Online Social Networks and Media

Introduction

Instructors:

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Goal

Understand the importance of networks in life, technology and applications
Study the theory underlying social networks
Learn about algorithms that make use of network structure
Learn about the tools to analyze them

Today:

A taste of the topics to be covered
Some logistics
Some basic graph theory

Logistics

Textbooks:

Easley and Kleinberg free text-book on Networks, Crowds and Markets

M. E. J. Newman, The structure and function of complex networks, SIAM Reviews, 45(2): 167-256, 2003

Reza Zafarani, Mohammad Ali Abbasi, Huan Liu, free text-book on Social Media Mining

Web page:

www.cs.uoi.gr/~tsap/teaching/cs-l14

20% Presentations and class participation

30% Assignments

50% Term Project (in 2 Phases)

No Final Exam

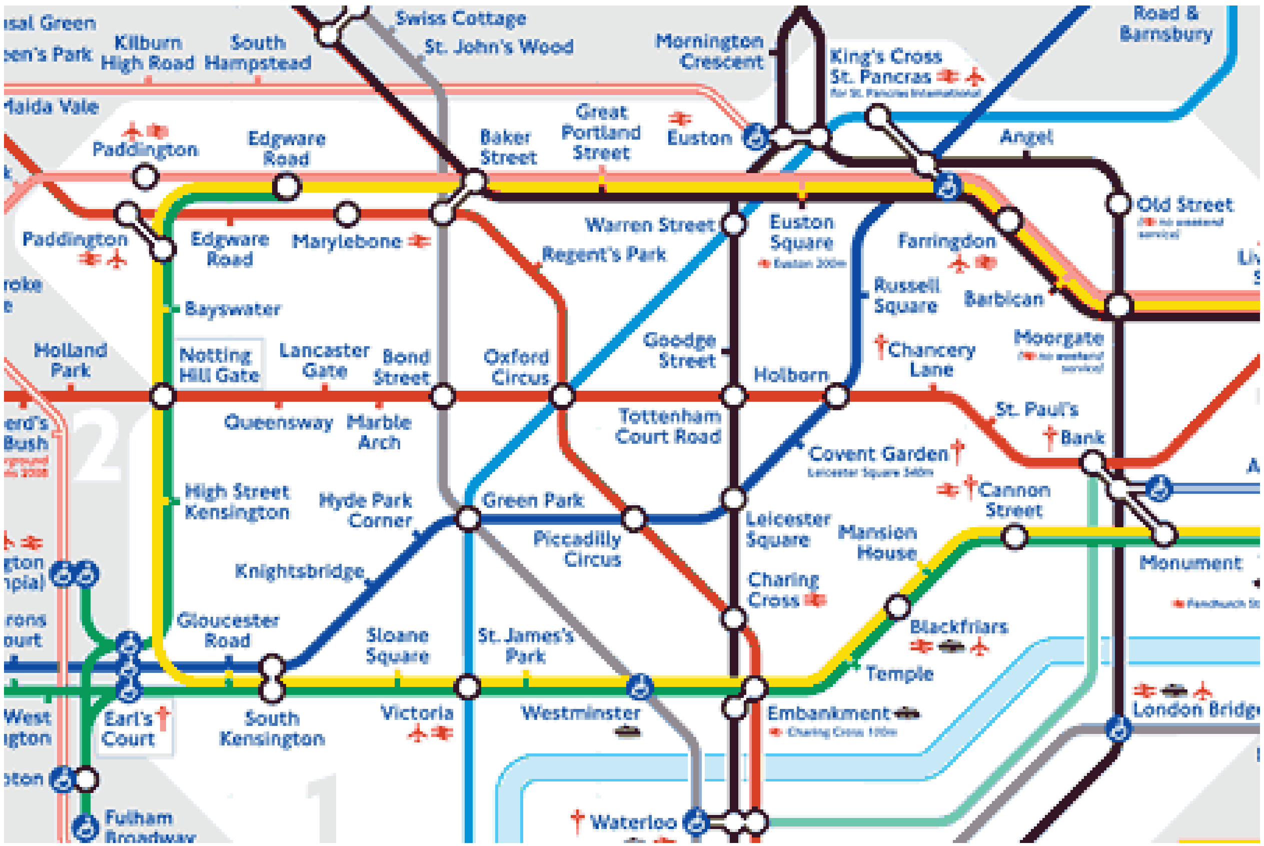
WHAT DO THE FOLLOWING COMPLEX SYSTEMS HAVE IN COMMON?

The Economy

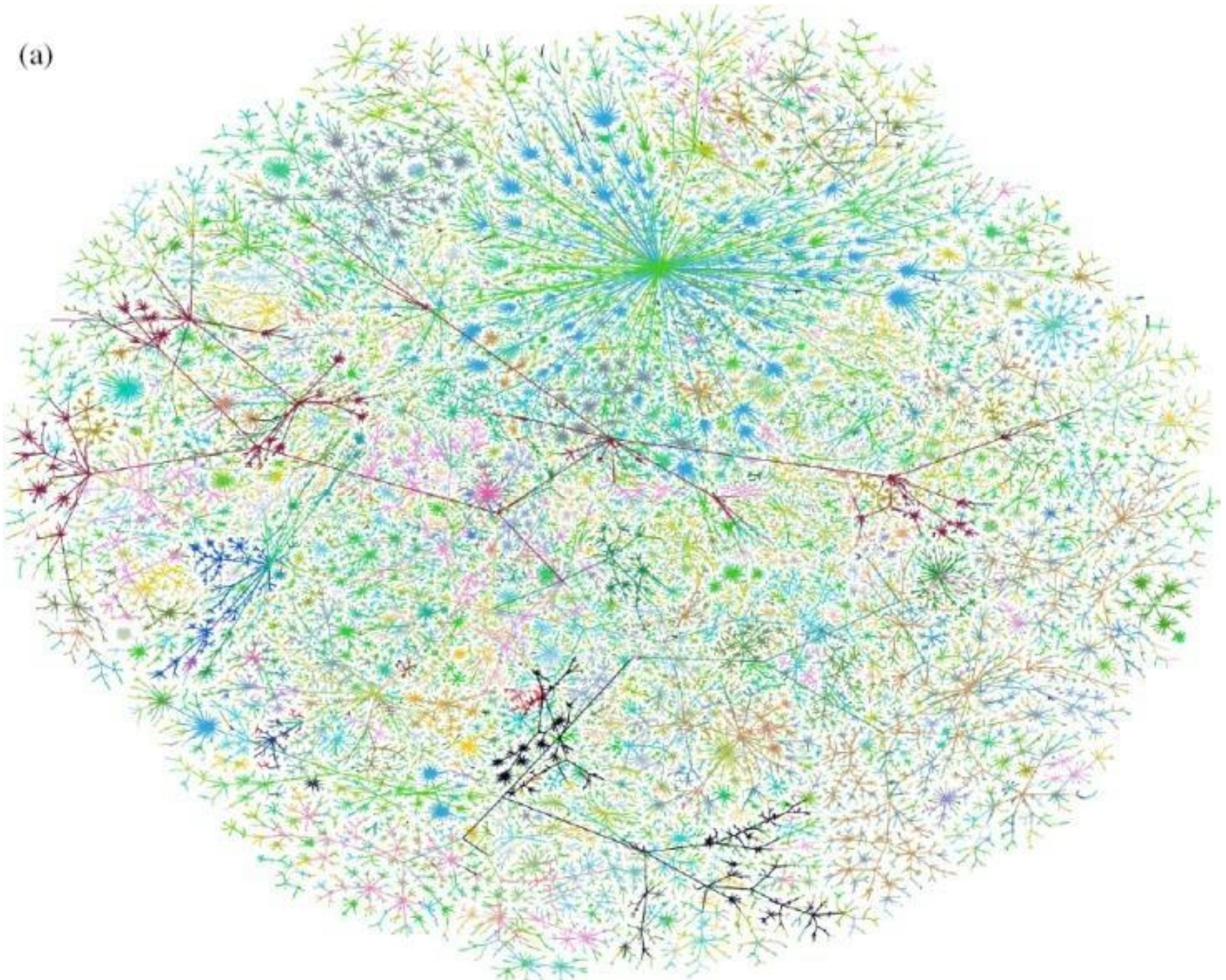

NASDAQ
KB Home
-2.2%
-1.16
50.96
+1.5%
+0.44
30.89
+2.0%
+0.35
17.84
BUY ORDERS
19.12
+1.10
+6.1%
19.09
+1.0%
+0.17
17.15
+1.2%
+0.27
23.46
30.89
NDTV PROFIT
NASDAQ
NASDAQ
NASDAQ
NASDAQ
NASDAQ

The Human Cell

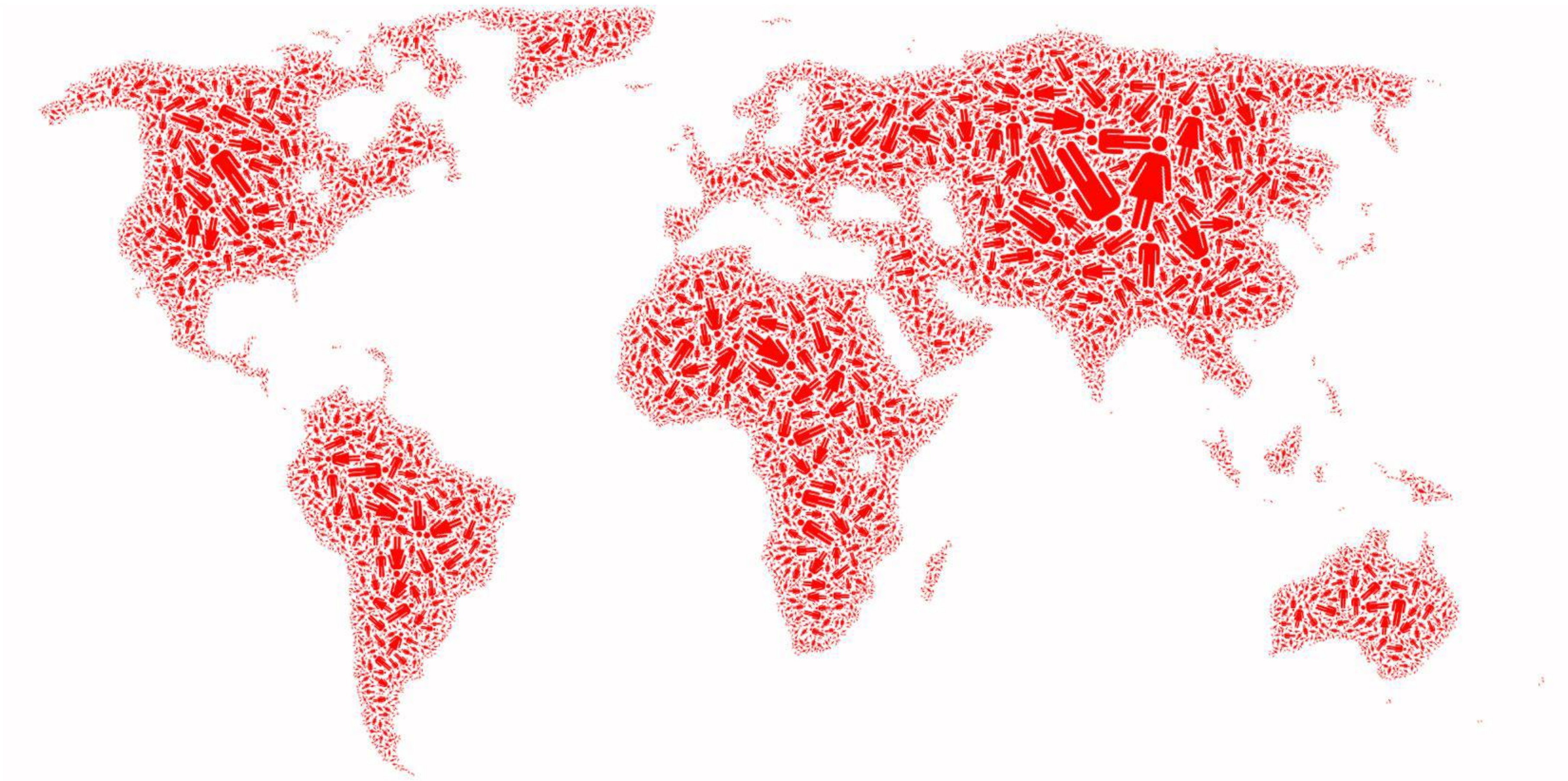
Traffic and roads



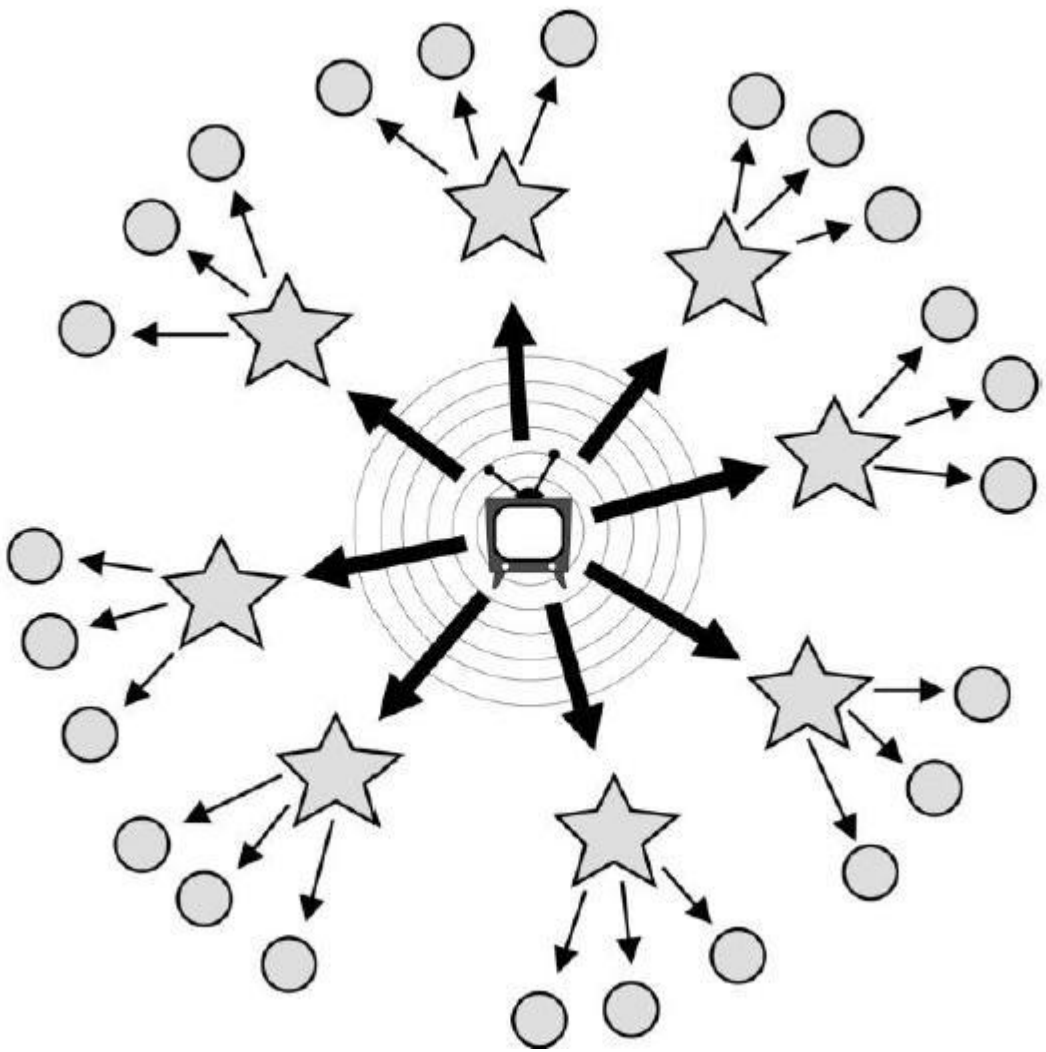
Internet



Society



Media and Information



THE NETWORK!

All of these systems can be modeled as networks

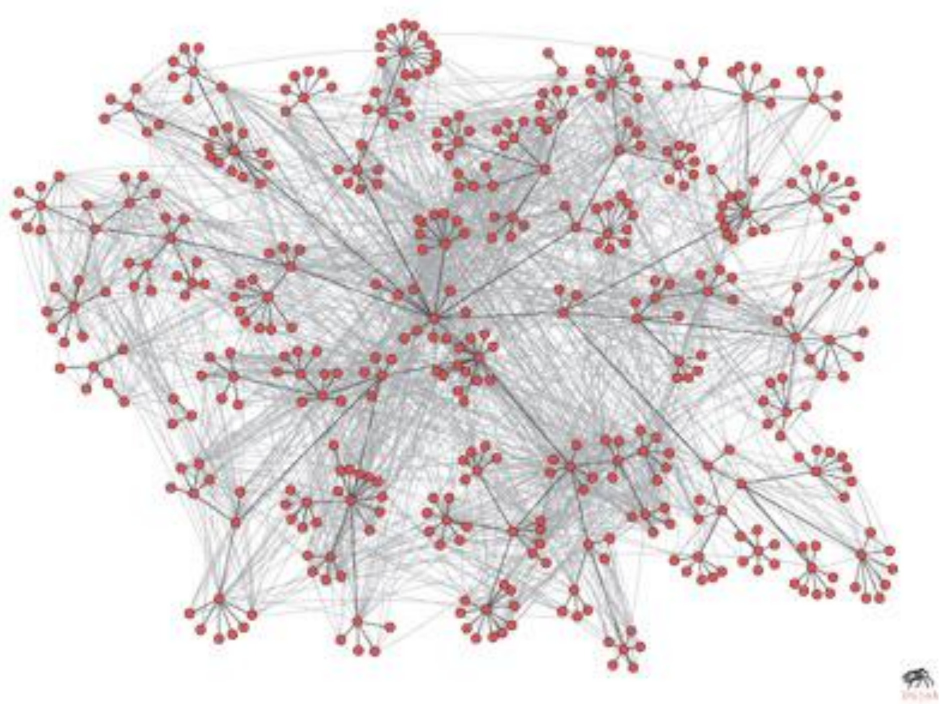
What is a network?

- Network: a collection of entities that are interconnected with links.

Social networks

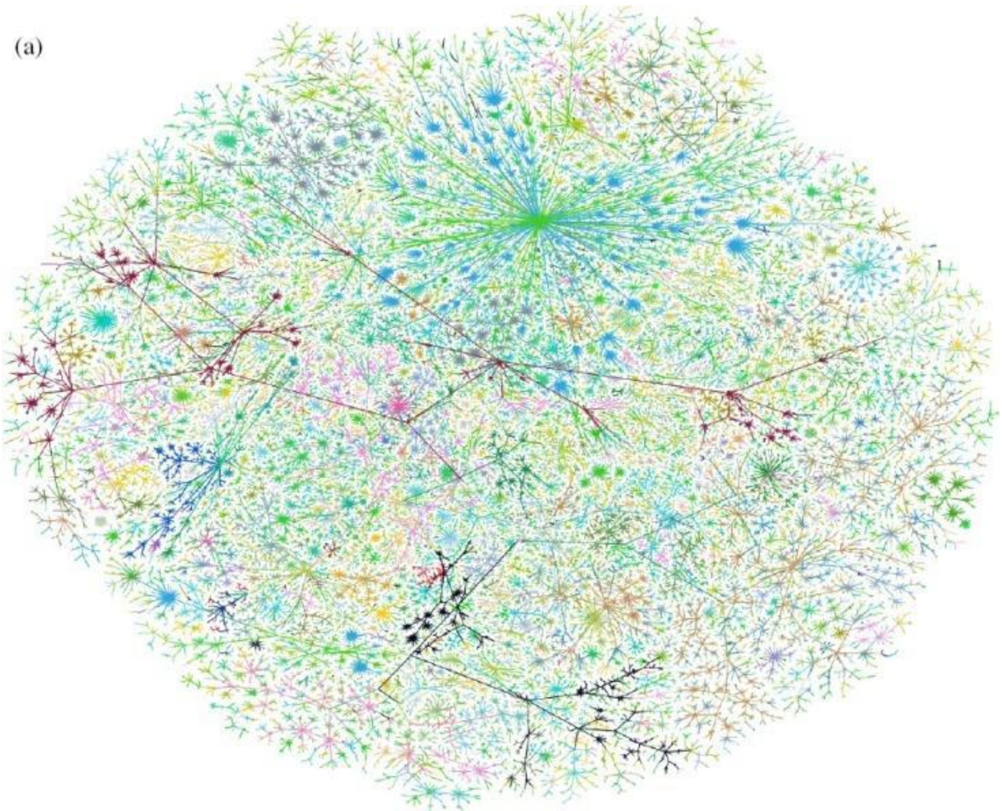
- Entities: People
- Links: Friendships

Communication networks



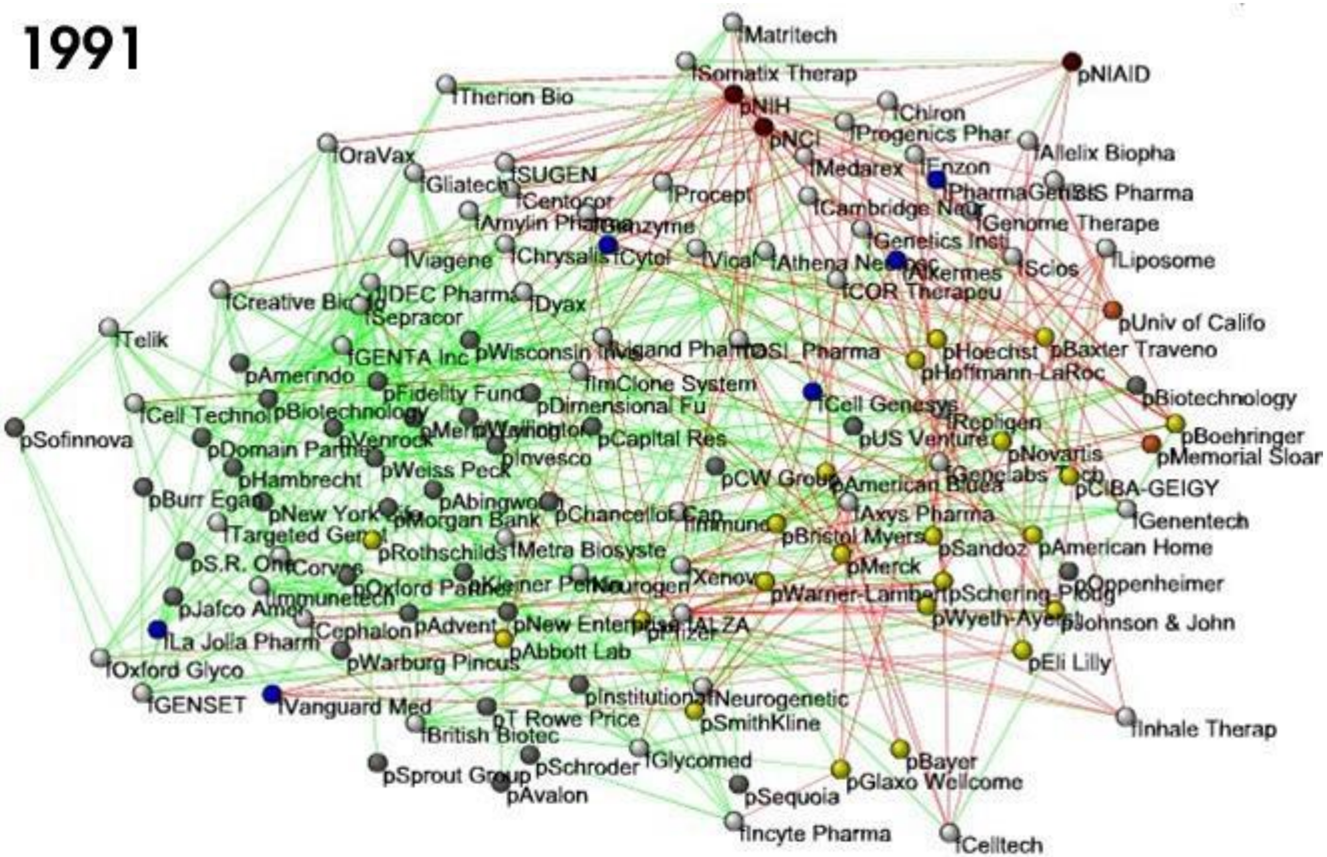
- Entities: People
- Links: email exchange

Communication networks



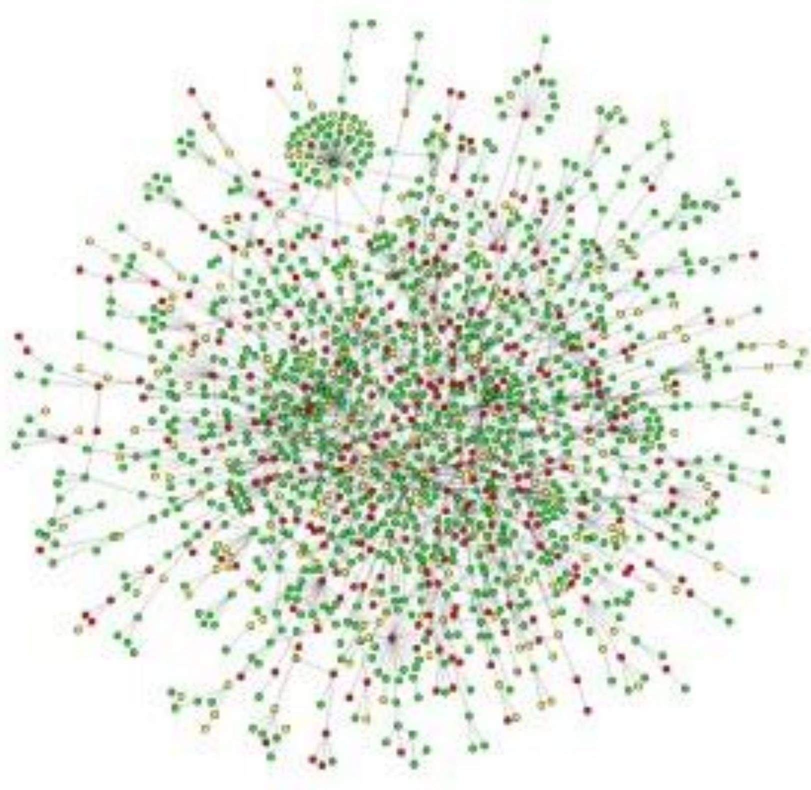
- Entities: Internet nodes
- Links: communication between nodes

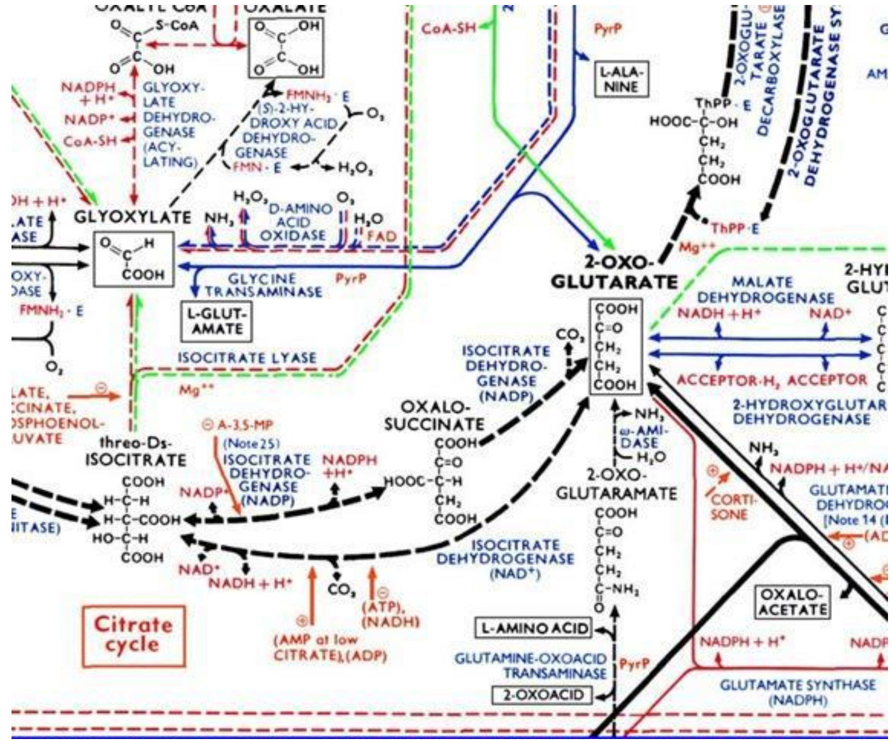
Financial Networks



- Entities: Companies
- Links: relationships (financial, collaboration)

Biological networks

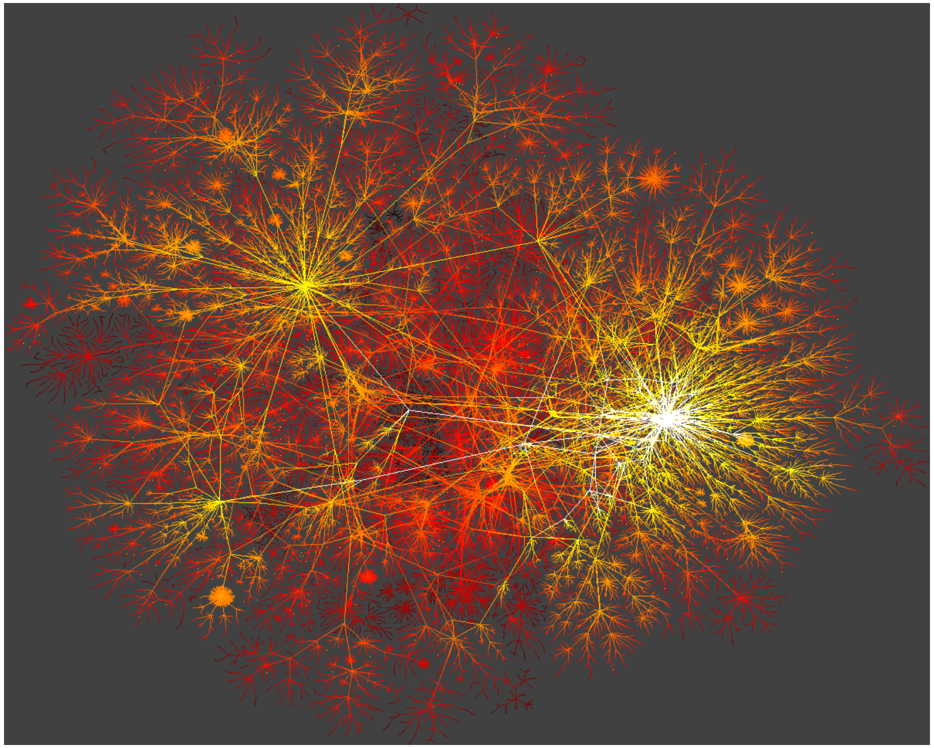




- Entities: Proteins
- Links: interactions

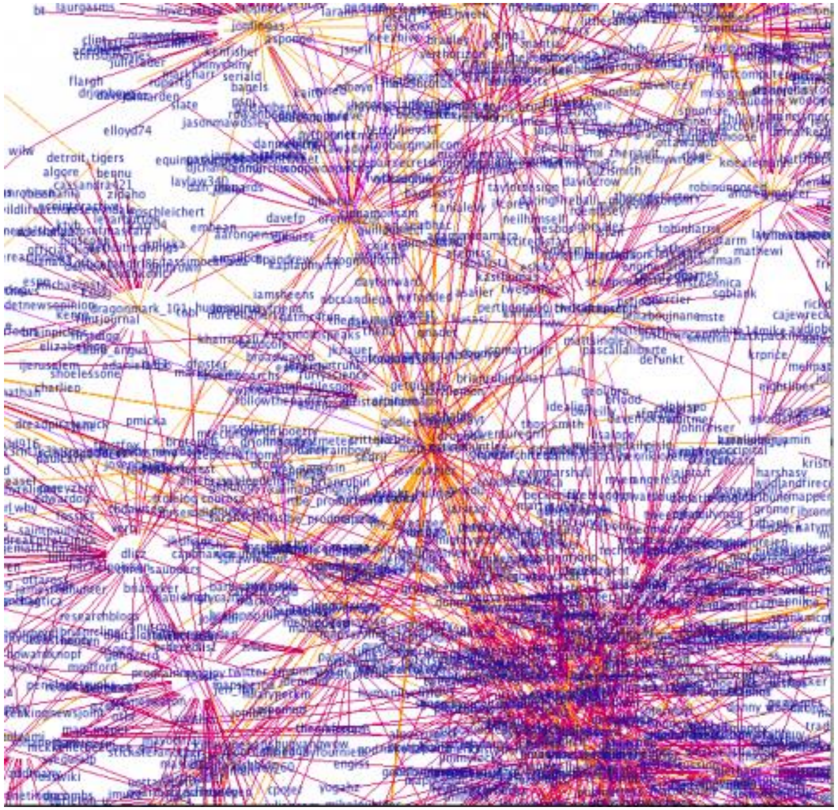
- Entities: metabolites, enzymes
- Links: chemical reactions

Information networks



- Entities: Web Pages
- Links: Links

Information/Media networks



- Entities: Twitter users
- Links: Follows/conversations

Many more

- Wikipedia
- Brain
- Highways
- Software
- Etc…

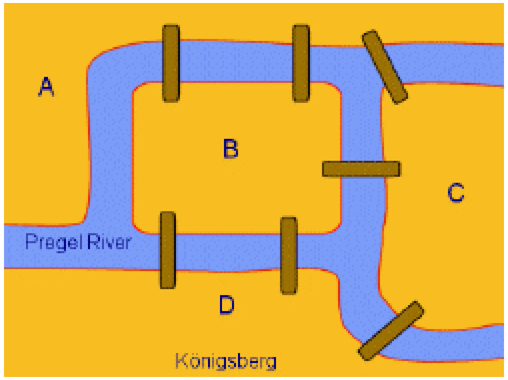
Why networks are important?

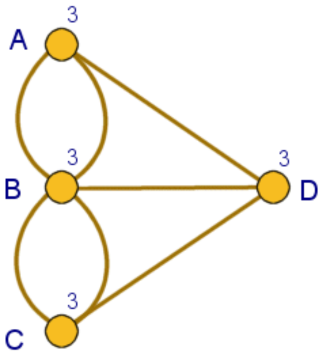
- We cannot truly understand a complex system unless we understand the underlying network.
  - Everything is connected, studying individual entities gives only a partial view of a system

- Two main themes:
  - What are the structural properties of the network?
  - How do processes happen in the network?

Graphs

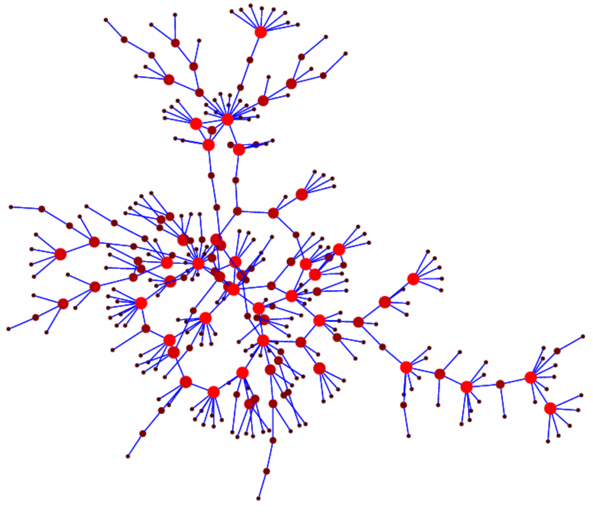
- In mathematics, networks are called graphs, the entities are nodes, and the links are edges
- Graph theory starts in the 18th century, with Leonhard Euler
  - The problem of Königsberg bridges
  - Since then graphs have been studied extensively.





Networks in the past

- Graphs have been used in the past to model existing networks (e.g., networks of highways, social networks)
  - usually these networks were small
  - network can be studied visual inspection can reveal a lot of information



Networks now

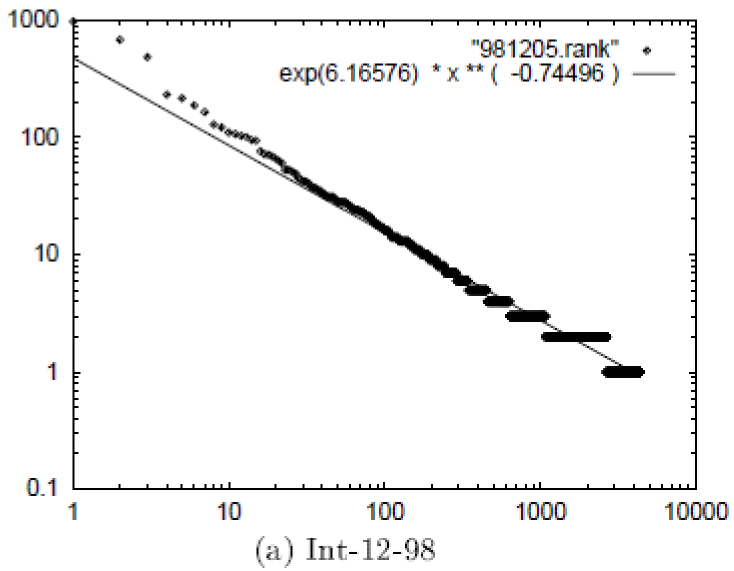
- More and larger networks appear
  - Products of technology
    - e.g., Internet, Web, Facebook, Twitter
  - Result of our ability to collect more, better, and more complex data
    - e.g., gene regulatory networks
  - Result of the willingness of users to contribute data
    - e.g., users making their relationships public online
- Networks of thousands, millions, or billions of nodes
  - Impossible to process visually
  - Problems become harder
  - Processes are more complex

Topics

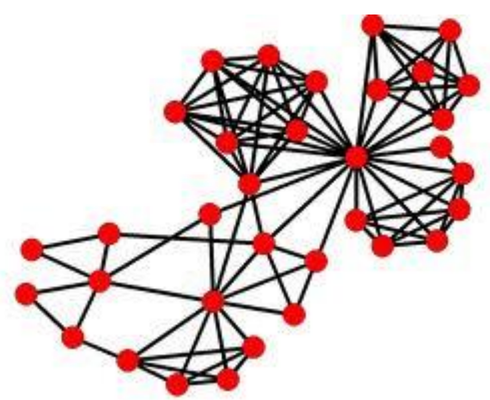
- Measuring Real Networks
- Modeling the evolution and creation of networks
- Identifying important nodes in the graph
- Understanding information cascades and virus contagions
- Finding communities in graphs
- Link Prediction
- Storing and processing huge networks
- Other special topics

Understanding large graphs

- What does a network look like?
  - Measure different properties to understand the structure



degree of nodes



Triangles in the graph

Real network properties

- Most nodes have only a small number of neighbors (degree), but there are some nodes with very high degree (power-law degree distribution)
  - scale-free networks
- If a node x is connected to y and z, then y and z are likely to be connected
  - high clustering coefficient
- Most nodes are just a few edges away on average.
  - small world networks
- Networks from very diverse areas (from internet to biological networks) have similar properties
  - Is it possible that there is a unifying underlying generative process?

Generating random graphs

- Classic graph theory model (Erdös-Renyi)
  - each edge is generated independently with probability p
- Very well studied model but:
  - most vertices have about the same degree
  - the probability of two nodes being linked is independent of whether they share a neighbor
  - the average paths are short

Modeling real networks

- Real life networks are not "random"
- Can we define a model that generates graphs with statistical properties similar to those in real life?

- The rich-get-richer model

We need to accurately model the mechanisms that govern the evolution of networks (for prediction, simulations, understanding)

Ranking of nodes on the Web

- Is my home page as important as the facebook page?
- We need algorithms to compute the importance of nodes in a graph
- The PageRank Algorithm
  - A success story of network use

It is impossible to create a web search engine without understanding the web graph

Information/Virus Cascade

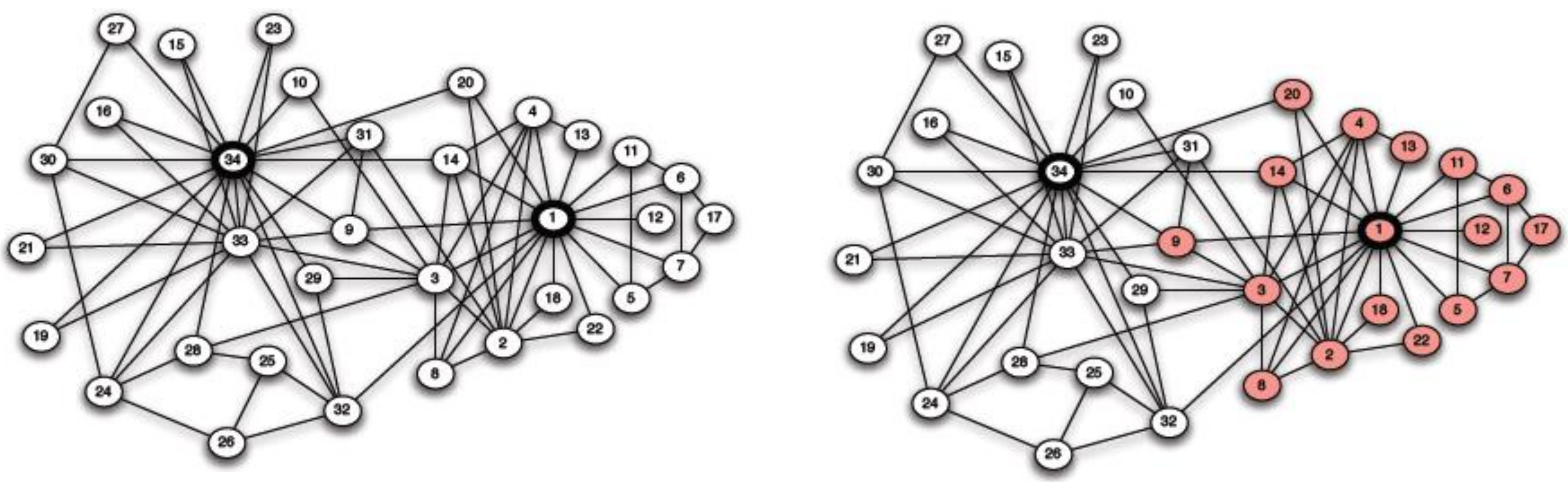
- How do viruses spread between individuals? How can we stop them?
- How does information propagates in social and information networks? What items become viral? Who are the influencers and trend-setters?
- We need models and algorithms to answer these questions

Online advertising relies heavily on online social networks and word-of-mouth marketing. There is currently need for models for understanding the spread of Ebola virus.

Clustering and Finding Communities

- What is community?
  - "Cohesive subgroups are subsets of actors among whom there are relatively strong, direct, intense, frequent, or positive ties." [Wasserman & Faust '97]

Karate club example [W. Zachary, 1970]



Clustering and Finding Communities

- Input: a graph G=(V,E)
  - edge (u, v) denotes similarity between u and v
  - *weighted graphs*: weight of edge captures the degree of similarity
- Clustering: Partition the nodes in the graph such that nodes within clusters are well interconnected (high edge weights), and nodes across clusters are sparsely interconnected (low edge weights)

Community Evolution

- **Homophily:**“Birds of a feather flock together”
- Caused by two related social forces [Friedkin98, Lazarsfeld54]
  - *Social influence:* People become similar to those they interact with
  - *Selection:* People seek out similar people to interact with

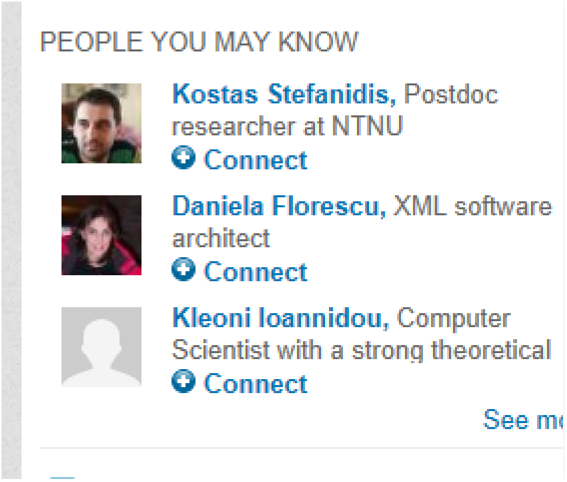
- Both processes contribute to homophily, but
  - Social influence leads to community-wide homogeneity
  - Selection leads to fragmentation of the community

- Applications in online marketing
  - *viral marketing* relies upon social influence affecting behavior
  - *recommender systems* predict behavior based on similarity

How do we define and discover communities in large graphs? How do communities evolve?

Link Prediction

- Given a snapshot of a social network at time t, we seek to accurately predict the edges that will be added to the network during the interval from time t to a given future time t'.
- Applications:
  - Accelerate the growth of a social network (e.g., Facebook, LinkedIn, Twitter) that would otherwise take longer to form.
  - Identify suspect relationships



How do we predict future links?

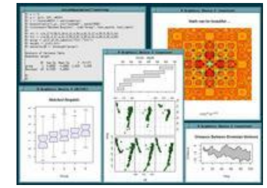
Network content

- Users on online social networks generate content.
- Mining the content in conjunction with the network can be useful
  - Do friends post similar content on Facebook?
  - Can we understand a user's interests by looking at those of their friends?
    - The importance of homophily
  - Social recommendations: Can we predict a movie rating using the social network?

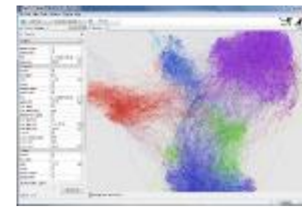
Social Media

- Today Social Media (Twitter, Facebook, Instagram) have supplanted the traditional media sources
  - Information is generated and disseminated mostly online by users
    - E.g., the assassination of Bin Laden appeared first on Twitter
  - Twitter has become a global "sensor" detecting and reporting everything
- Interesting problems:
  - Automatically detect events using Twitter
    - Earthquake prediction
    - Crisis detection and management
  - Sentiment mining
  - Track the evolution of events: socially, geographically, over time.

Tools



R: free software environment for statistical computing and graphics. http://www.r-project.org/



Gephi: interactive visualization and exploration platform for all kinds of networks and complex systems, dynamic and hierarchical graphs http://gephi.org/

Stanford Network Analysis Platform (SNAP): general purpose, high performance system for analysis and manipulation of large networks written in C++ http://snap.stanford.edu/snap/index.html

NetworkX: a Python language software package for the creation, manipulation, and study of the structure, dynamics, and functions of complex networks. http://networkx.lanl.gov/

Frameworks for Processing Large Graphs

Large scale (in some cases billions of vertices, trillions of edges)

How to process graphs in parallel?

- Write *your own code*
- Use *MapReduce (general parallel processing) **
- *Pregel* (bulk synchronous parallel model) introduced by Google in 2010*
- *Giraph* http://incubator.apache.org/giraph/ (part of Hadoop software)

Storage?

*J. Dean, S. Ghemawat. *MapReduce: Simplified Data Processing on Large Clusters.* OSDI 2004: 137-150
** G. Malewicz, M. H. Austern, A. J. C. Bik, J. C. Dehnert, I. Horn, N. Leiser: *Pregel: a system for large-scale graph processing*. SIGMOD Conference 2010: 135-146

Data

Collected using available APIs (Twitter, Facebook, etc)

Using existing collections, e.g., from SNAP (more in the webpage), permission may be required

Stanford Large Network Dataset Collection
60 large social and information network datasets
Coauthorship and Citation Networks
DBLP: Collaboration network of computer scientists
KDD Cup Dataset
Internet Topology
AS Graphs: AS-level connectivities inferred from Oregon route-views, Looking glass data and Routing registry data
Yelp Data
Yelp Review Data: reviews of the 250 closest businesses for 30 universities for students and academics to explore and research
Youtube dataset
Youtube data: YouTube videos as nodes. Edge a->b means video b is in the related video list (first 20 only) of a video a.
Amazon product copurchasing networks and metadata
Amazon Data: The data was collected by crawling Amazon website and contains product metadata and review information about 548,552 different products (Books, music CDs, DVDs and VHS video tapes).
Wikipedia
Wikipedia page to page link data: A list of all page-to-page links in Wikipedia
DBPedia: The DBpedia data set uses a large multi-domain ontology which has been derived from Wikipedia.
Edits and talks: Complete edit history (all revisions, all pages) of Wikipedia since its inception till January 2008.
Movie Ratings
IMDB database: Movie ratings from IMDB
User rating data: Movie ratings from MovieLens

Acknowledgements

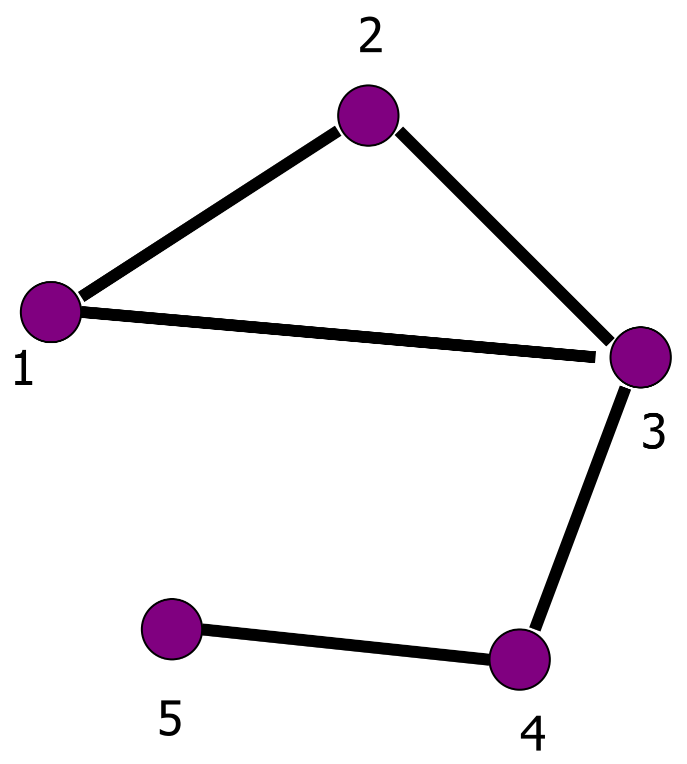
- Thanks to Jure Leskovec for some of the material from his course notes.

- M. E. J. Newman, The structure and function of complex networks, SIAM Reviews, 45(2): 167-256, 2003

Graph Theory Reminder

Undirected Graph

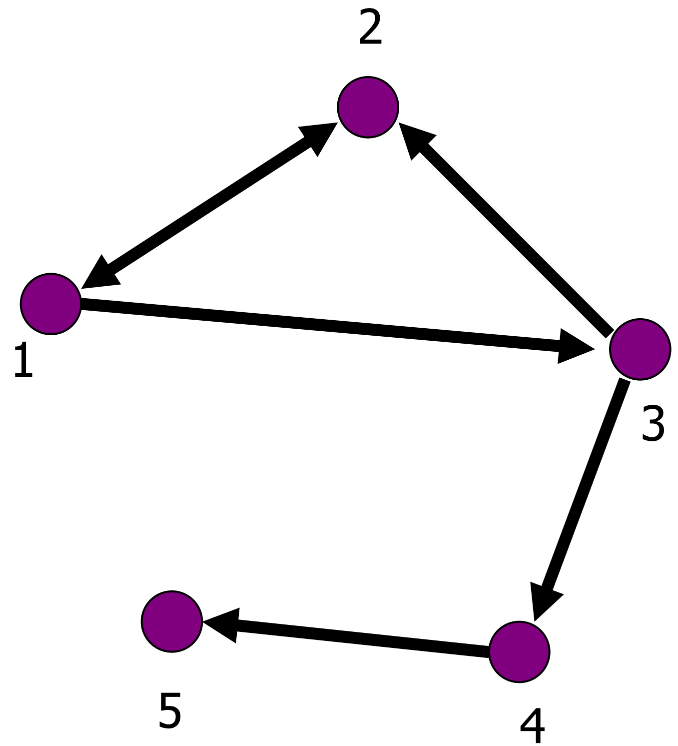
- Graph G=(V,E)
  - V = set of vertices (nodes)
  - E = set of edges



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

Directed Graph

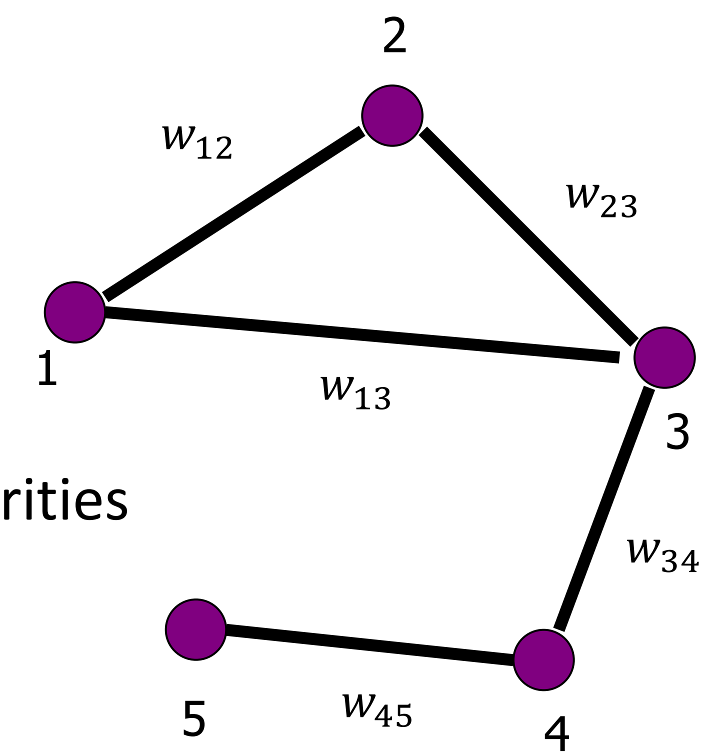
- Graph G=(V,E)
  - V = set of vertices (nodes)
  - E = set of edges



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 (nodes)
  - E = set of edges and their weights

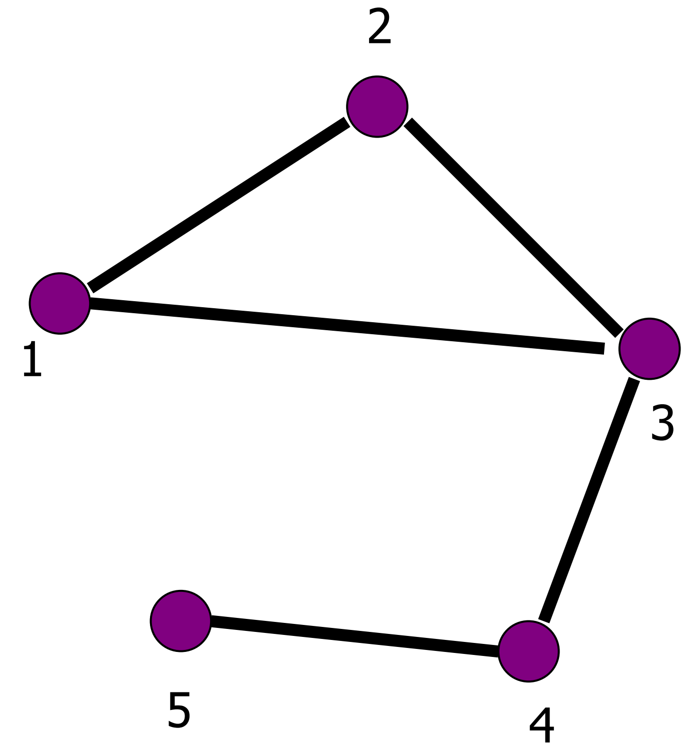


Weights can be either distances or similarities

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})}

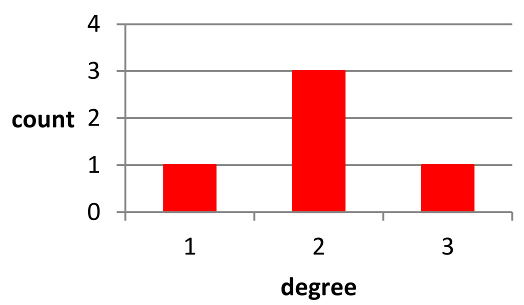
Undirected graph

- 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

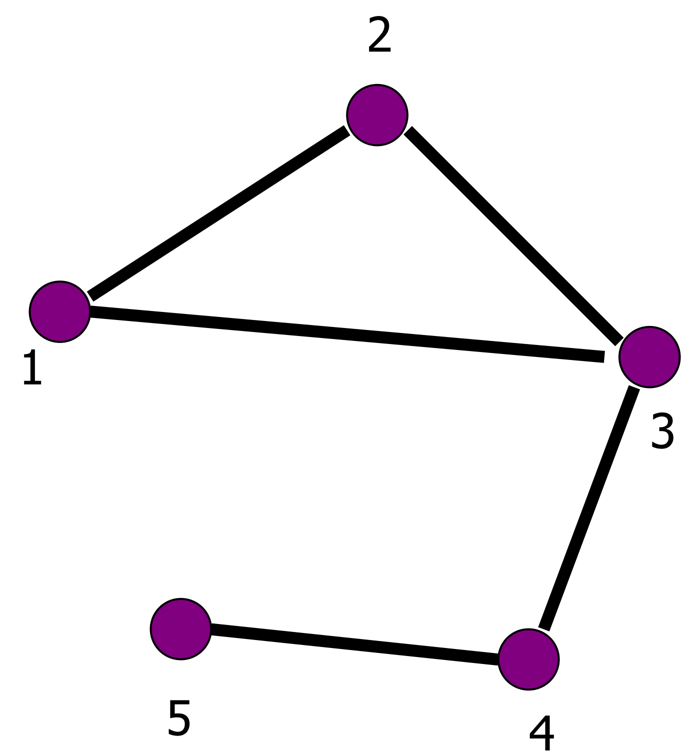


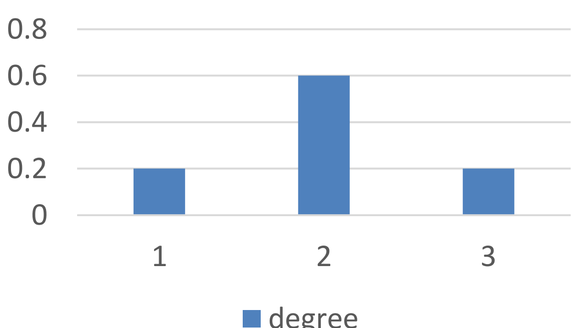
Undirected graph

- 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)]



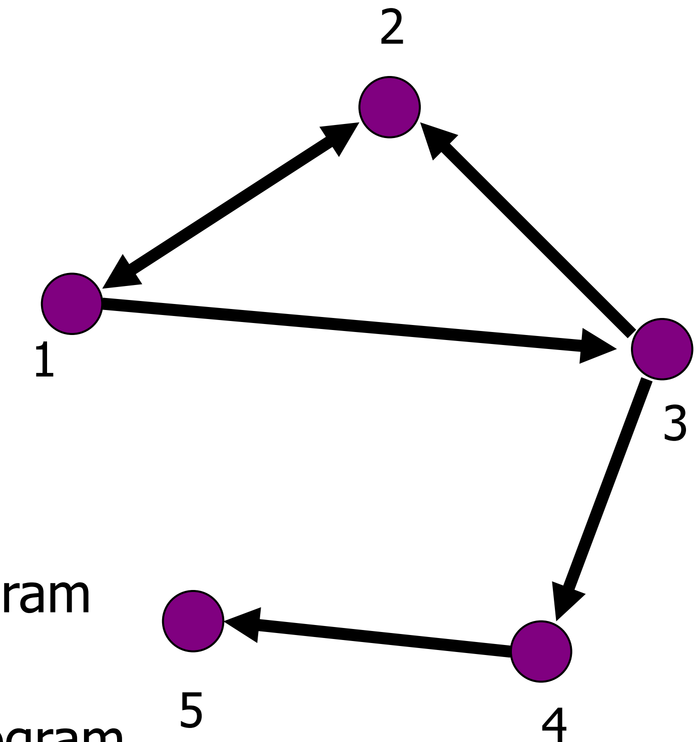
- degree distribution
  - [(1:0.2),(2:0.6),(3,0.2)]





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
  - [(1:3),(2:1)]
- out-degree histogram
  - [(0:1),(1:2),(2:2)]

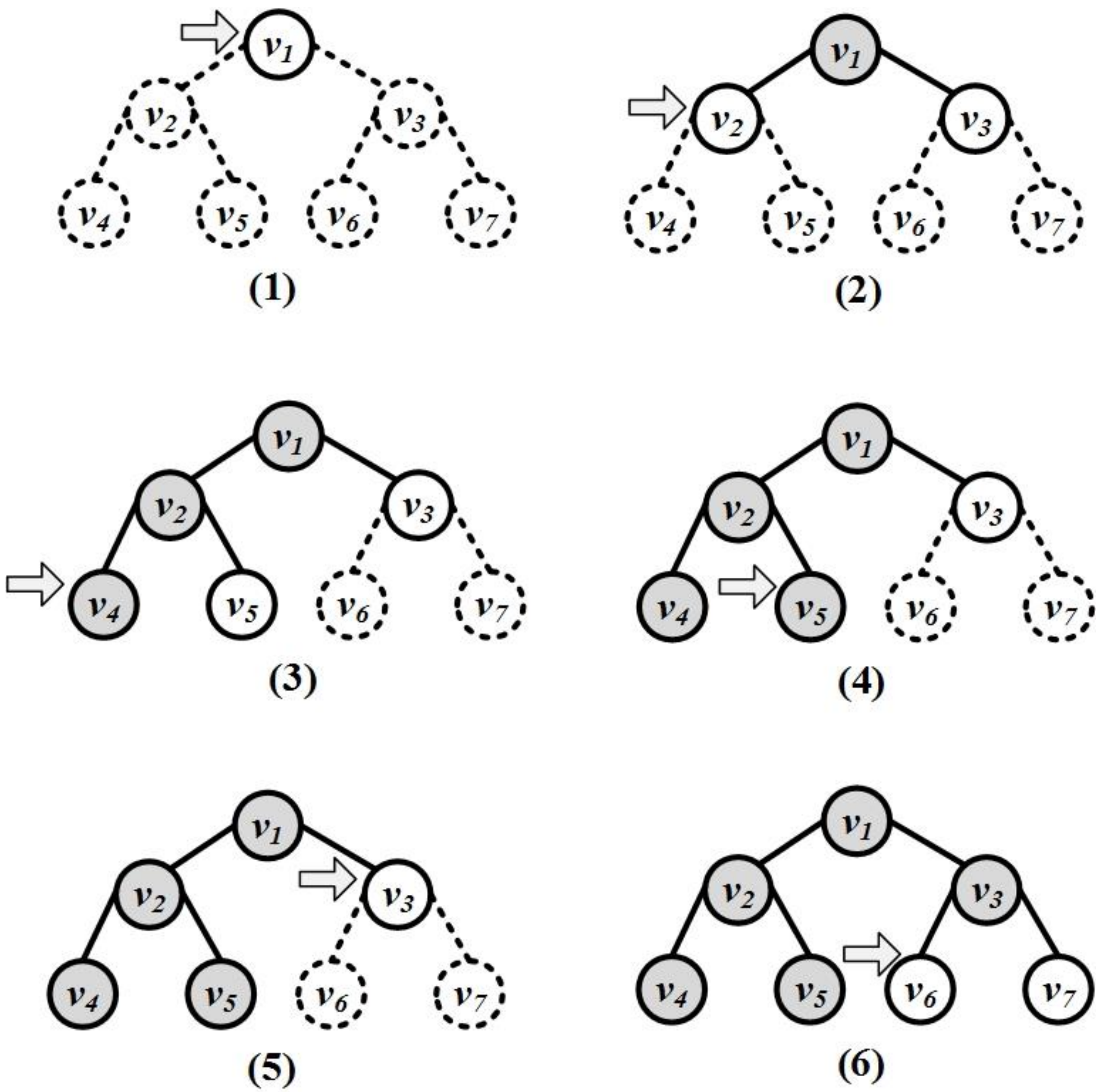
Graph Traversals

- A traversal is a procedure for visiting (going through) all the nodes in a graph

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*

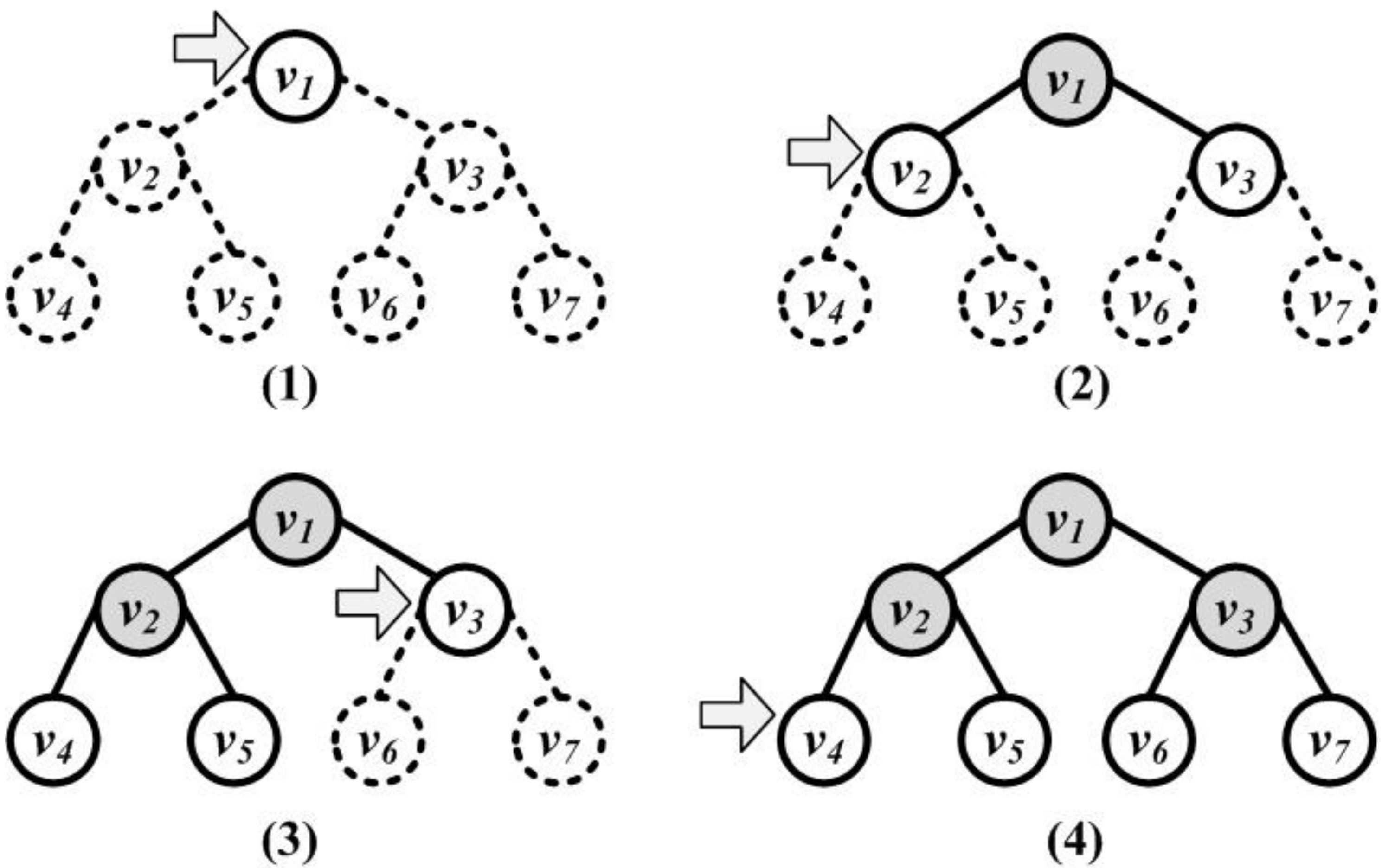
Example for a tree graph



Breadth First Search Traversal

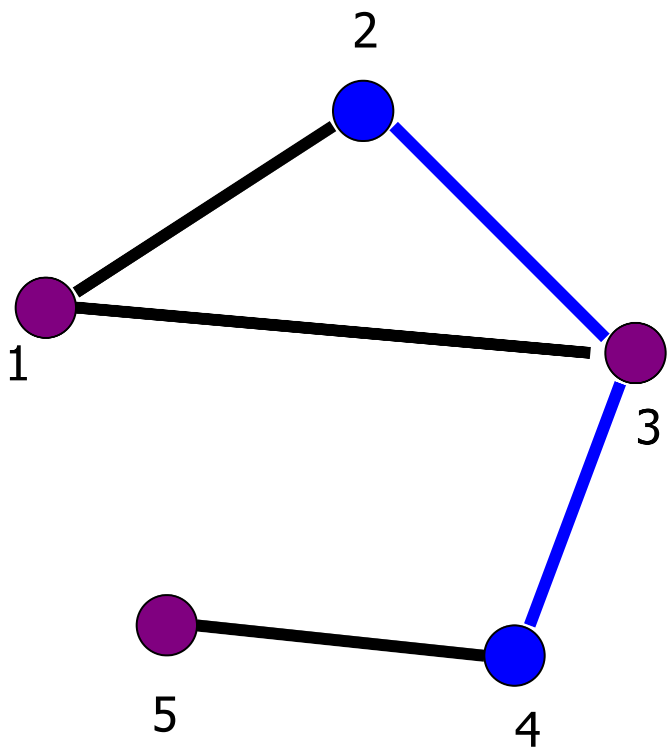
- Breadth-First-Search (BFS) starts from a node, visits all its immediate neighbors first, and then moves to the second level by traversing their neighbors.
  - The algorithm can be implemented using a *queue structure*

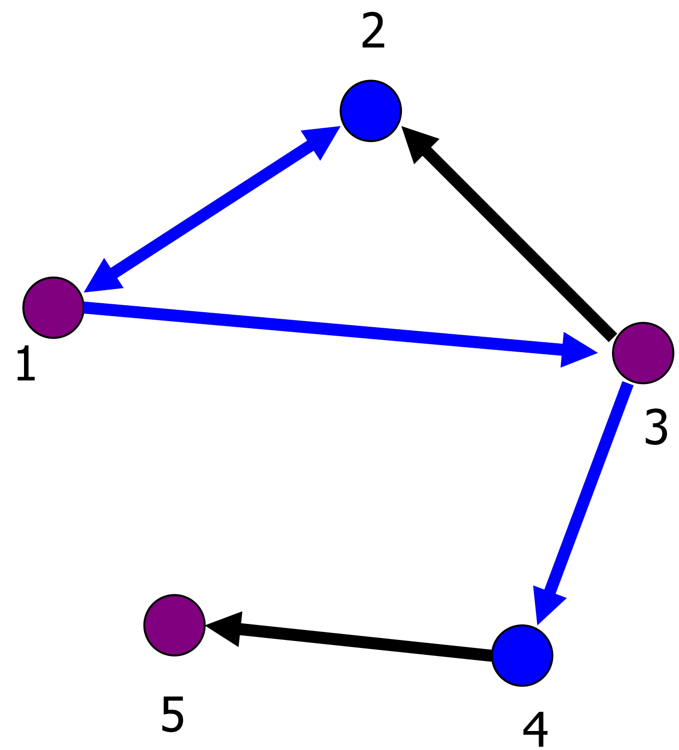
Example of BFS on a tree



Paths

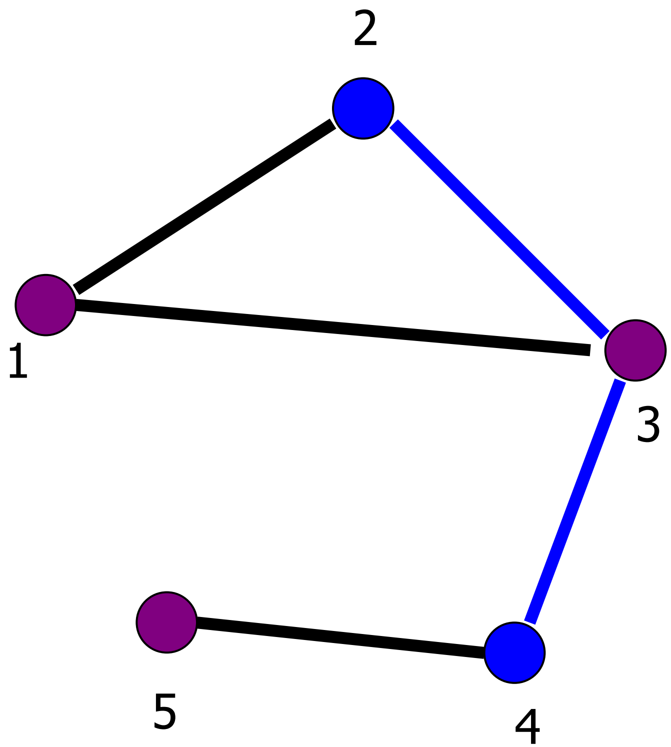
- Path from node i to node j: a sequence of edges (directed or undirected) from node i to node j
  - path length: number of edges on the path
  - nodes i and j are connected
  - cycle: a path that starts and ends at the same node

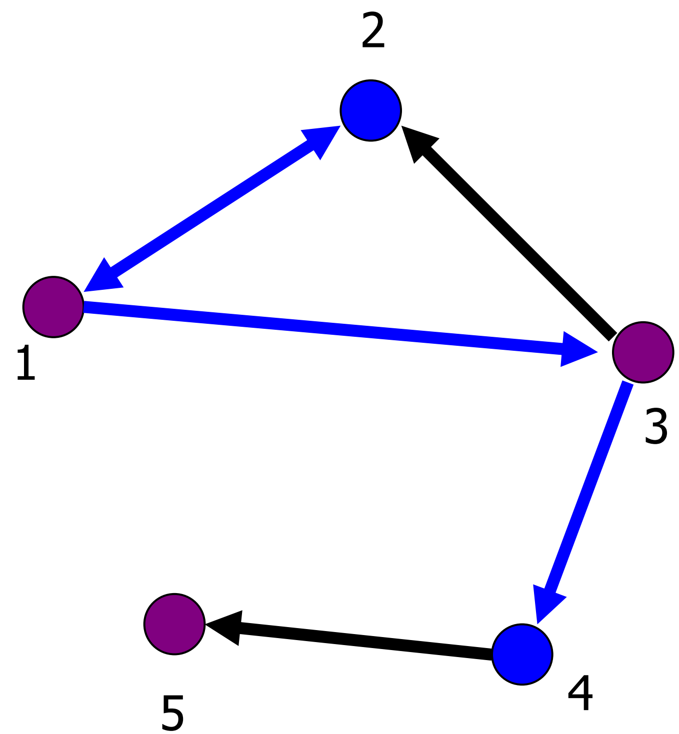




Shortest Paths

- Shortest Path from node i to node j
  - also known as BFS path, or geodesic path
  - We can find all shortest paths from a node using BFS



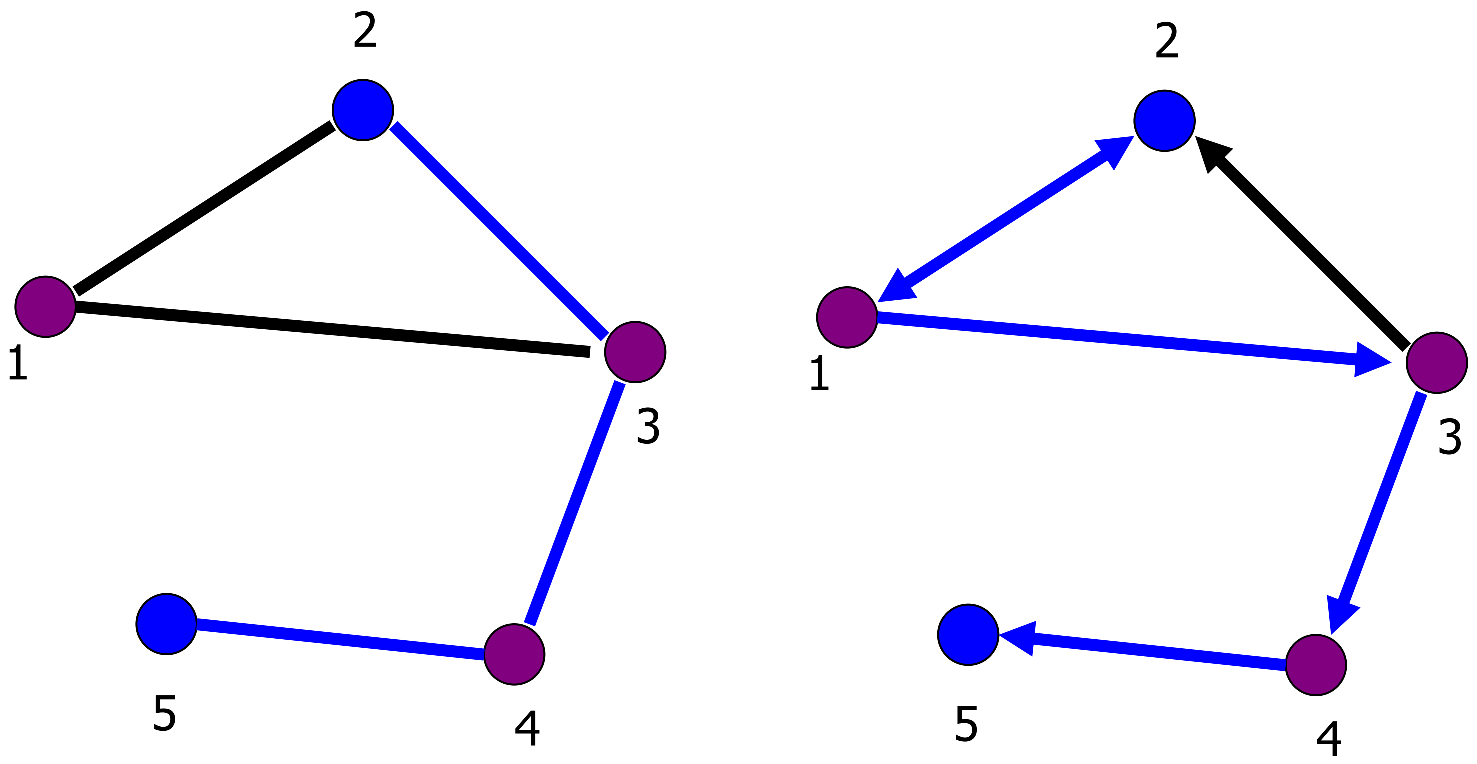


Shortest paths on weighted graphs

- 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

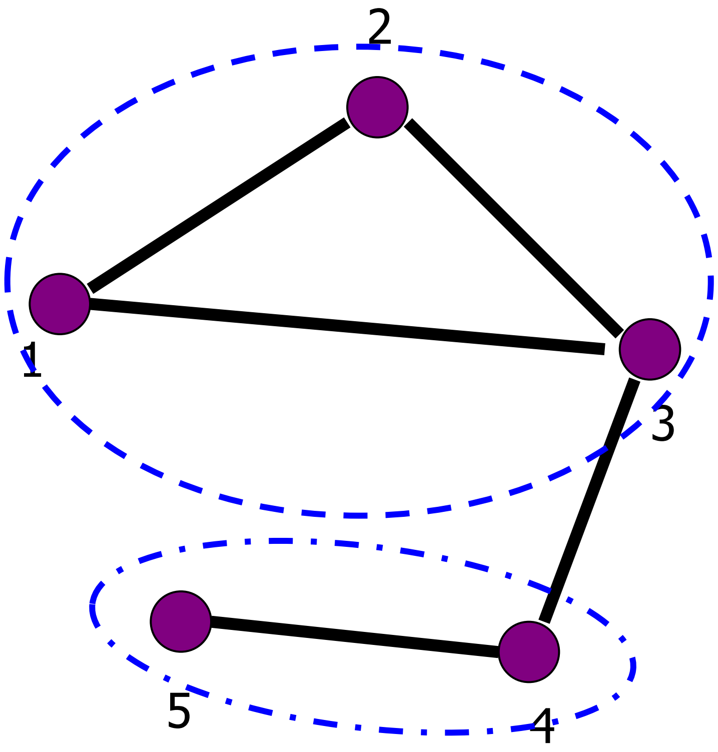
Diameter

- The longest shortest path in the graph



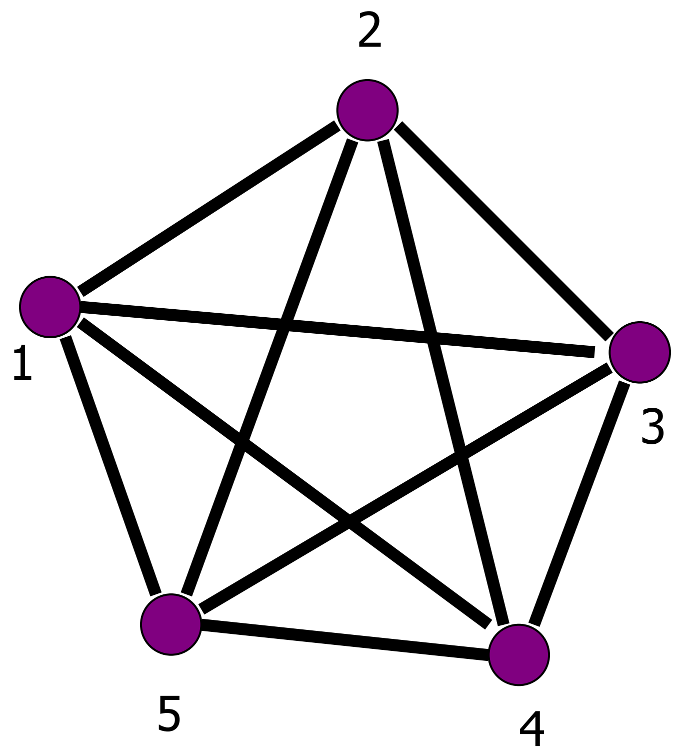
Undirected graph

- 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

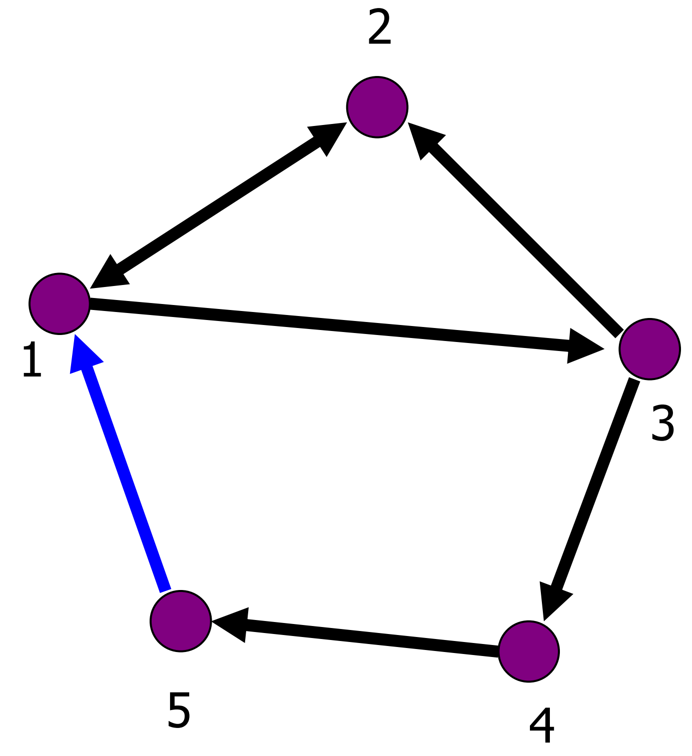
- Clique K_n
- A graph that has all possible $n(n-1)/2$ edges



Directed Graph

- Strongly connected graph: there exists a path from every i to every j

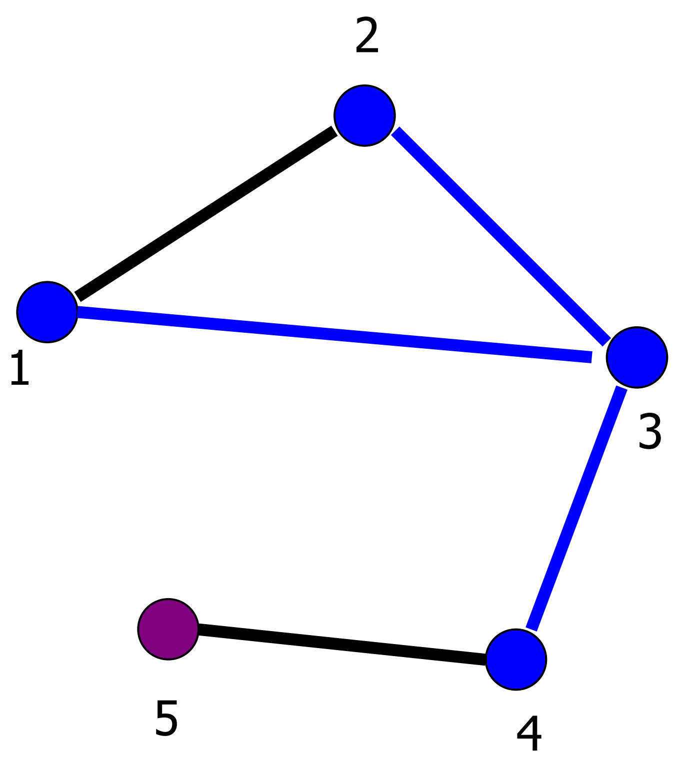
- Weakly connected graph: If edges are made to be undirected the graph is connected



Subgraphs

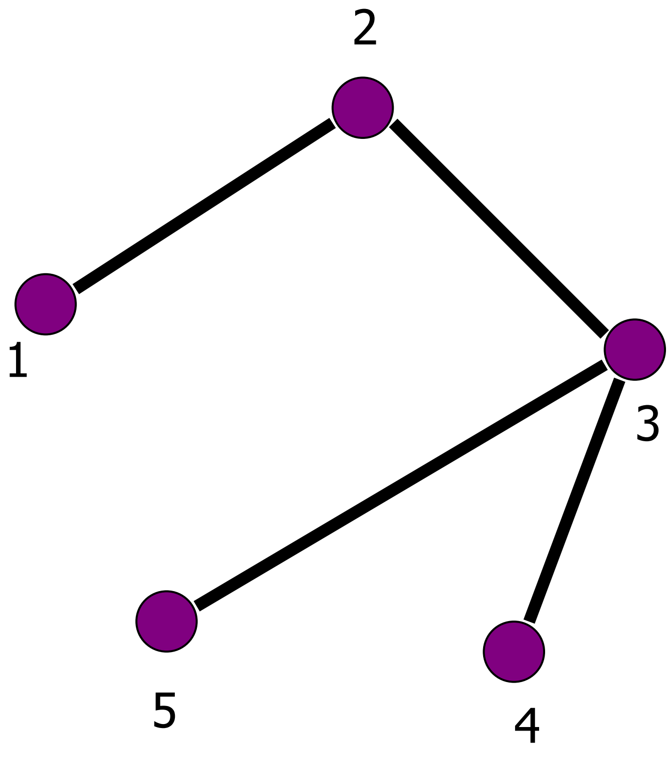
- Subgraph: Given $V' \subseteq V$, and $E' \subseteq E$, the graph $G'=(V',E')$ is a subgraph of G.

- 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



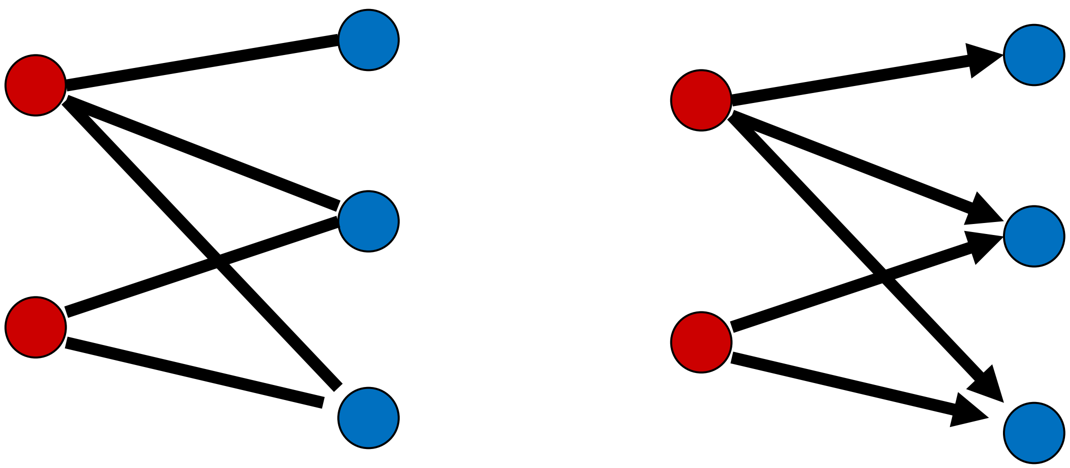
Trees

- Connected Undirected graphs without cycles



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

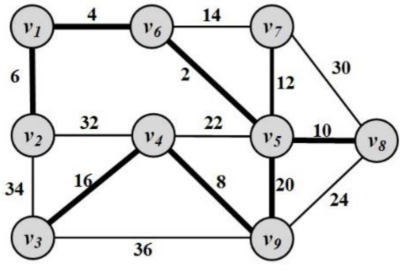


Spanning Tree

- 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

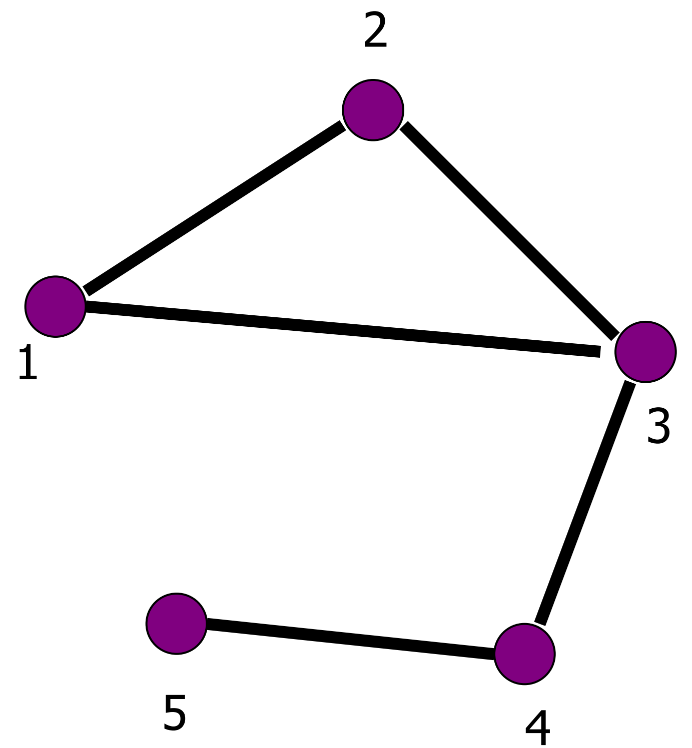
minimum spanning tree (MST)



Graph Representation

- Adjacency Matrix
  - symmetric matrix for undirected graphs

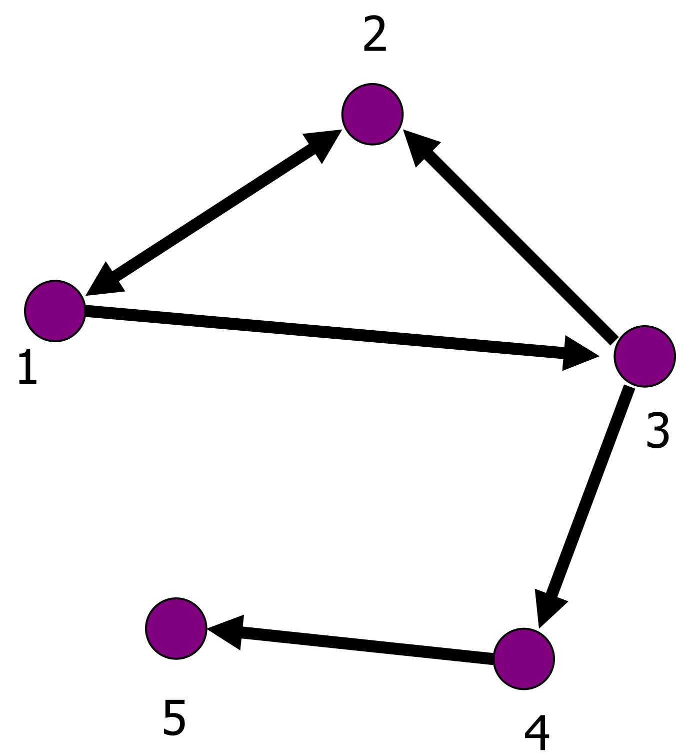
$$A = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$



Graph Representation

- Adjacency Matrix
  - unsymmetric matrix for undirected graphs

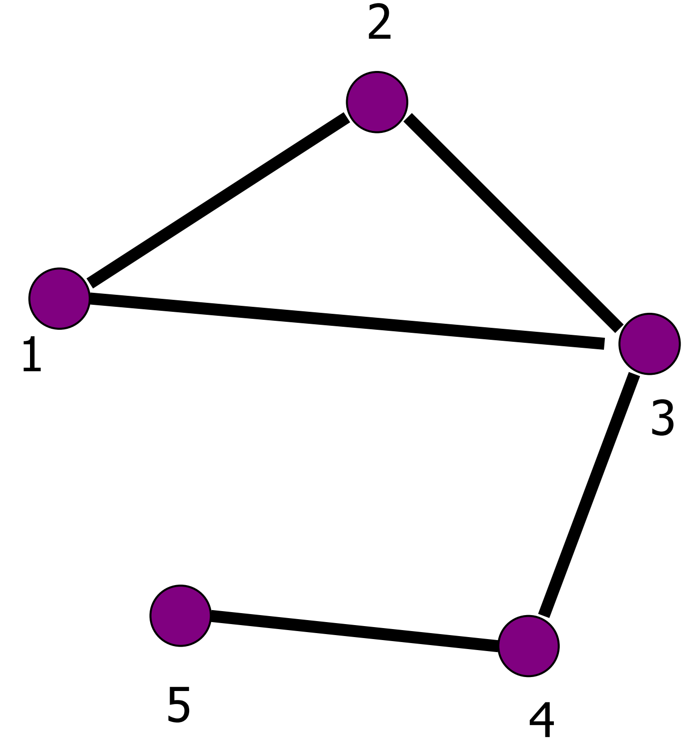
$$A = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$



Graph Representation

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

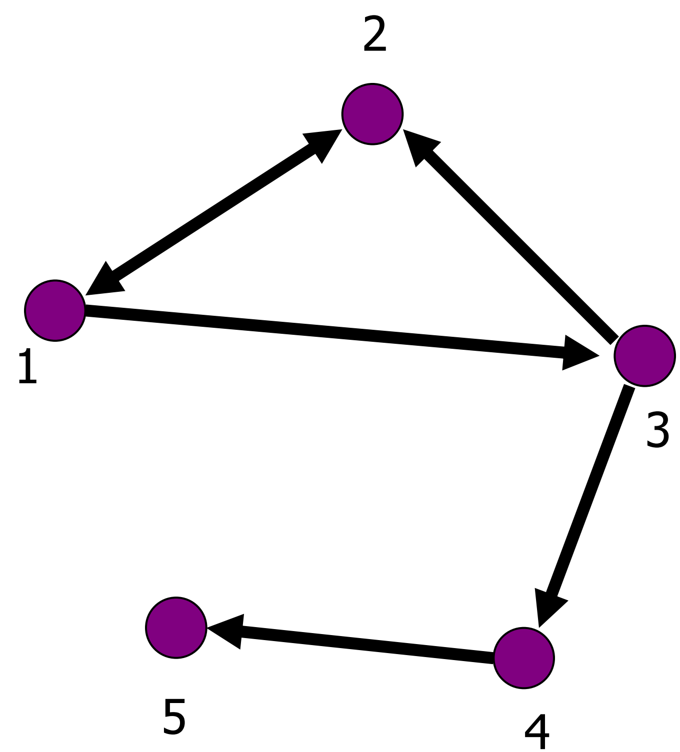
1: [2, 3]
2: [1, 3]
3: [1, 2, 4]
4: [3, 5]
5: [4]



Graph Representation

- Adjacency List
  - For each node keep a list of the nodes it points to

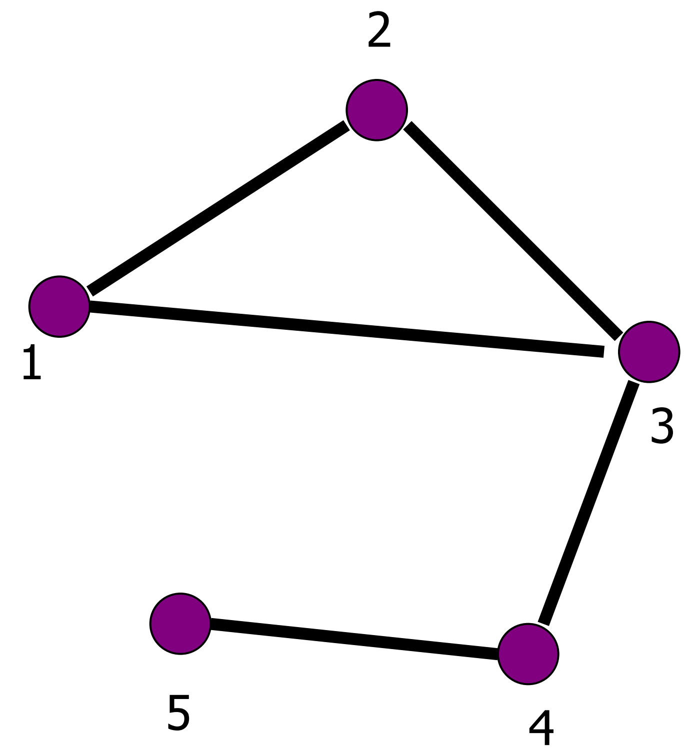
1: [2, 3]
2: [1]
3: [2, 4]
4: [5]
5: [null]



Graph Representation

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

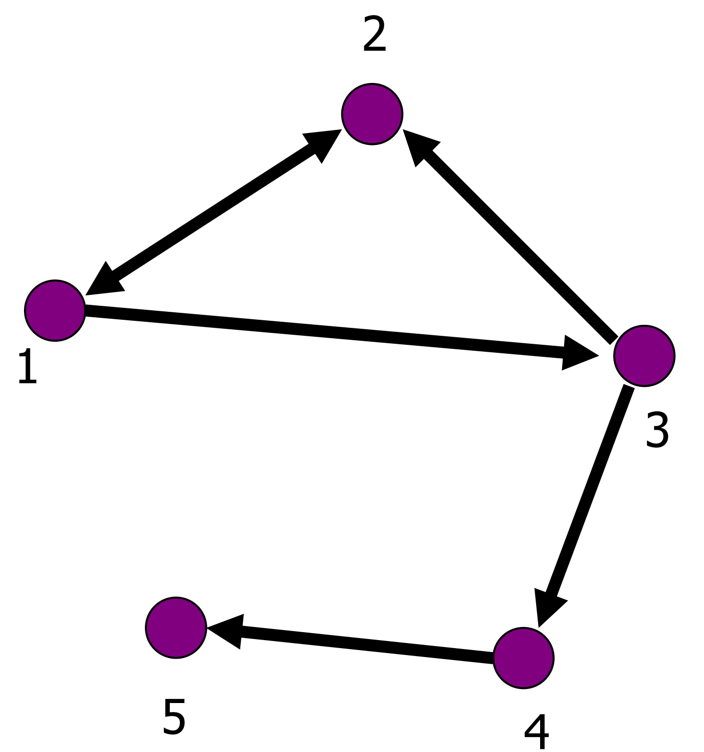
(1,2)
(2,3)
(1,3)
(3,4)
(4,5)



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)



P and **NP**

- **P**: the class of problems that can be solved in polynomial time
- **NP**: the class of problems that can be verified in polynomial time, but there is no known solution in polynomial time
- **NP**-hard: problems that are at least as hard as any problem in **NP**