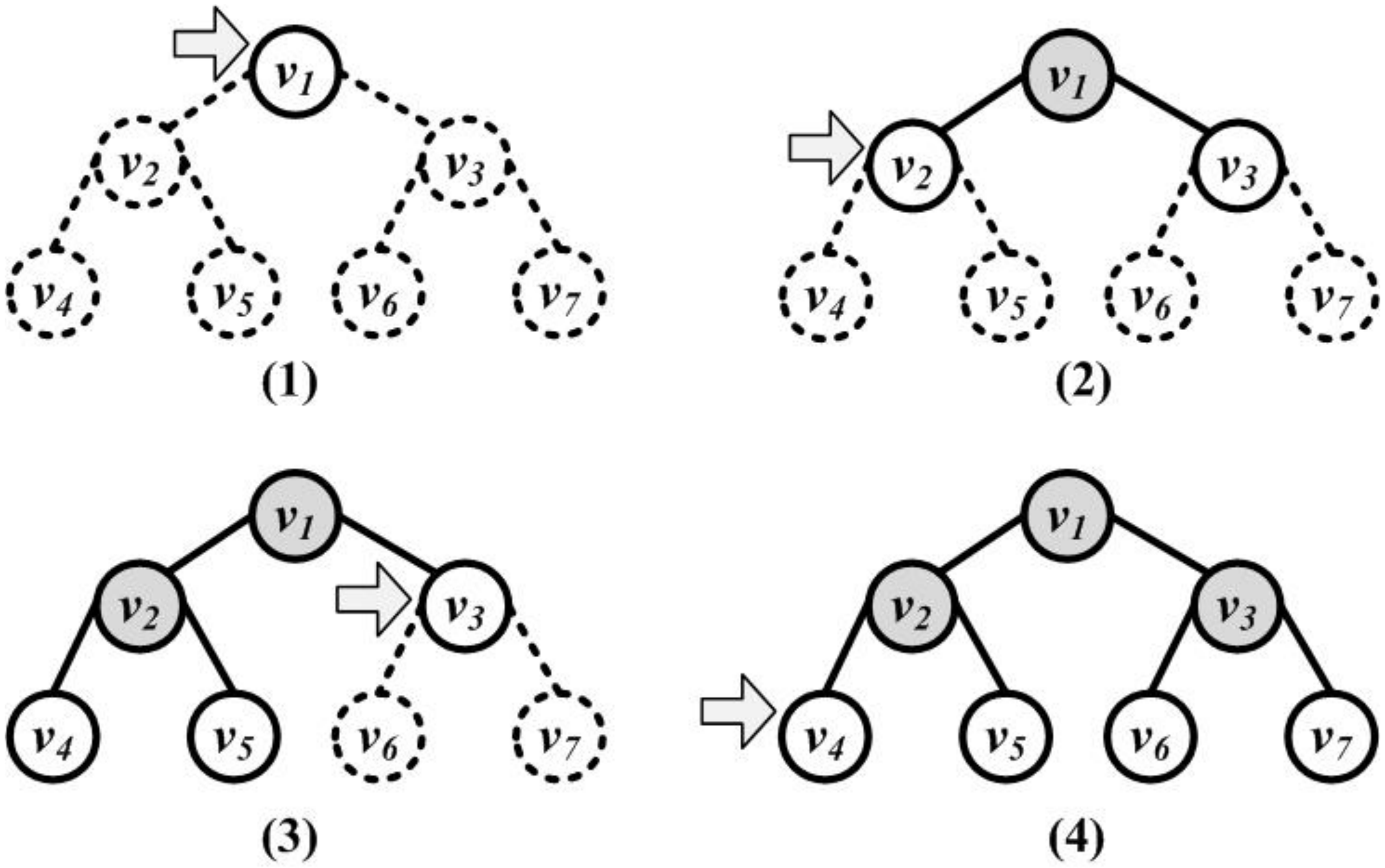
Example of DFS



Breadth First Search Traversal

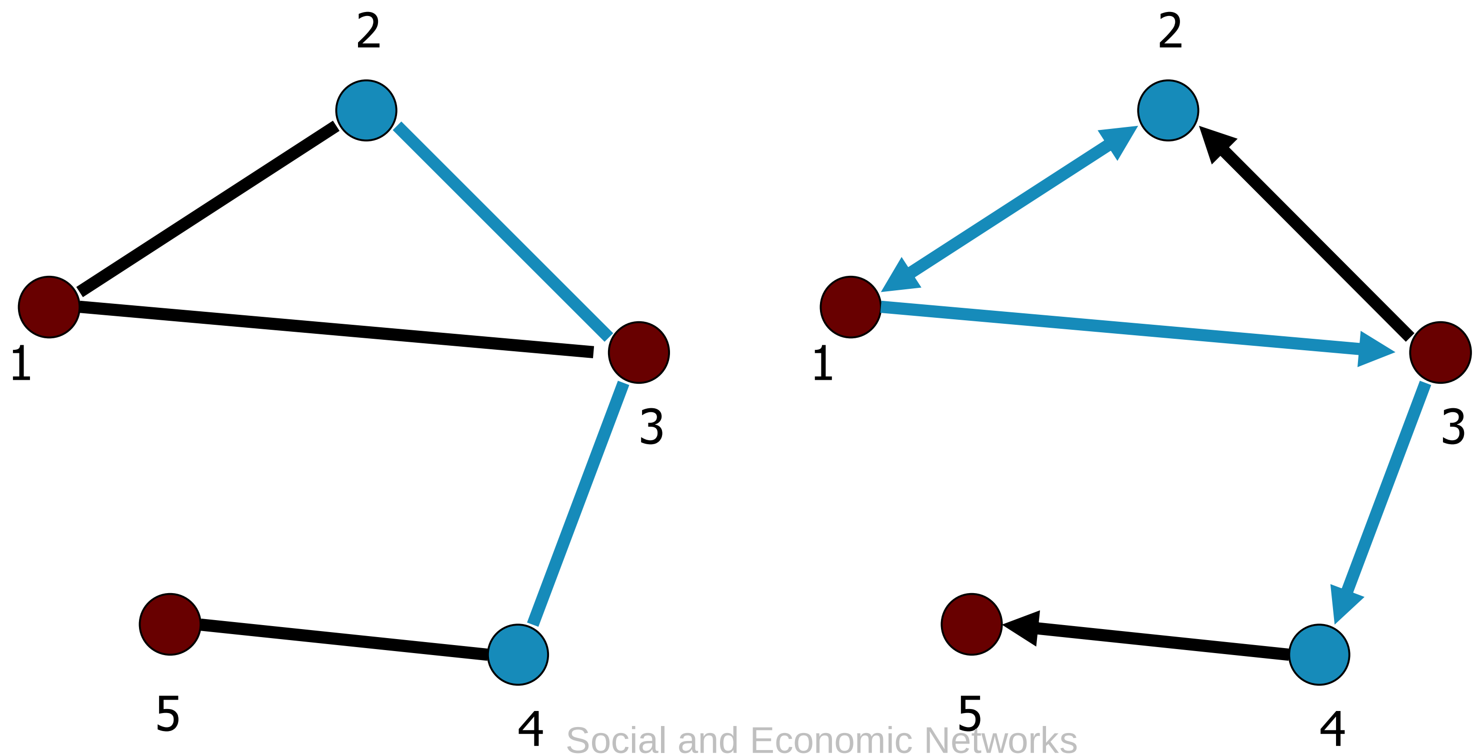
- Breadth-First-Search (BFS) starts from a node, visits all its immediate neighbors first, and then moves to the second level by traversing their neighbors.
  - The algorithm can be implemented using a *queue structure*

Example of BFS



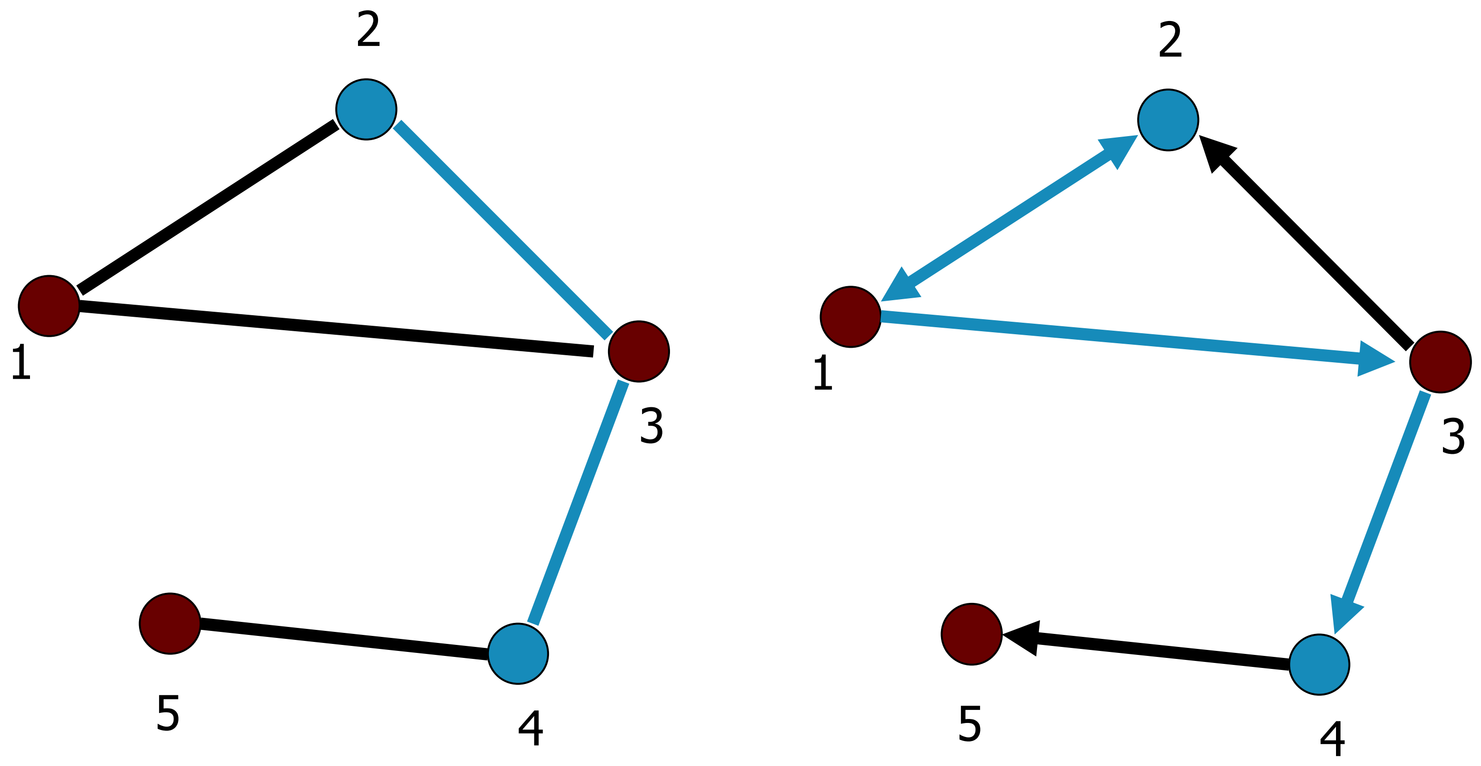
Paths

- Path from node i to node j: a sequence of edges (directed or undirected from node i to node j)
  - **path length**: number of edges on the path nodes i and j are connected
  - **cycle**: a path that starts and ends at the same node



Shortest Paths

- Shortest Path from node i to node j
  - also known as BFS path, or geodesic path

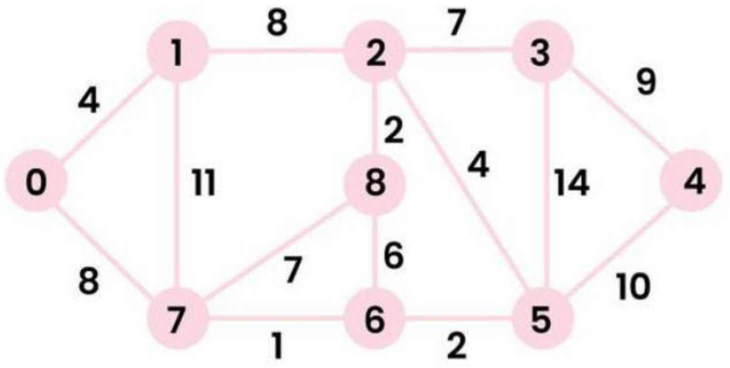


Shortest paths on weighted graphs

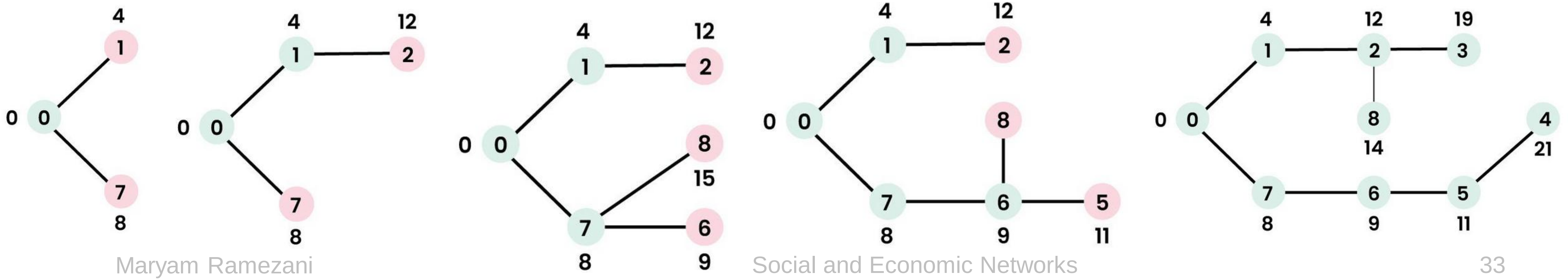
- Shortest paths on weighted graphs are harder to construct
  - There are several well known algorithms for finding single-source, or all-pairs shortest paths
  - For example: Dijkstra's Algorithm

Dijkstra’s Algorithm

- To understand the Dijkstra’s Algorithm lets take a graph and find the shortest path from source to all nodes. Consider below graph and src = 0.

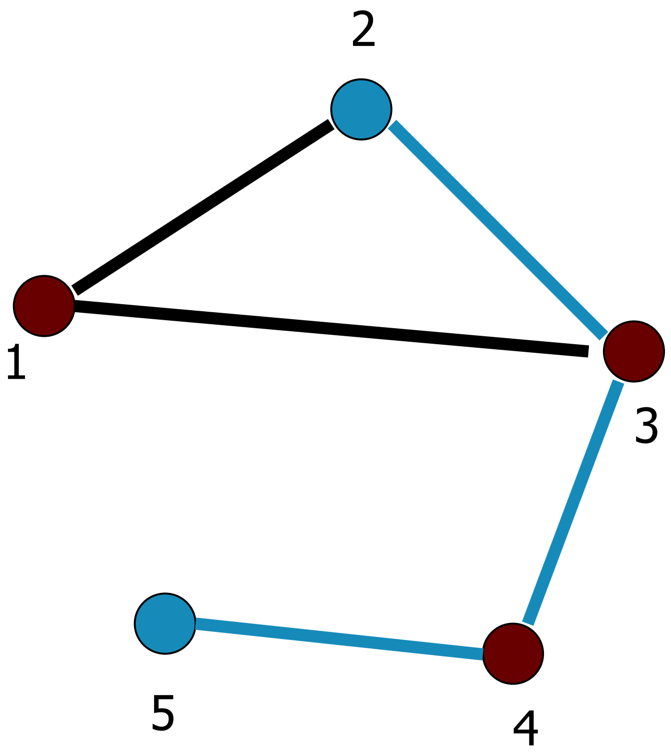


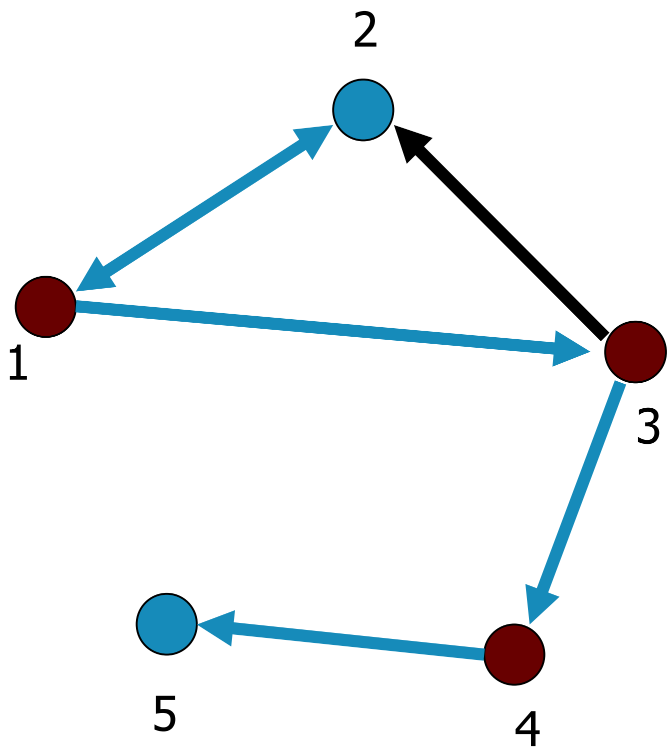
sptSet={0, INF, INF, INF, INF, INF, INF, INF}



Diameter

- The longest shortest path in the graph



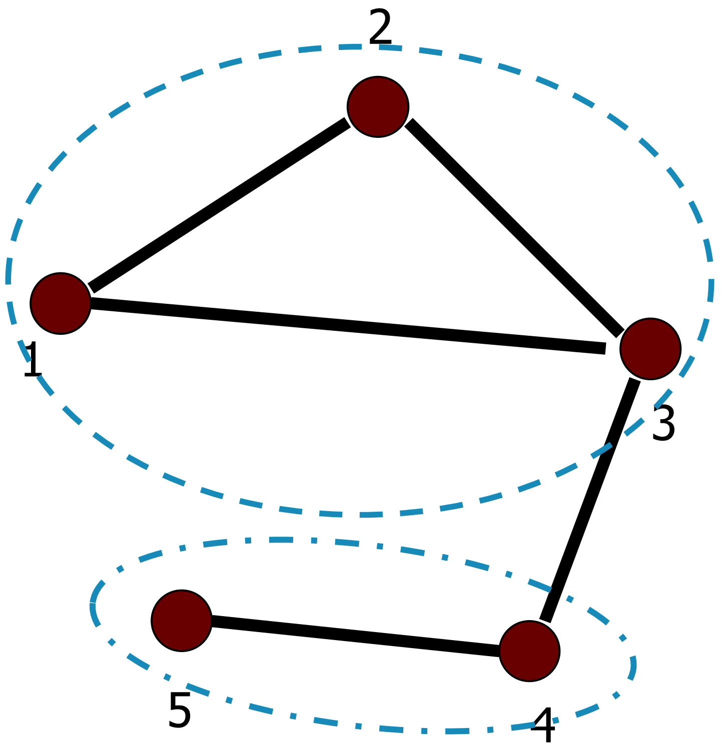


04

Graph Connectivity

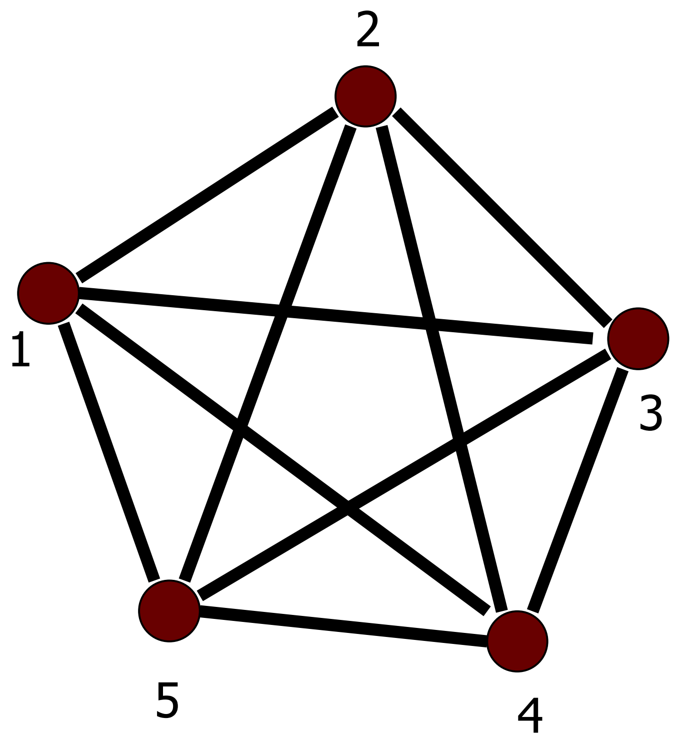
Undirected graph

- **Connected graph**: a graph where there every pair of nodes is connected
- **Disconnected graph**: a graph that is not connected
- **Connected Components**: subsets of vertices that are connected



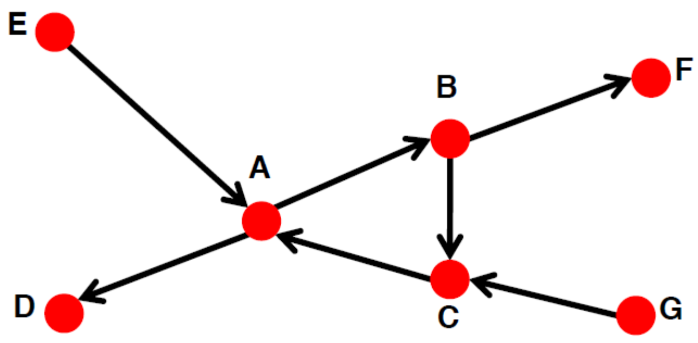
Fully Connected Graph

- Clique K_n
- A graph that has all possible n(n-1)/2 edges

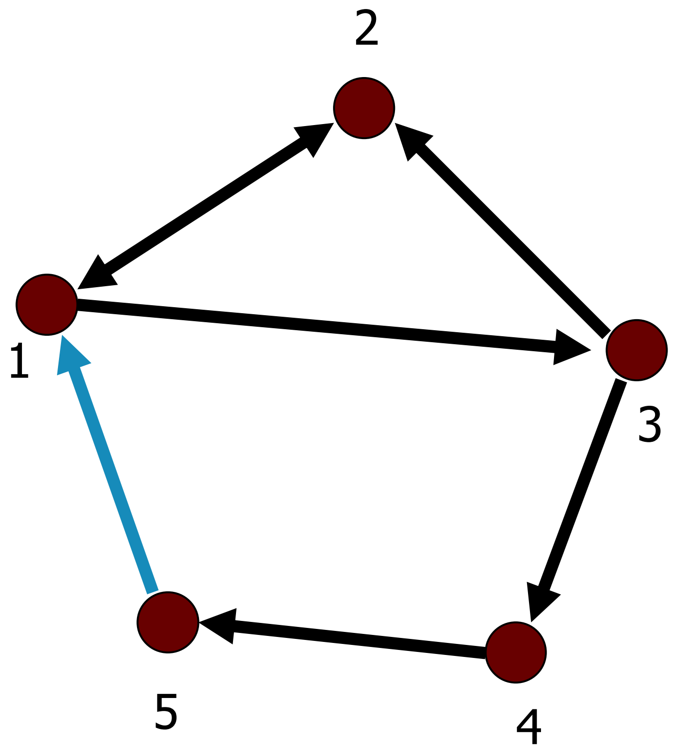


Connectivity of Directed Graph

- **Strongly connected graph**: there exists a path from every i to every j. has a path from each node to every other node and vice versa (e.g., A-B path and B-A path)
- **Weakly connected graph**: If edges are made to be undirected the graph is connected

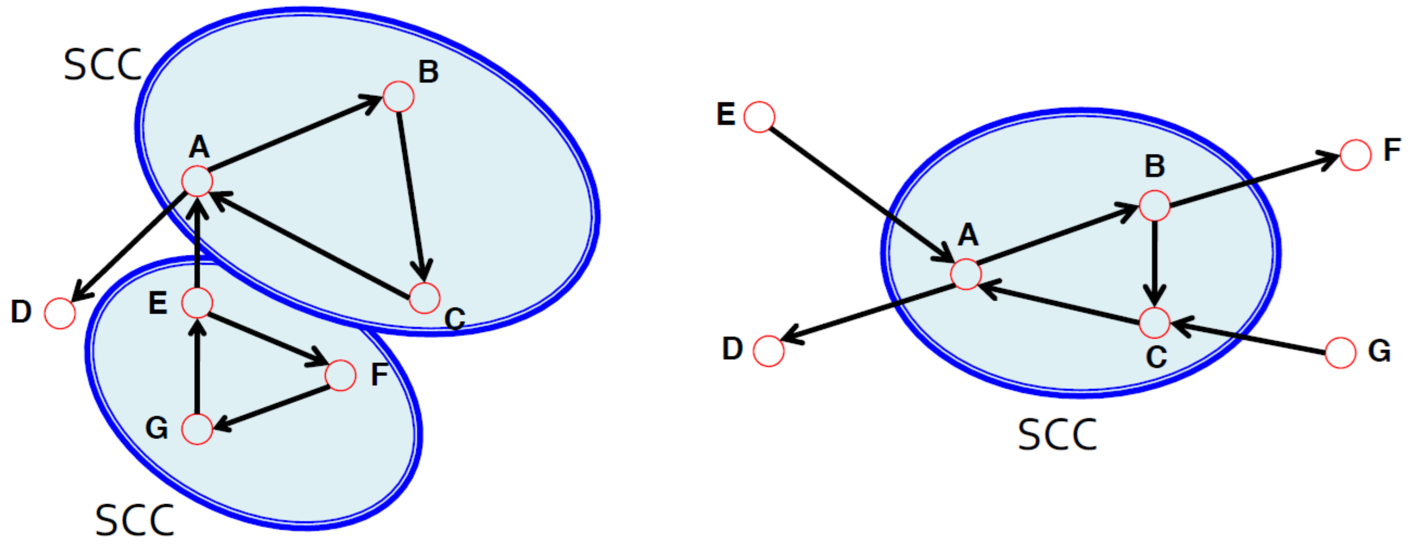


Graph on the left is connected but not strongly connected (e.g., there is no way to get from F to G by following the edge directions).



Connectivity of Directed Graph

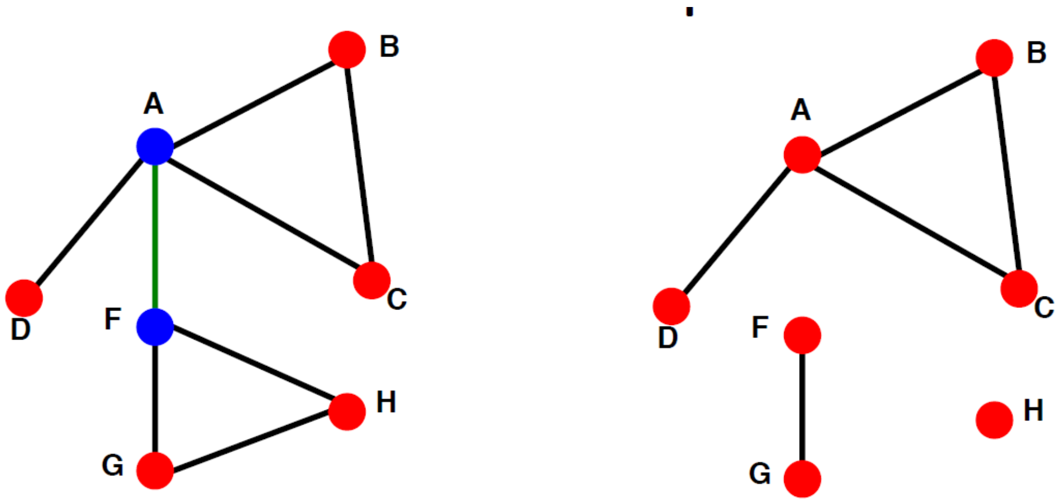
- **Strongly connected components (SCCs) can be identified, but not every node is part of a nontrivial strongly connected component.**



- In-component: nodes that can reach the SCC,
- Out-component: nodes that can be reached from the SCC.

Connectivity of Undirected Graphs

- **Connected (undirected) graph:**
  - Any two vertices can be joined by a path
- A disconnected graph is made up by two or more connected components



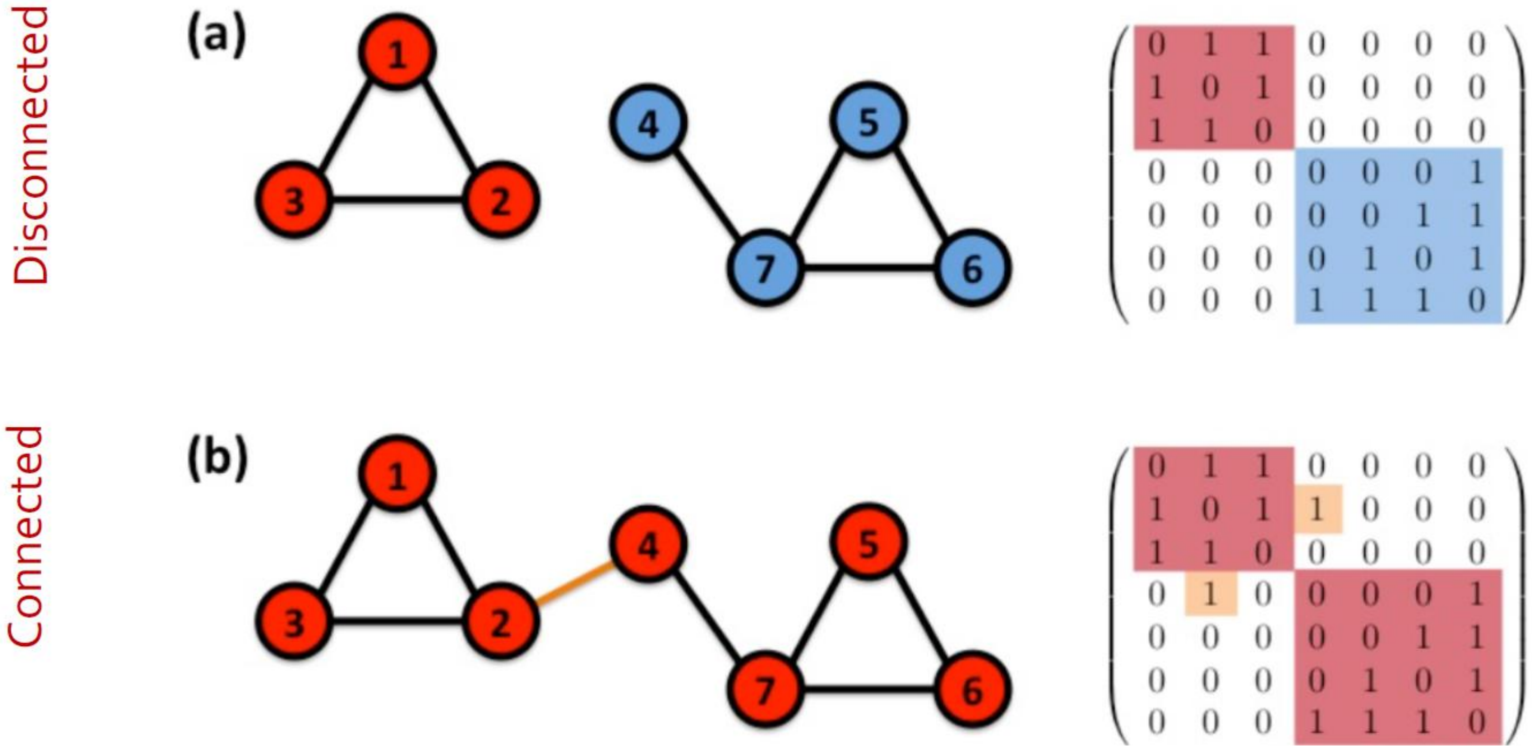
Largest Component:
Giant Component

Isolated node (node H)

- **Bridge edge:** If we erase the **edge**, the graph becomes disconnected
- **Articulation node:** If we erase the **node**, the graph becomes disconnected

Connectivity Example

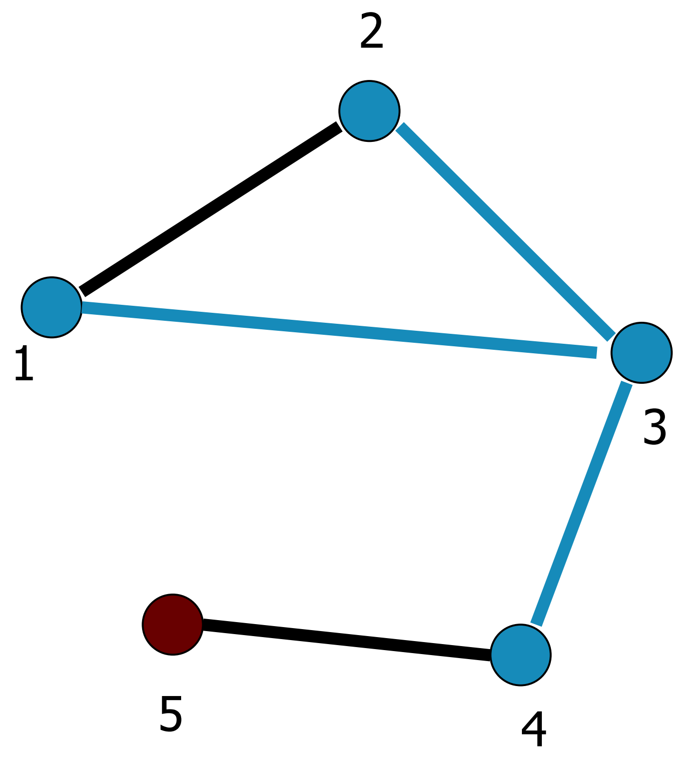
- The adjacency matrix of a network with several components can be written in a block-diagonal form, so that nonzero elements are confined to squares, with all other elements being zero:



Subgraphs

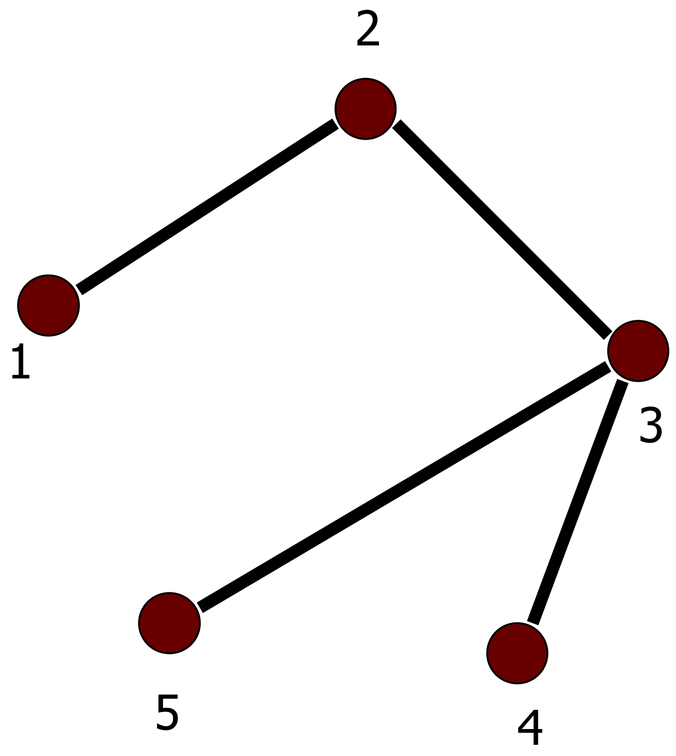
- Subgraph: Given $V' \subseteq V$, and $E' \subseteq E$, the graph $G'=(V',E')$ is a subgraph of G.

- Induced subgraph: Given $V' \subseteq V$, let $E' \subseteq E$ is the set of all edges between the nodes in V'. The graph $G'=(V',E')$, is an induced subgraph of G



Trees

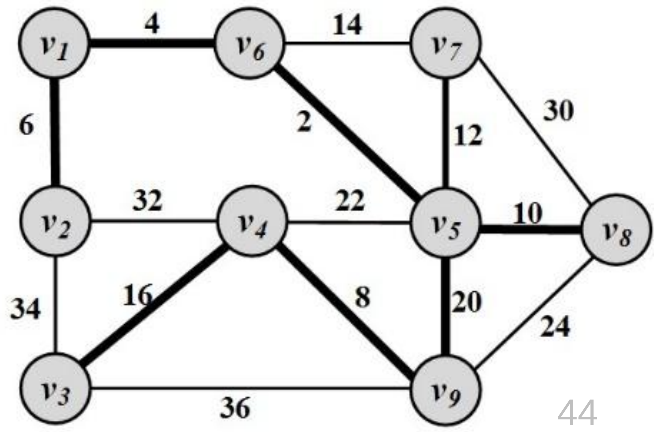
- Connected Undirected graphs without cycles



Spanning Tree

- For any connected graph, the spanning tree is a subgraph and a tree that includes all the nodes of the graph
- There may exist multiple spanning trees for a graph.
- For a weighted graph and one of its spanning tree, the weight of that spanning tree is the summation of the edge weights in the tree.
- Among the many spanning trees found for a weighted graph, the one with the minimum weight

  is called the minimum spanning tree (MST)



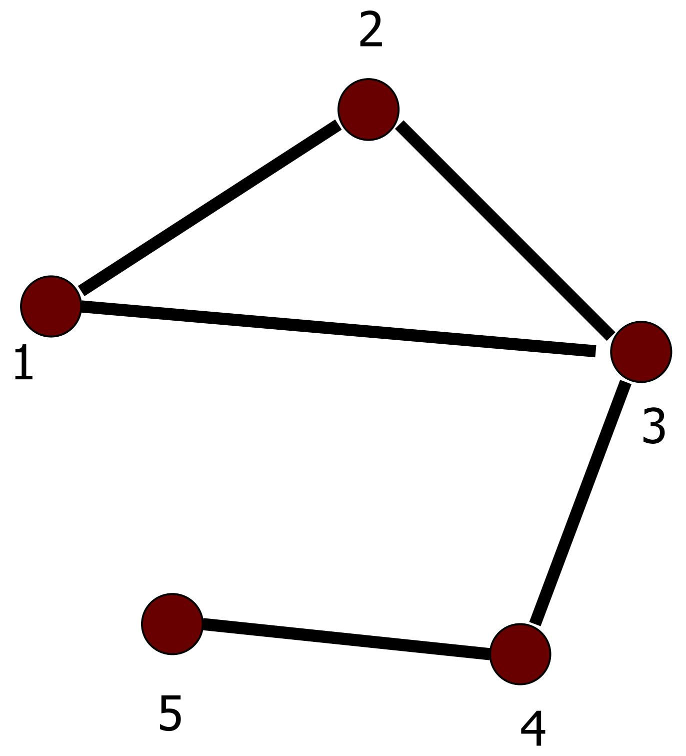
04

Graph Representation

Graph Representation

- Adjacency Matrix
  - symmetric matrix for undirected graphs

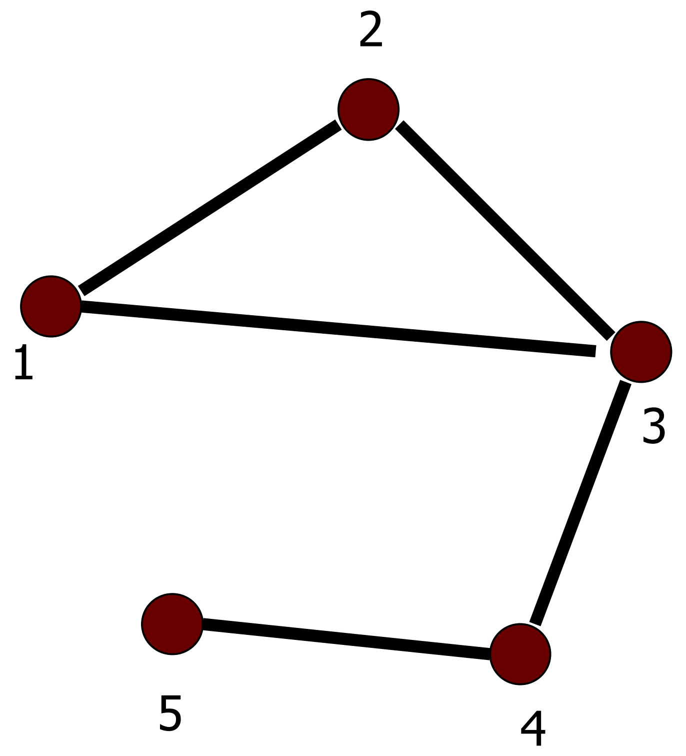
$$A = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$



Graph Representation

- Adjacency List
  - For each node keep a list with neighboring nodes

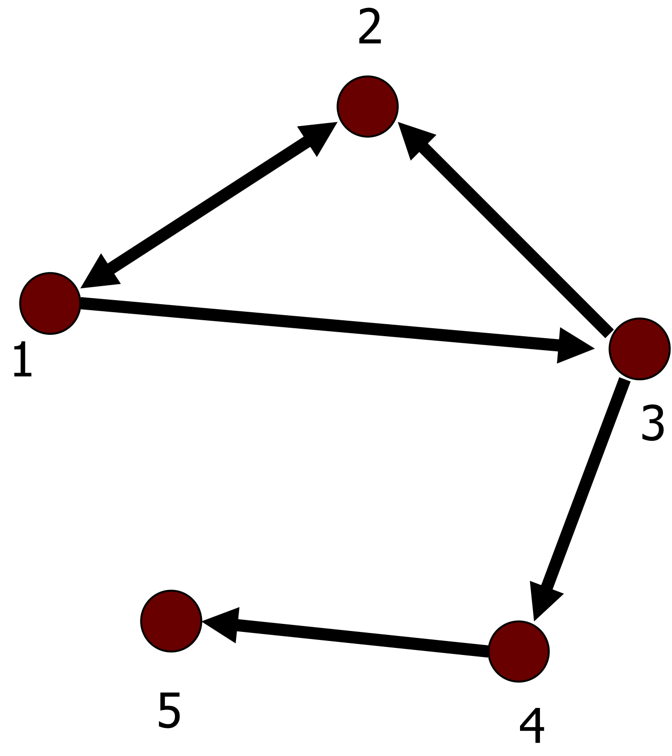
1: [2, 3]
2: [1, 3]
3: [1, 2, 4]
4: [3, 5]
5: [4]



Graph Representation

- Adjacency List
  - For each node keep a list of the nodes it points to
  - Easier to work with if network is
    - Large
    - Sparse
  - Allows us to quickly retrieve all neighbors of a given node

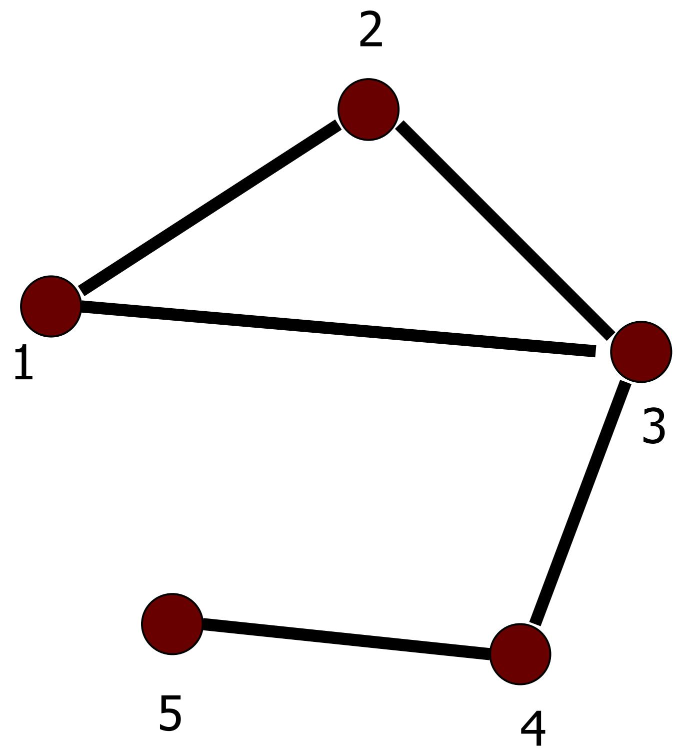
1: [2, 3]
2: [1]
3: [2, 4]
4: [5]
5: [null]



Graph Representation

- List of Edges
  - Keep a list of all the edges in the graph

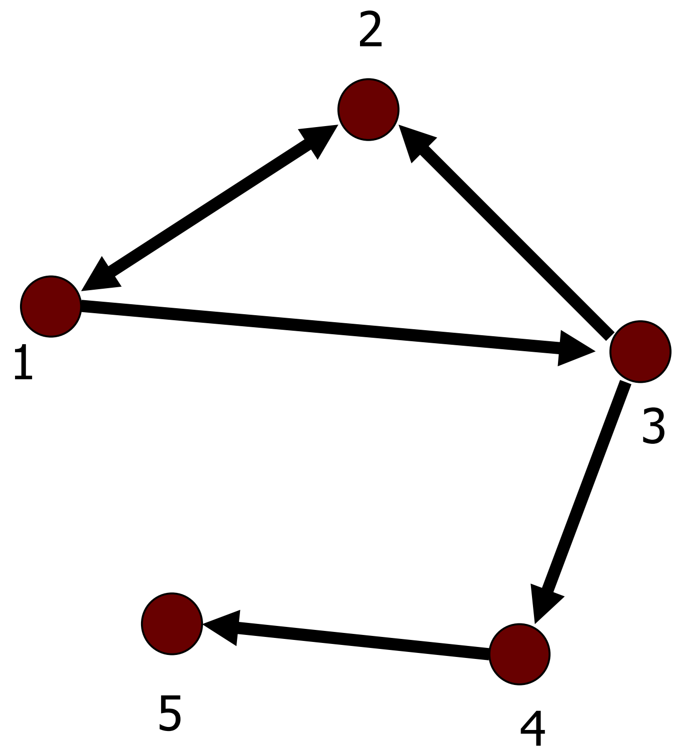
(1,2)
(2,3)
(1,3)
(3,4)
(4,5)



Graph Representation

- List of Edges
  - Keep a list of all the directed edges in the graph

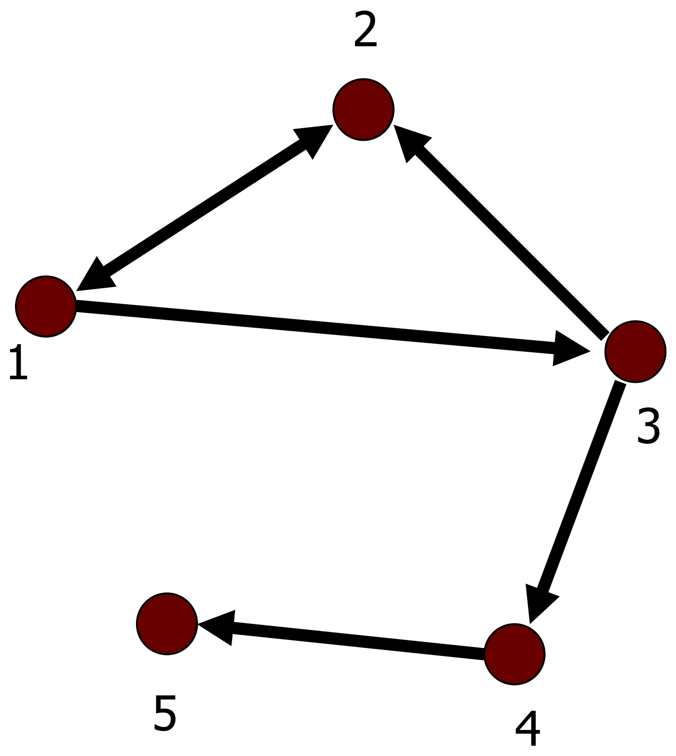
(1,2)
(2,1)
(1,3)
(3,2)
(3,4)
(4,5)



Graph Representation

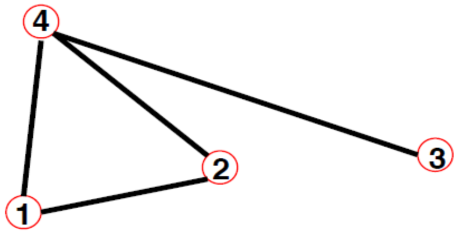
- Adjacency Matrix
  - unsymmetric matrix for undirected graphs

$$A = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$



Adjacency Matrix

Undirected



$$A_{ij} = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}$$

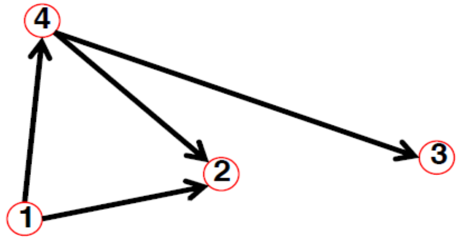
$$A_{ij} = A_{ji}$$
$$A_{ii} = 0$$

$$k_i = \sum_{j=1}^{N} A_{ij}$$

$$k_j = \sum_{i=1}^{N} A_{ij}$$

$$L = \frac{1}{2}\sum_{i=1}^{N} k_i = \frac{1}{2}\sum_{ij}^{N} A_{ij}$$

Directed



$$A = \begin{pmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \end{pmatrix}$$

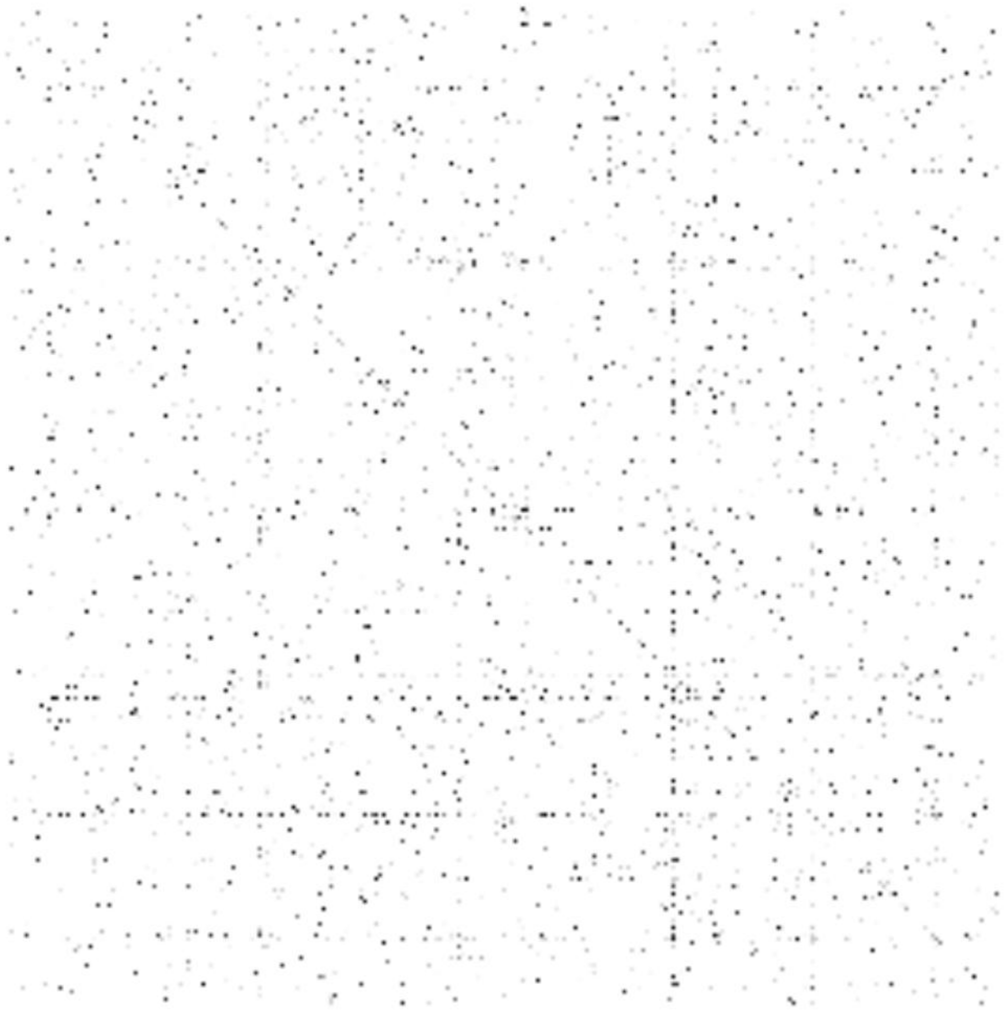
$$A_{ij} \neq A_{ji}$$
$$A_{ii} = 0$$

$$k_i^{out} = \sum_{j=1}^{N} A_{ij}$$

$$k_j^{in} = \sum_{i=1}^{N} A_{ij}$$

$$L = \sum_{i=1}^{N} k_i^{in} = \sum_{j=1}^{N} k_j^{out} = \sum_{i,j}^{N} A_{ij}$$

Adjacency Matrices are Sparse



Networks are Sparse Graphs

Most real-world networks are sparse

$$E \ll E_{max} \quad (\text{or } \bar{k} \ll N-1)$$

WWW (Stanford-Berkeley):	$N=319{,}717$	$\langle k\rangle=9.65$
Social networks (LinkedIn):	$N=6{,}946{,}668$	$\langle k\rangle=8.87$
Communication (MSN IM):	$N=242{,}720{,}596$	$\langle k\rangle=11.1$
Coauthorships (DBLP):	$N=317{,}080$	$\langle k\rangle=6.62$
Internet (AS-Skitter):	$N=1{,}719{,}037$	$\langle k\rangle=14.91$
Roads (California):	$N=1{,}957{,}027$	$\langle k\rangle=2.82$
Proteins (S. Cerevisiae):	$N=1{,}870$	$\langle k\rangle=2.39$

(Source: *Leskovec et al., Internet Mathematics, 2009*)

Consequence: Adjacency matrix is filled with zeros!

(**Density of the matrix (E/N^2):** WWW=1.51×10^{-5}, MSN IM = 2.27×10^{-8})

Network Representations

Email network >> directed multigraph with self-edges

Facebook friendships >> undirected, unweighted

Citation networks >> unweighted, directed, acyclic

Collaboration networks >> undirected multigraph or weighted graph

Mobile phone calls >> directed, (weighted?) multigraph

Protein Interactions >> undirected, unweighted with self-interactions

05

Linear Algebra Review

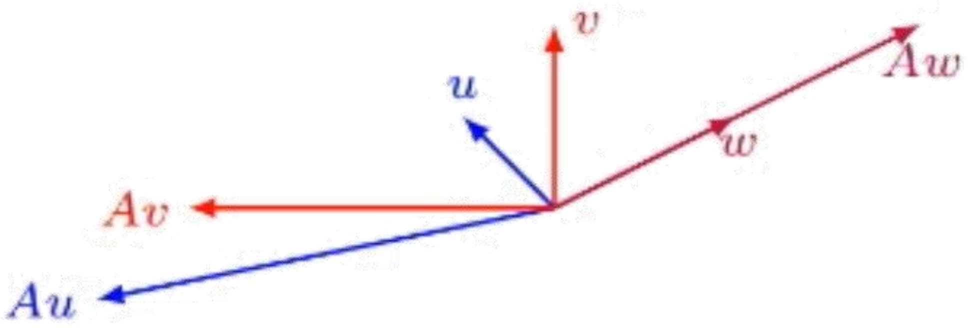
Motivation

- $A = \begin{bmatrix} 3 & -2 \\ 1 & 0 \end{bmatrix}$

$$u = \begin{bmatrix} -1 \\ 1 \end{bmatrix} \Rightarrow Au = \begin{bmatrix} 3 & -2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} -1 \\ 1 \end{bmatrix} = \begin{bmatrix} -5 \\ -1 \end{bmatrix}$$

$$v = \begin{bmatrix} 0 \\ 2 \end{bmatrix} \Rightarrow Av = \begin{bmatrix} 3 & -2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 0 \\ 2 \end{bmatrix} = \begin{bmatrix} -4 \\ 0 \end{bmatrix}$$

$$w = \begin{bmatrix} 2 \\ 1 \end{bmatrix} \Rightarrow Aw = \begin{bmatrix} 3 & -2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 4 \\ 2 \end{bmatrix}$$



- Vector “w” keeps the straight, but changes the scale.

Definition

Definition

An **eigenvector** of a square $n \times n$ matrix A is nonzero vector v such that $Av = \lambda v$ for some scalar λ. A scalar λ is called an **eigenvalue** of A if there is a nontrivial solution v of $Av = \lambda v$; such an v is called an *eigenvector corresponding to* λ.

- **An eigenvector must be nonzero, by definition, but an eigenvalue may be zero.**

Example

- $A = \begin{bmatrix} 3 & -2 \\ 1 & 0 \end{bmatrix}$, $v = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$, $\lambda = 2$
- Show that 7 is an eigenvalue of matrix B, and find the corresponding eigenvectors.

$$B = \begin{bmatrix} 1 & 6 \\ 5 & 2 \end{bmatrix}$$

Eigenspace

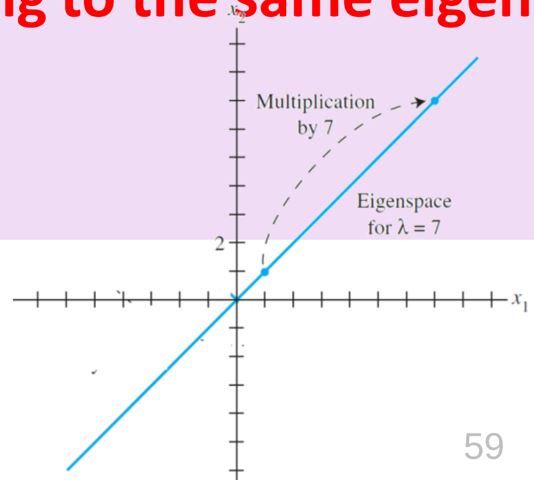
Note

λ is an eigenvalue of an $n \times n$ matrix:

$$Av = \lambda v \Rightarrow (A - \lambda I)v = 0$$

The set of all solutions of above is just the null space of the matrix $A - \lambda I$. So this set is the *subspace* of $\mathbb{R}^n$ and is called the **eigenspace** of A corresponding to λ . The eigenspace consists of the zero vector and all the eigenvectors corresponding to λ.

Eigenspace: A vector space formed by eigenvectors corresponding to the same eigenvalue and the origin point. $\boldsymbol{span\{corresponding\ eigenvectors\}}$



Definitions

Note

- $Av \ = \ \lambda v \Rightarrow Av - \lambda v I = 0 \Rightarrow \boldsymbol{(A - \lambda I)v = 0} \ \ \boldsymbol{v \neq 0}$
  - $\boldsymbol{v \in N(A - \lambda I)}$
  - $\boldsymbol{A - \lambda I}$ **must be singular.**
  - **Proof that for finding the eigenvalue we should solve the determinate zero equation. Look at nullspace, rank and nullity theorem, singular matrix, and det zero!**
- **Characteristic polynomial** $\mathbf{det}(\boldsymbol{A} - \boldsymbol{\lambda}\mathbf{I})$

- **Characteristic equation** $\mathbf{det}(\boldsymbol{A} - \boldsymbol{\lambda}\mathbf{I})$ **= 0**
- If λ is an eigenvalue of A, then the subspace E_λ = {span{v} | Av = λv} is called the eigenspace of A associated with λ. (This subspace contains all the span of eigenvectors with eigenvalue λ, and also the zero vector.)
- **Eigenvector is basis for eigenspace.**
- Set of all eigenvalues of matrix is $\sigma(A)$ *named spectrum of a matrix*

Definitions

Note

- Instead of $\det(A - \lambda I)$, we will compute $\mathbf{det}(\boldsymbol{\lambda}\mathbf{I} - \boldsymbol{A})$. Why?
  - $\det(A - \lambda I) = (-1)^{\mathrm{n}} \det(\lambda I - \mathrm{A})$
  - Matrix $n \times n$ with real values has …… eigenvalues.

Finding Eigenvalues and Eigenvectors

Let A be an $n \times n$ matrix.

1. First, find the eigenvalues λ of A by solving the equation $\det(\lambda I - A) = 0$.
2. For each λ, find the basic eigenvectors $X \neq 0$ by finding the basic solutions to $(\lambda I - A) X = 0$.

To verify your work, make sure that $AX = \lambda X$ for each λ and associated eigenvector X.

Example

Find eigenvalues and eigenvectors, eigenspace (E), and *spectrum* of matrix $A = \begin{bmatrix} \mathbf{3} & \mathbf{-2} \\ \mathbf{1} & \mathbf{0} \end{bmatrix}$**:**

$$\det(A - \lambda I) = \begin{vmatrix} 3-\lambda & -2 \\ 1 & -\lambda \end{vmatrix} = \lambda^2 - 3\lambda + 2 = 0 \Rightarrow \begin{cases} \lambda_1 = 1 \\ \lambda_2 = 2 \end{cases}$$

$$\left.\begin{matrix} \lambda_1 = 1 \\ (A - \lambda_1 I)q_1 = 0 \end{matrix}\right\} \Rightarrow q_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \Rightarrow \begin{bmatrix} 3 & -2 \\ 1 & 0 \end{bmatrix}\begin{bmatrix} 1 \\ 1 \end{bmatrix} = 1\begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\left.\begin{matrix} \lambda_2 = 2 \\ (A - \lambda_2 I)q_2 = 0 \end{matrix}\right\} \Rightarrow q_2 = \begin{bmatrix} 2 \\ 1 \end{bmatrix} \Rightarrow \begin{bmatrix} 3 & -2 \\ 1 & 0 \end{bmatrix}\begin{bmatrix} 2 \\ 1 \end{bmatrix} = 2\begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

Eigenvalues={1,2}

Eigenvectors= $\left\{\begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \end{bmatrix}\right\}$

$E_1(A) = span\left\{\begin{bmatrix} 1 \\ 1 \end{bmatrix}\right\}$ $E_2(A) = span\left\{\begin{bmatrix} 2 \\ 1 \end{bmatrix}\right\}$

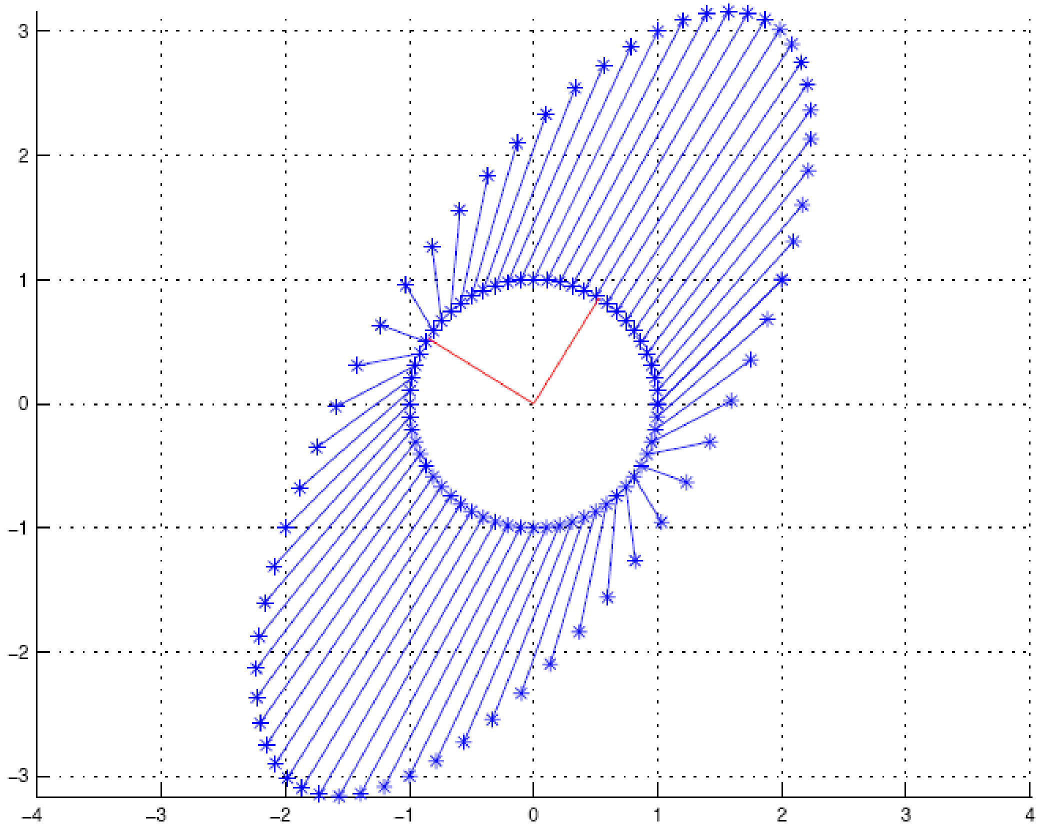
$\sigma(A)$={1,2}

$$\boldsymbol{AQ = Q\Lambda} \Rightarrow \begin{bmatrix} \mathbf{3} & \mathbf{-2} \\ \mathbf{1} & \mathbf{0} \end{bmatrix}\begin{bmatrix} \mathbf{1} & \mathbf{2} \\ \mathbf{1} & \mathbf{1} \end{bmatrix} = \begin{bmatrix} \mathbf{1} & \mathbf{2} \\ \mathbf{1} & \mathbf{1} \end{bmatrix}\begin{bmatrix} \mathbf{1} & \mathbf{0} \\ \mathbf{0} & \mathbf{2} \end{bmatrix}$$

Eigenvalues and Eigenvectors

- The value λ is an eigenvalue of matrix A if there exists a non-zero vector x, such that $Ax=\lambda x$. Vector x is an eigenvector of matrix A
  - The largest eigenvalue is called the principal eigenvalue
  - The corresponding eigenvector is the principal eigenvector
  - Corresponds to the direction of maximum change

Eigenvalues



Linear Algebra Methods for Data Mining, Spring 2005, University of Helsinki

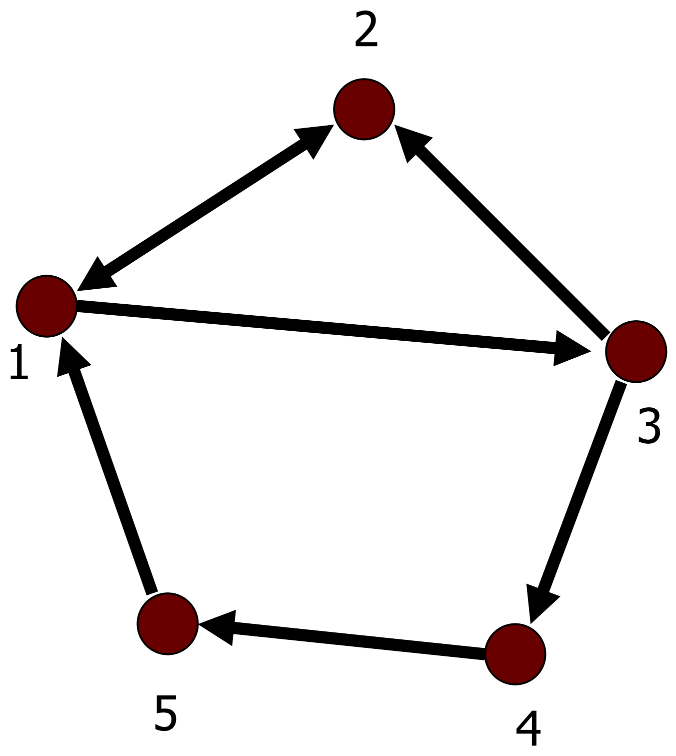
Random Walks

- Start from a node, and follow links uniformly at random.
- Stationary distribution: The fraction of times that you visit node i, as the number of steps of the random walk approaches infinity
  - if the graph is strongly connected, the stationary distribution converges to a unique vector.

Random Walks

- stationary distribution: principal left eigenvector of the normalized adjacency matrix
  - x = xP
  - for undirected graphs, the degree distribution

$$P = \begin{bmatrix} 0 & 1/2 & 1/2 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1/2 & 0 & 1/2 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$



Any Question?