Web Mining

Web Structure Mining

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Web Structure Mining

Definition

Discovery and interpretation of patterns in
- the hyperlink structure of webpages
- the social ties among actors that interact on the Web

Focuses on the structure, but can of course also be combined with content or usage mining techniques.

Typical Sources of Data
1. Web crawls including HTML pages and hyperlinks
2. Crawls of the blogosphere
3. Social networks including explicit relations between actors (your Facebook friend network)
4. Other types of community data (discussion forums, email conversations, …)
Chapter Outline

1. Describing Networks
   1. Basic Concepts and Terminology

2. Community Detection
   1. Connected Components
   2. K-Cores and Cliques
   3. Clustering-based Techniques

3. Prominence
   1. Centrality
   2. Prestige

4. Patterns in Real-World Networks
   1. Power-Law Distributions
   2. Small-World Networks


- Lots of thanks to Lada Adamic, Albert-László Barabási, Lei Tang and Huan Liu for the original versions of the slides.
Software that we will use in the Exercise

- Tool for the analysis and visualization of large networks
- Download: http://pajek.imfm.si/doku.php?id=pajek
1. Describing Networks: Terminology

A Graph is a collection of vertices that are connected by lines.

Network often refers to real systems
Graph: mathematical representation of a network
But often: “Network” ≡ “Graph”

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Directed and Undirected Graphs

**Undirected**

Lines: undirected (symmetrical) ➔ edge

Graph:

- Undirected edges:
  - co-authorship links
  - roads (mostly)

**Directed**

Lines: directed ➔ arcs

Digraph = directed graph:

- Directed arcs:
  - hyperlinks on the WWW
  - following on Twitter
  - phone calls
Vertices, arcs and edges can have attributes.

Example of Network with vertex and arc attributes:

- girls’ school dormitory dining-table partners (Moreno, *The sociometry reader*, 1960)
- first and second choices shown

![Network Diagram with Vertex and Arc Attributes](image-url)
Degree: the number of edges connected to the vertex.

\[ k_A = 1 \quad k_B = 4 \]

In directed graphs we can define an in-degree and out-degree. The (total) degree is the sum of in- and out-degree.

\[ k_C^{\text{in}} = 2 \quad k_C^{\text{out}} = 1 \quad k_C = 3 \]

Source: a vertex with \( k^{\text{in}} = 0 \); Sink: a vertex with \( k^{\text{out}} = 0 \).
Degree Distribution

Summarizes the degrees of all vertices.

Alternative representations:

1. A frequency count of the vertices of each degree

2. $P(k)$: probability that a randomly chosen vertex has degree $k$

$$P(k) = \frac{N_k}{N}$$
Degree Distribution of the WDC Hyperlink Graph

Covers 3.5 billion web pages and 128 billion hyperlinks, extracted from Common Crawl 2012

Website: http://webdatacommons.org/hyperlinkgraph/
Average Degree

Undirected

\[ \langle k \rangle = \frac{1}{N} \sum_{i=1}^{N} k_i \]

\[ \langle k \rangle = \frac{2L}{N} \]

N – the number of vertices in the graph

L – the number of lines in the graph

Directed

\[ \langle k^{in} \rangle = \frac{1}{N} \sum_{i=1}^{N} k^{in}_i \]

\[ \langle k^{out} \rangle = \frac{1}{N} \sum_{i=1}^{N} k^{out}_i \]

\[ \langle k^{in} \rangle = \langle k^{out} \rangle \]
Graph Density

- Of the connections that may exist between vertices:
  - directed graph
    \[ L_{\text{max}} = N(N-1) \]
    since each of the \( N \) vertices can connect to \( (N-1) \) other vertices
  - undirected graph
    \[ L_{\text{max}} = \frac{N(N-1)}{2} \]
    since edges are undirected, count each one only once

- What fraction is present?
  \[ \text{Density} = \frac{L}{L_{\text{max}}} \]
  - For example, out of 12 possible connections, this graph has 7, giving it a density of \( \frac{7}{12} = 0.583 \)
Clustering Coefficient

- Density of connections among one’s friends.
- What portion of your neighbors are connected?

\[ C_i = \begin{cases} \frac{k_i}{d_i \times (d_i - 1)/2} & d_i > 1 \\ 0 & d_i = 0 \text{ or } 1 \end{cases} \]

- \( k_i \) number of edges among \( V_i \)’s neighbors
- \( d_i \) degree of vertex \( V_i \)

- \( C_i \) in \([0,1]\)
Example: Clustering Coefficient

\[ d_6 = 4, \quad N_6 = \{4, 5, 7, 8\} \]
\[ k_6 = 4 \text{ as } e(4,5), \ e(5,7), \ e(5,8), \ e(7,8) \]
\[ C_6 = \frac{4}{(4 \times 3)/2} = \frac{2}{3} \]

Average Clustering Coefficient

\[ C = \frac{C_1 + C_2 + \ldots + C_n}{N} \]

\[ C = 0.61 \text{ for the left network} \]

In a random graph, the expected coefficient is \( \frac{14}{9 \times 8/2} = 0.19 \).
Adjacency Matrix

\[ A_{ij} = \begin{cases} 
1 & \text{if there is a link between vertices } i \text{ and } j \\
0 & \text{if vertices } i \text{ and } j \text{ are not connected to each other.}
\end{cases} \]

For an undirected graph:

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

For a directed graph:

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

Note that for a directed graph (right) the matrix is not symmetric.
Adjacency Matrix and Node Degrees

**Undirected**

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

\[ A_{ij} = A_{ji} \]
\[ A_{ii} = 0 \]

\[ k_i = \sum_{j=1}^{N} A_{ij} \]
\[ L = \frac{1}{2} \sum_{i=1}^{N} k_i = \frac{1}{2} \sum_{ij} A_{ij} \]

**Directed**

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

\[ A_{ij} \neq A_{ji} \]
\[ A_{ii} = 0 \]

\[ k_{i^{in}} = \sum_{i=1}^{N} A_{ij} \]
\[ k_{i^{out}} = \sum_{j=1}^{N} A_{ij} \]
\[ L = \sum_{i=1}^{N} k_{i^{in}} = \sum_{j=1}^{N} k_{j^{out}} = \sum_{i,j} A_{ij} \]
Graphology

Unweighted / Simple
(undirected)

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

Weighted
(undirected)

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

Example: Road networks
**Graphology**

**Self-Interactions**

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

*Example: Webpages that may link to themselves*

**Multigraph (undirected)**

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

*Example: Social networks with different types of interactions*
Bipartite graph (or bigraph) is a graph whose vertices can be divided into two disjoint sets $U$ and $V$ such that every line connects a vertex in $U$ to one in $V$; that is, $U$ and $V$ are independent sets.

**Examples:**

- Movie/actor network
- Disease/symptom network
- Group collaboration networks
## Paths

A path is a sequence of vertices in which each vertex is adjacent to the next one.

A path $P_{i_0, i_n}$ of length $n$ between vertices $i_0$ and $i_n$ is an ordered collection of $n+1$ vertices and $n$ lines.

$$P_{i_0, i_n} = \{i_0, i_1, i_2, \ldots, i_n\}$$

$$P_{i_0, i_n} = \{(i_0, i_1), (i_1, i_2), (i_2, i_3), \ldots, (i_{n-1}, i_n)\}$$

- A path can intersect itself and pass through the same line repeatedly. Each time a line is crossed, it is counted separately.

- A legitimate path on the graph on the right:
  
  $$\text{A B C B C A D E E B A}$$

- In a directed graph, the path can follow only the direction of the arcs.
The *distance* (*shortest path, geodesic path*) between two vertices is defined as the number of edges along the shortest path connecting them.

If the two nodes are disconnected, the distance is infinity.

In directed graphs each path needs to follow the direction of the arcs.

Thus in a digraph the distance from vertex A to B (on an AB path) is generally different from the distance from vertex B to A (on a BCA path).
Diameter

$d_{\text{max}}$ the maximum distance between any pair of nodes in the graph.

**Caution:** Some people use the term ‘diameter’ to be the average shortest path length.

Average Distance / Average Shortest Path Length

$\langle d \rangle$ for a connected graph:

$$\langle d \rangle = \frac{1}{N(N-1)} \sum_{i,j} d_{ij}$$

where $d_{ij}$ is the distance from vertex $i$ to vertex $j$ and $N$ is the number of vertices.

- The average shortest path length distinguishes an easily navigable network from one which is complicated and inefficient (i.e. for information or mass transport).
- Average Distance of the WDC Hyperlink Graph: 12.84 (but only 48% of all node pairs are connected by directed path).
Please calculate the following measures for the graph below:

1. Average shortest path length
2. Diameter
3. Degree distribution
4. Clustering coefficients
2. Community Detection

A **community** is a set of actors between which interactions are (relatively) frequent.

- Communities are also called groups, cohesive subgroups, clusters, or modules in different contexts.
- Finding a community in a social network is to identify a set of nodes such that they interact with each other more frequently than with those nodes outside the group.

![Diagram showing community detection process]

- Applications: Recommendation based on communities, network compression, visualization of huge networks
Subjectivity of Community Definition

A densely-knit community?

Each component is a community?

Definition of a community can be subjective. (unsupervised learning)
2.1 Graph Connectivity and Components

**Connected graph:** Any two vertices of an undirected graph are joined by a path.

A disconnected graph is made up by two or more connected components.

**Bridge:** if we remove it, the graph becomes disconnected (red line).

**Cut vertex:** if we remove it, the graph becomes disconnected (F and A).
If the largest component encompasses a significant fraction of the graph, it is called the **giant component**.

The other smaller components are called **isolates**.
Connectivity of Directed Graphs

**Strongly connected directed graph:** has a path from each vertex to every other vertex and vice versa (e.g. AB path and BA path).

**Weakly connected directed graph:** is connected if we disregard the arc directions.
Connected Components of Directed Graphs

**Strongly Connected Component**
Maximal subgraph in which every vertex can be reached from every other vertex by following directed arcs.

- Strongly connected components
  - B C D E
  - A
  - G H
  - F

**Weakly Connected Component**
Maximal subgraph in which every vertex can be reached from every other vertex by following lines in either direction.

- Weakly connected components
  - A B C D E
  - G H F
Example: Strong Components and Vertex Attributes

- Contours: Strong Components
- Numbers: Family-Friendship-Grouping
Example: Link Structure of the Web: Bow-Tie

Four major components (Border at al., WWW2000)

- **Central Strongly Connected Component (SCC)**
  - pages that can reach one another along directed links
  - about 30% of the Web (normal pages)

- **IN Group**
  - can reach SCC but cannot be reached from it
  - about 20% (maybe new pages or boring ones)

- **OUT Group**
  - can be reached from SCC but cannot reach it
  - about 20% (maybe company pages that don’t link)

- **Tendrils**
  - cannot reach SCC and cannot be reached by it
  - about 20%

- **Unconnected**
  - about 10%

*Probability of path between 2 nodes is 24%*
Probability of path between 2 nodes is 48%

Exercise: Components

How many strong components has the graph below?
A K-Core is a maximal subgraph in which each vertex has at least degree k within the subgraph.

- A K-Core does not need to be connected. The one 3-Core above consists of two parts.
- K-Cores are nested, meaning every vertex in the 3-Core also belongs to the 2-Core.
K-Cores and Communities

- A vertex is displayed belonging to the highest k-core of which it is a part.

- Finding communities: Remove lower cores until the graph breaks up into multiple components that form cohesive subgroups.
Exercise: K-Cores

- Count the number of 3-cores in the graph.

Vertex colors indicate the level of k:
- White: k=1
- Light gray: k=2
- Dark gray: k=3
- Black: k=4
2.3 Cliques and Complete Subgraphs

A clique is the maximal complete subgraph containing three vertices or more.

- Cliques are the strongest form of community as all vertices need to be directly adjacent to each other.

- Problems:
  - Finding cliques in larger graphs is computationally expensive.
  - The definition is often too restrictive to detect communities in real-world networks (result: large number of very small cliques)
Overlapping Complete Subgraphs

- Alternative less restrictive approach: Consider overlapping complete subgraphs (triads) as cohesive group.
- Triads overlap if they share one or more vertices.

Finding overlapping complete subgraphs is supported by Pajek.
Procedure for the Analysis of Cohesive Subgroups

- Idea: Successively increase the minimal density required.
- After each step: Check if discovered groups make sense based on your knowledge about the application domain.
2.4 Clustering based on Vertex Similarity

- **Idea**: Apply k-means to vertices.
- **Vertex similarity** can be defined in terms of the similarity of their neighborhood.
- **Structural equivalence**: Two vertices are structurally equivalent if they are connecting to the same set of vertices.

Vertex 1 and 3 are structurally equivalent; So are vertex 5 and 6.

**Structural equivalence is too restrict for practical use.**
Vertex Similarity

- **Jaccard Similarity**

  \[
  Jaccard(v_i, v_j) = \frac{|N_i \cap N_j|}{|N_i \cup N_j|}
  \]

- **Cosine similarity**

  \[
  Cosine(v_i, v_j) = \frac{|N_i \cap N_j|}{\sqrt{|N_i| \cdot |N_j|}}
  \]

  

  For example:

  \[
  Jaccard(4, 6) = \frac{|\{5\}|}{|\{1, 3, 4, 5, 6, 7, 8\}|} = \frac{1}{7}
  \]

  \[
  cosine(4, 6) = \frac{1}{\sqrt{4 \cdot 4}} = \frac{1}{4}
  \]
2.5 Divisive Hierarchical Clustering

Goal: Build a hierarchical structure of communities based on the network topology.
- Allows the analysis of a network at different resolutions

Approach: Recursively remove the “weakest” edge
1. Find the edge with the least strength.
2. Remove the edge and update the corresponding strength of each edge.
3. Recursively apply the above two steps until a network is decomposed into desired number of components.
4. Consider each component to form a community.
Edge Betweenness

- The strength of an edge can be measured by edge betweenness.

- **Edge betweenness:** The number of shortest paths that pass along with the edge.

  The edge betweenness of $e(1, 2)$ is 4 ($=6/2 + 1$), as all the shortest paths from 2 to $\{4, 5, 6, 7, 8, 9\}$ have to either pass $e(1, 2)$ or $e(2, 3)$, and $e(1,2)$ is the shortest path between 1 and 2

- The edge with higher betweenness tends to be the bridge between two communities.
Divisive Clustering based on Edge Betweenness

After remove $e(4,5)$, the betweenness of $e(4,6)$ becomes 20, which is the highest;

After remove $e(4,6)$, the edge $e(7,9)$ has the highest betweenness value 4, and should be removed.
2.6 Islands

- Community detection method for **weighted graphs**, e.g.
  - number of interactions on a social network
  - number of times author A cited author B
  - overall duration of phone calls

An island is a maximal subnetwork of vertices connected directly or indirectly by **lines with a value greater than** the lines to vertices outside the subnetwork.
Backbone of the WDC Hyperlink Graph

Websites connected by more than 500,000 links (The colors refer to DMOZ categories)

http://webdatacommons.org/hyperlinkgraph/topology.html
2.7 Graph Partition

A partition of a graph is a classification or clustering of the vertices in the graph such that each vertex is assigned to exactly one class of cluster.

- Can be generated based on
  1. existing vertex attributes.
  2. applying traditional classification or clustering algorithms to vertex attributes.
  3. analyzing the graph structure.
  4. combinations of all the above.

- Partitions are a central concept in Pajek.
Partitioning of the WDC Hyperlink Graph by TLD

TLD = Top-Level-Domain

http://webdatacommons.org/hyperlinkgraph/topology.html
3. Prominence

Who are the “most important” actors in a social network?

Centrality

- A **central actor** is one involved in many edges.
- The direction of lines is not considered.

Prestige

- A **prestigious actor** is one who is the target of many arcs.
- The direction of arcs is considered.
3.1 Centrality

- Which nodes are most ‘central’?
  - Calculated for undirected graph

- Definition of ‘central’ varies by context / purpose:

- Local measure:
  - Degree centrality

- Relative to rest of network:
  - Closeness centrality
  - Betweenness centrality

- How evenly is centrality distributed among nodes?
  - Centralization
  - graph-level view
Degree Centrality

Idea: Measure centrality as the number of edges to other vertices in the graph.

Answers the question: How many people can a person directly reach or influence?

Degree Centrality

\[ C_D(n_i) = d(n_i) \]

- Focuses only on direct or adjacent choices

Normalized Degree Centrality

\[ C'_D(n_i) = \frac{d(n_i)}{N-1} \]

- Degree divided by the maximal possible degree, i.e. number of vertices – 1
- Proportion of all nodes that are adjacent to \( n_i \)
Examples: Normalized Degree Centrality $C'_D$
Centralization

How much variation is there in the centrality scores among the vertices?

Freeman’s general formula for centralization:

\[ C_D = \frac{\sum_{i=1}^{g} [C_D(n^*) - C_D(i)]}{(N - 1)(N - 2)} \]

1. calculate the sum of differences in centrality between the most central vertex in a graph and all other vertices;
2. divide this quantity by the theoretically largest sum of differences in any graph of the same degree (star shape graph).

Value Range [0,1]
Examples: Degree Centralization

\[ C_D = 1.0 \]

\[ C_D = 0.167 \]
Examples: Degree Centralization

Financial trading networks

high centralization: one node trading with many others

low centralization: trades are more evenly distributed
When degree isn’t everything

- In what ways does degree fail to capture centrality in the following graphs?

- In what contexts may degree be insufficient to describe centrality?
  1. Ability to broker between groups
  2. Likelihood that information originating from anywhere in the network reaches you
Betweenness Centrality

Intuition: How many pairs of individuals would have to go through you in order to reach one another in the minimum number of hops?

Assumptions:

- Interactions between two non-adjacent actors might depend on the other actors in the set of actors, especially the actors who lie on the paths between the two nodes.

- “Actor in the middle” between the others has some control over paths in the network – “interpersonal influence”.

Who has higher betweenness centrality, X or Y?

![Diagram showing betweenness centrality example]
Betweenness Centrality: Definition

\[ C_B(i) = \sum_{j<k} \frac{g_{jk}(i)}{g_{jk}} \]

Where \( g_{jk} \) = the number of shortest paths connecting \( jk \), and \( g_{jk}(i) \) = the number that actor \( i \) is on.

Usually normalized by dividing through maximal theoretical value for \( C'_b(i) \):

\[ C'_B(i) = \frac{C_B(i)}{\left[ (n - 1)(n - 2) / 2 \right]} \]

number of pairs of vertices excluding the vertex itself
Betweenness Centrality on Toy Networks

- Non-normalized version:

A lies between no two other vertices
B lies between A and 3 other vertices: C, D, and E
C lies between 4 pairs of vertices (A,D),(A,E),(B,D),(B,E)

Note that there are no alternate paths for these pairs to take, so C gets full credit.
Non-normalized version:

Why do C and D each have betweenness 1?
They are both on shortest paths for pairs (A,E), and (B,E), and so must share credit:
\[ \frac{1}{2} + \frac{1}{2} = 1 \]

Can you figure out why B has betweenness 3.5 while E has betweenness 0.5?
Exercise: Facebook Network

- vertices are sized by degree centrality and colored by betweenness centrality

1. Can you spot nodes with high betweenness but relatively low degree?
2. Explain how this might arise.
Closeness Centrality

- The measure focuses on how close an actor is to all the other actors in the network.
  - for instance to spread information or interact with others
  - or to be reached by information that spreads through the network

- Closeness centrality is based on the length of the average shortest path between a vertex and all vertices in the graph.

Closeness Centrality:
\[ C_c(i) = \left[ \sum_{j=1}^{N} d(i, j) \right]^{-1} \]

Normalized Closeness Centrality:
\[ C'_c(i) = C_c(i)(N - 1) \]
Example: Closeness Centrality

\[ C'_c(A) = \left( \sum_{j=1}^{N} \frac{d(A, j)}{N - 1} \right)^{-1} \]

\[ = \left[ \frac{1 + 2 + 3 + 4}{4} \right]^{-1} = \left[ \frac{10}{4} \right]^{-1} = 0.4 \]

More toy examples:
Correlation of Centrality Metrics

- Generally different centrality metrics will be positively correlated.
- When they are not, there is likely something interesting about the vertex.

- **degree** denoted by size
- **closeness** denoted by color
3.2 Prestige

Prestige refers to a class of prominence metrics which take the direction of arcs into account.

- Translates to: choices received

- Examples where direction matters:
  - Votes in an election
  - Hyperlinks on the WWW
  - Citations of scientific papers

- Examples when ‘prestige’ may not be the right word
  - dislikes
  - distrusts
The simplest vertex-level measure of prestige (in-degree)

The idea is that actors who are prestigious tend to receive many nominations or choices

- a paper that is cited by many others has high prestige
- a person nominated by many others for a reward has high prestige

Degree Prestige / Popularity

\[ P_D(n_i) = d_{in}(n_i) \]

Normalized Degree Prestige

\[ C'_D(n_i) = \frac{d_{in}(n_i)}{N-1} \]

- Indegree divide by the maximal possible indegree
- Proportion of all nodes that choose \( n_i \)
Degree prestige only counts actors who are adjacent to actor $n_i$, but we might also want to take indirect choices into account.

The **Input Domain** of a vertex in a directed network is the number or percentage of all other vertices that are connected by a path to this vertex.

Also called **Influence domain**, which makes for instance sense for the use case of following on Twitter.
Proximity Prestige

- Prestige measure based on distances in the input domain.
  - Direct nominations (choices) should count more than indirect ones
  - Nominations from second degree neighbors should count more than third degree ones

\[ P_p(n_i) = \frac{\text{fraction of all vertices that are in } i\text{'s input domain}}{\text{average distance from } i \text{ to vertex in input domain}} \]

\[ P_P(n_i) = \frac{(I_i / (g - 1))}{\sum d(n_i, n_j) / I_i} \]

Example:
Rank Prestige and Page Rank

- **Rank Prestige**
  - Prestige measure which considers the prestige of the actors who do the “choosing”.
  - You are more prestigious if you have lots of other prestigious people in your input domain.

  \[
P_R(i) = \sum_{(j,i) \in E} P_R(j)
  \]

  \(j\): Vertex in the input domain of \(i\)

- **Page Rank**
  - Variation of rank prestige in which the prestige of a voting node is shared between all link targets.

  \[
P_{PR}(i) = \sum_{(j,i) \in E} P_{PR}(j) / D_{out}(j)
  \]

- **Advantages of PageRank in the search context**
  - hard to trick with SPAM links
  - The score is independent of actual search engine query

- **Calculation of PageRank Score**: See Bing Lui: Web Data Mining. Chapter 7.3
# Publicly Accessible Ranking of Websites

## The Common Crawl WWW Ranking

Here you can browse a ranking of more than 100 million sites of the World Wide Web. Every single step leading to this ranking is open and accessible. Enjoy!

[Learn more](http://wwwranking.webdatacommons.org/)

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<td>vimeo.com</td>
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<td>153</td>
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</tr>
</tbody>
</table>

4. Patterns in Real-World Networks

Large-scale networks in the real world often demonstrate similar patterns:

1. Power-law distributions
2. Small-world networks
Power-Law Distributions

- Degree distribution in large-scale networks often follows a power law.

\[ p(x) = C x^{-\alpha}, \quad x \geq x_{\text{min}}, \quad \alpha > 1 \]

- The preferential attachment process (Barabási and Albert, 1999) explains power-law distributions: Vertices prefer to link to vertices with a high degree.

- Translates to “The rich get richer” or “The famous get more famous”.
Examples of Power Law Distributions

- Power law distribution becomes a **straight line** if plot in a log-log scale.

Friendship Network on Flickr  
Friendship Network on YouTube
Small-World Networks

are characterized by

1. **high average clustering coefficient**
   - which indicates strong community structures.
   - Explanation: Friends of a friend are likely to be friends as well.

2. **small average shortest path length**
   - which is also known as “six degrees of separation” (Travers and Milgram, 1969)
   - Explanation: *Hub-* or bridge-vertices interconnect communities and help shortening the average path length.
### Small-World Properties of Social Networks

The clustering coefficient is significantly higher compared to random networks.

<table>
<thead>
<tr>
<th>Network</th>
<th>$C$</th>
<th>Ratio to Random Graphs</th>
<th>Power-Law</th>
</tr>
</thead>
<tbody>
<tr>
<td>Web [2]</td>
<td>0.081</td>
<td>7.71</td>
<td>-</td>
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<tr>
<td>Flickr</td>
<td>0.313</td>
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<tr>
<td>YouTube</td>
<td>0.136</td>
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<td>69.4</td>
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</tbody>
</table>

Users with few friends are more tightly clustered.