A Gentle Introduction to Computational Social Network Analysis

Track 3: Tools for Social Network Analysis

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Acknowledgements

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- Sir Rick Jason Obrero for using his network so that we can share what we know a little about computational social networks

Objectives

- Main: To introduce to the workshop participants the computational aspects of social network analysis.

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- Specific:
  - To describe the computational data structures of social networks
  - To discuss some quantitative metrics of social networks
  - To introduce a free software system for social network analysis

Workshop Outline

- Computational data structures
  - Graphs and Sociograms
  - Matrices
  - Linked list

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  - Linked list
- Network metrics
  - Basic Metrics
  - Network Centralities
  - Classifying Nodes

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Free software system

Pajek*

*Batagelj V and Mrvar A. 2003. *Pajek - Analysis and Visualization of Large Networks*. In **Graph Drawing Software**, Springer pp. 77-103,

Data Structures

What
is this?!

Ay, ano ga
are?!

Atwhay
isway isthay?!

How to represent social network data?

- Visual: Graphs and Sociograms*

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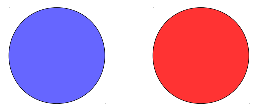
How to represent social network data?

- Visual: Graphs and Sociograms*
  - Actors, Entities, Nodes, Vertices



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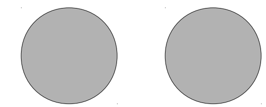
  - Actors, Entities, Nodes, Vertices 
  - Relations, Ties, Links, Edges, Arcs 

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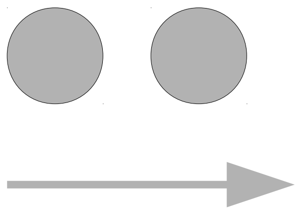

  - Example 1** "*perception of close friendship*"

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Blue nodes are males

Red nodes are females

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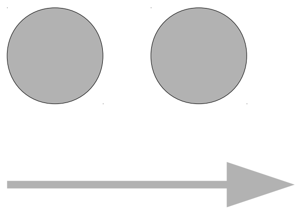

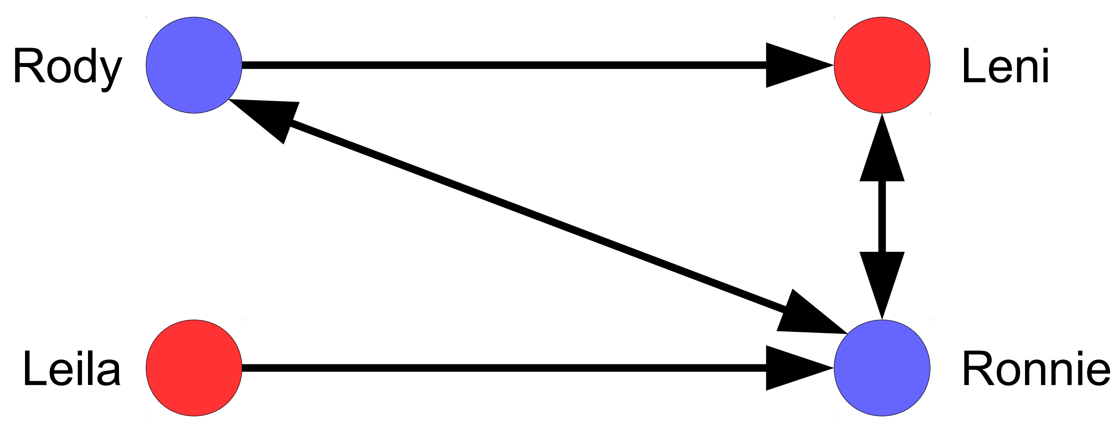

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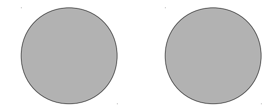
  - Actors, Entities, Nodes, Vertices 
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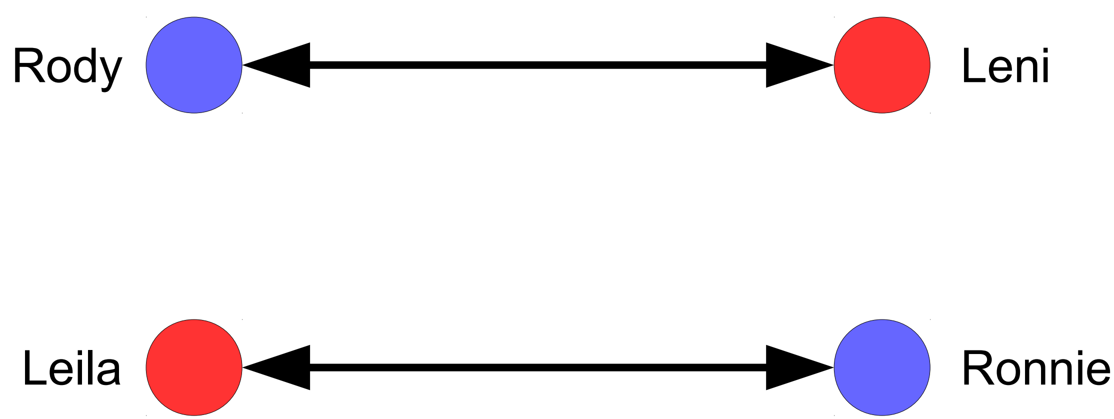
  - Example 2** “*spouse – reciprocated relations*”



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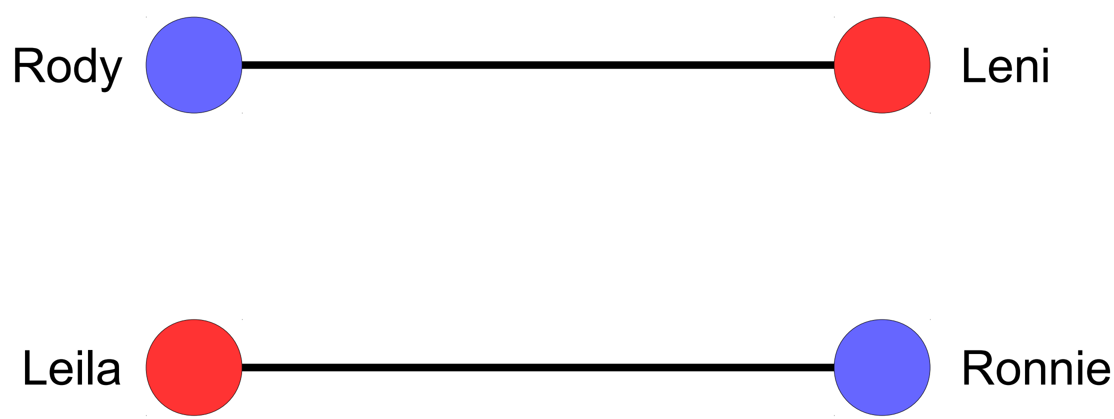

Let us just remove the arrows for clarity.

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How to represent social network data?

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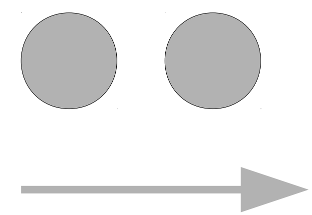
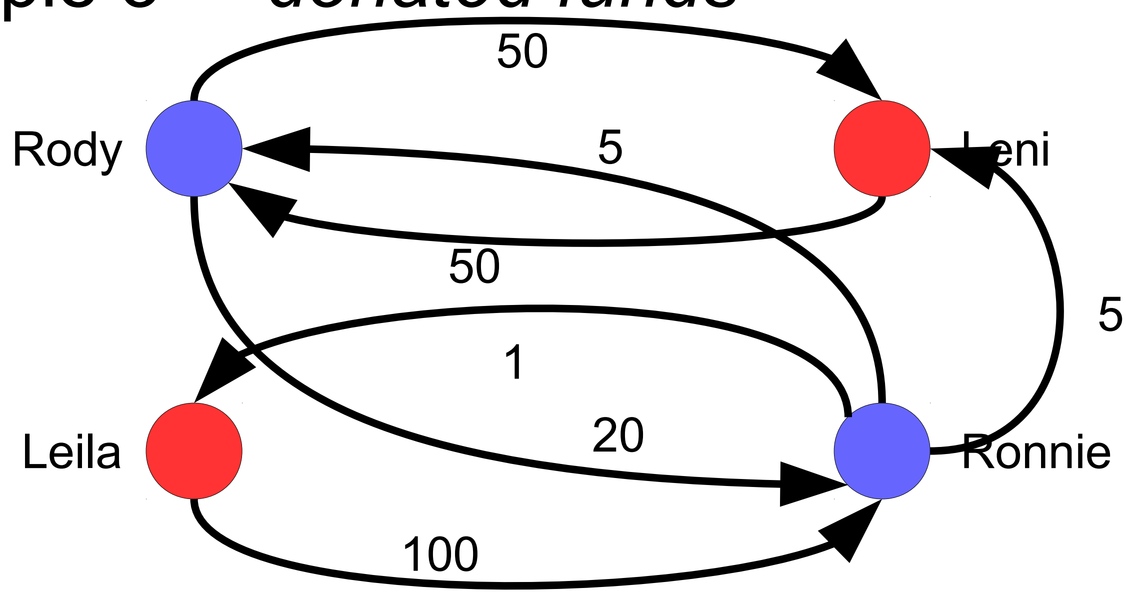
  - Example 3** “*donated funds*”





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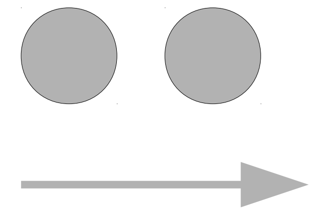
  - Example 1 "*perception of close friendship*"
    - Directed network



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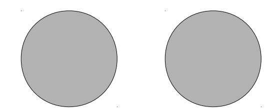
  - Actors, Entities, Nodes, Vertices 
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  - Example 2 "*spouse – reciprocated relations*"
    - Undirected network

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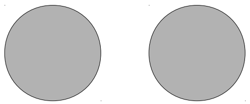

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  - Example 1 "*perception of close friendship*"
    - Directed network
  - Example 2 "*spouse – reciprocated relations*"
    - Undirected network
  - Example 3 "donated funds"
    - Directed, weighted network

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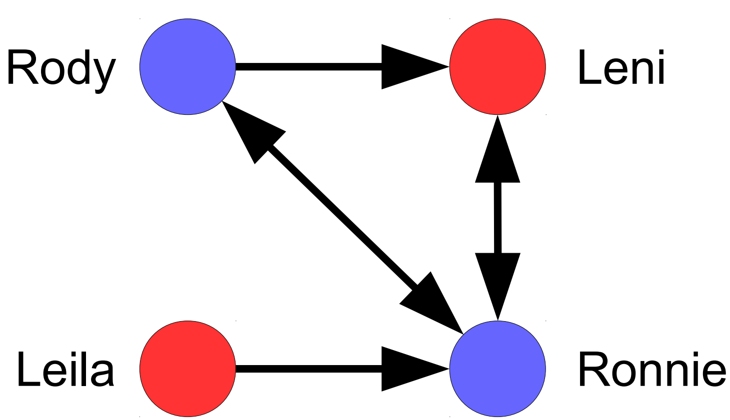
How to represent social network data?

- Matrices
  - Adjacency Matrix, A
    where $A_{j,k} = 1$ if entity j has a relation with entity k, otherwise $A_{j,k} = 0$.
  - Example, directed network



$$A = \begin{array}{c} \begin{array}{cccc} \text{Rody} & \text{Leni} & \text{Ronnie} & \text{Leila} \end{array} \\ \left(\begin{array}{cccc} 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{array}\right) \end{array} \begin{array}{l} \\ \text{Rody} \\ \text{Leni} \\ \text{Ronnie} \\ \text{Leila} \end{array}$$

How to represent social network data?

- Matrices
  - Adjacency Matrix, A
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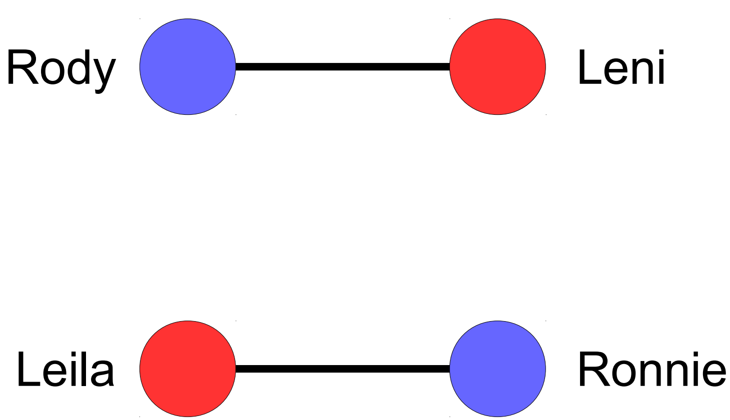
  - Example, undirected network



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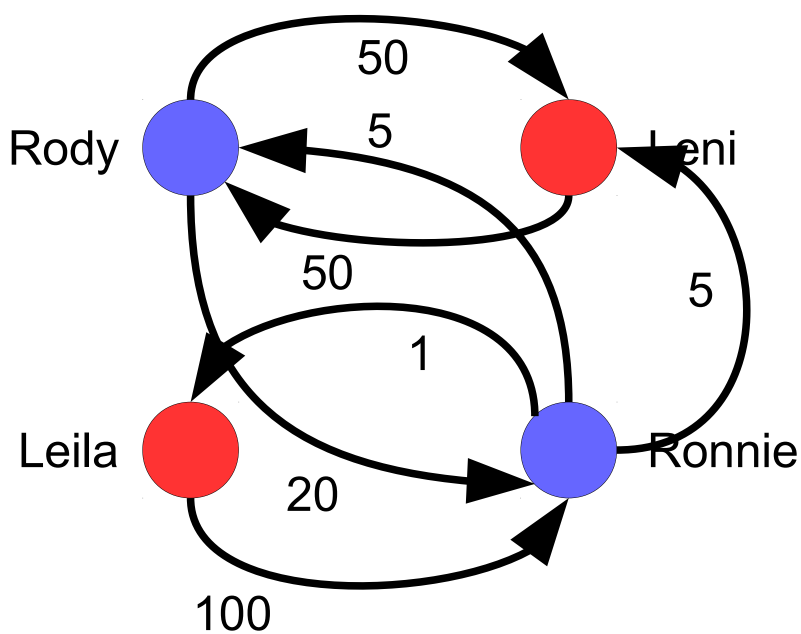
How to represent social network data?

- Matrices
  - Weighted Adjacency Matrix, W
    where $W_{j,k} = w$ if entity j has a weighted relation w with entity k, otherwise $W_{j,k} = 0$.
  - Example, weighted directed network



$$W = \begin{array}{cc} & \begin{array}{cccc} \text{Rody} & \text{Leni} & \text{Ronnie} & \text{Leila} \end{array} \\ & \left(\begin{array}{cccc} 0 & 50 & 20 & 0 \\ 50 & 0 & 0 & 0 \\ 5 & 5 & 0 & 1 \\ 0 & 0 & 100 & 0 \end{array} \right) \begin{array}{l} \text{Rody} \\ \text{Leni} \\ \text{Ronnie} \\ \text{Leila} \end{array} \end{array}$$

How to represent social network data?

- Other Matrices*
  - Degree matrix, *D*
  - Normalized adjacency matrix, *N*
  - Laplacian matrix, *L*
  - Normalized Laplacian matrix, *Z*
  - Stochastic adjacency matrix, *P*
  - Signless Laplacian, *K*
  - and many more

Unfortunately, they are “boring” things to talk about.

* *Brouwer AE and Haemers WH. 2011.* ***Spectra of Graphs****. Springer.*

How to represent social network data?

- Lists
  - List of vertices, V
  - List of edges, E

Efficient representation for computation

How to represent social network data?

- Lists
  - List of vertices, V
  - List of edges, E

  Efficient representation for computation

- Example 1: "*perception of close friendship*"
  - V = { Rody, Leni, Ronnie, Leila }
  - E = { (Rody, Leni), (Rody, Ronnie), (Leni, Ronnie), (Ronnie, Rody), (Ronnie, Leni), (Leila, Ronnie) }

How to represent social network data?

- Lists
  - List of vertices, *V*
  - List of edges, *E*

Efficient representation for computation

- Example 2: "*spouse – reciprocated relations*"
  - *V* = { Rody, Leni, Ronnie, Leila }
  - *E* = { (Rody, Leni), (Rody, Ronnie) }

How to represent social network data?

- Lists
  - List of vertices, V
  - List of edges, E

  Efficient representation for computation

- Example 2: "*donated funds*"
  - V = { Rody, Leni, Ronnie, Leila }
  - E = { (Rody, Leni, 50), (Rody, Ronnie, 20),
    (Leni, Rody, 50), (Ronnie, Rody, 5),
    (Ronnie, Lenie, 5), (Ronnie, Leila, 1),
    (Lenie, Ronnie, 100) }

Network Metrics

What
is this?!

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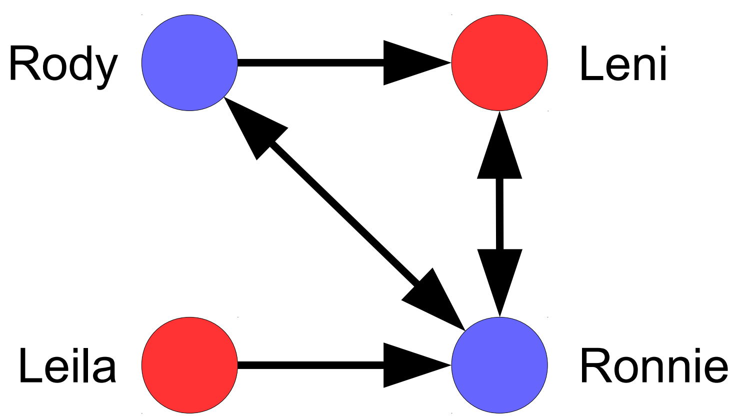
Atwhay
isway isthay?!

Network Metrics

- Basic Metrics
  - **Network size**, n – Total number of nodes
  - **Network volume**, m – Total number of edges
  - **Network weight**, w – Sum of absolute edge weights
  - **Average degree** (or Network density), $d = 2m/n$



$n = 4$

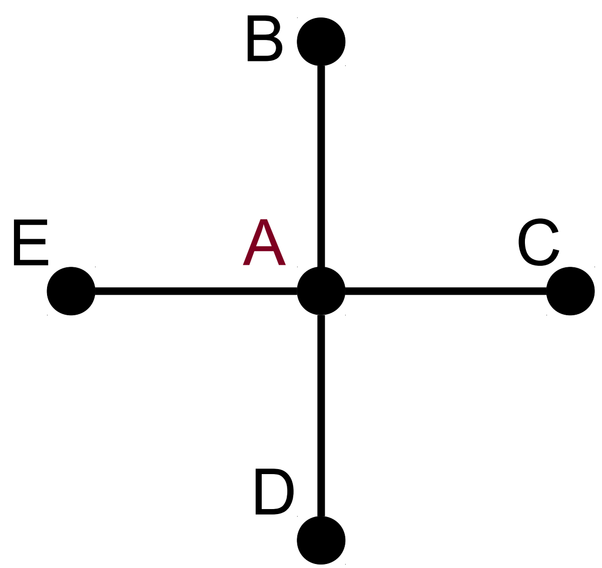
$m = 6$

$w = 6$

$d = 3$

Network Metrics

- Network centralities*
  - Which nodes are more "central" than others?
  - Central nodes are those in the "thick of things" or "focal" among the nodes*.



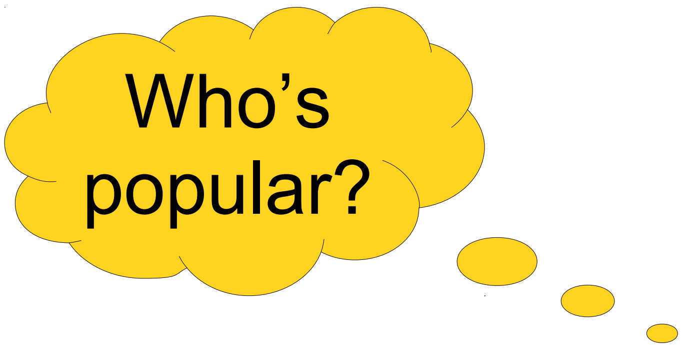
Here, Node A can be considered central because it:

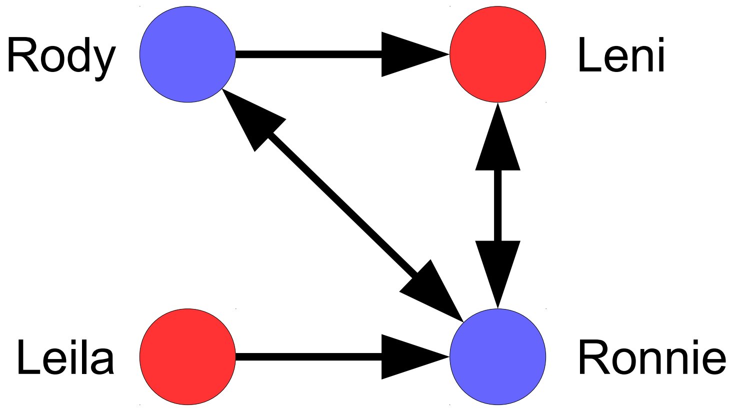
- has more ties;
- can reach others through one edge, while others need two edges;
- can control the flow of data to other nodes.

* *Freeman LC. 1978. Centrality in social networks: Conceptual clarification.* ***Social Networks*** *1, 215-239.*

Network Metrics

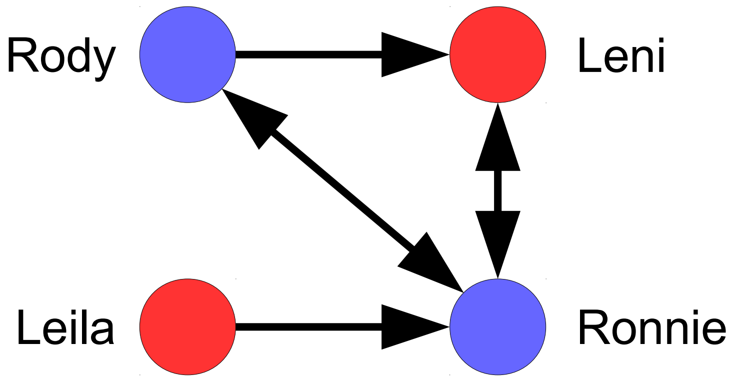
- Network centralities
  - **Degree centrality** – Number of links a node has
    - Concept 1: For undirected network, immediate risk of a node for catching whatever is flowing in the network (gossip, information, virus, etc)
    - Concept 2: For directed network, in-degree (number of edges that point towards the node, i.e., *popularity*) and out-degree (number of edges the point away from the node, i.e., *gregariousness*)





Network Metrics

- Network centralities
  - **Closeness centrality*** – Inverse of farness, which is the sum of distances to all other nodes.
    - Computational idea: Compute the shortest distance** between all pairs of nodes
    - Distance is the number of (directed) paths to take to reach another node from a given node.



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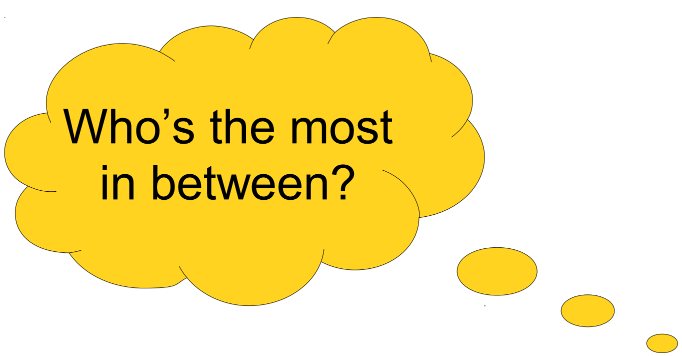
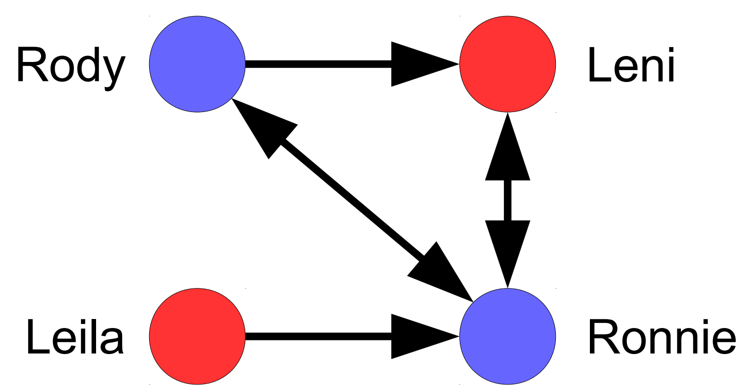
** *Dijkstra EW. 1959. A note on two problems in connexion with graphs.* ***Numerische Mathematik*** *1, 269-271.*

Network Metrics

- Network centralities
  - **Betweenness centrality*** – The extent for which a node is a <u>part of transactions</u> among other nodes.
    - In pinoy's red tape parlance, these are the fixers, go-betweeners, or *tulay*.
    - Intuitive computation is via Dijkstra's algorithm but a faster** one exists.





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*Brandes U. 2001. A Faster Algorithm for Betweenness Centrality. **Journal of Mathematical Sociology** 25, 163-177.*

Network Metrics

- Characterizing Nodes
  - Hubs and Authorities* (iterative definition)
    - Authorities are nodes that are sources of authoritative information. A good authority is one that is pointed to by many good hubs.
    - Hubs are nodes that are sources of authorities. A good hub is one that points to many good authorities.
    - Can only be performed on a directed network

* *Manning CD, Raghavan P and Schütze H. 2008.* ***Introduction to Information Retrieval****. Cambridge University Press.*

Network Metrics

- Workshop #1
  - Install Pajek into your PC Compatibles (Intel-based chipset running MS-Windows OS)
  - Prepare your data set
    - Using any word processor that can save an ASCII file, format the data file as follows:
    - Line 1: `*Vertices` <number of vertices, *n*>
    - Line 2 to Line *n*+1: <unique integer> "<name of vertex>"

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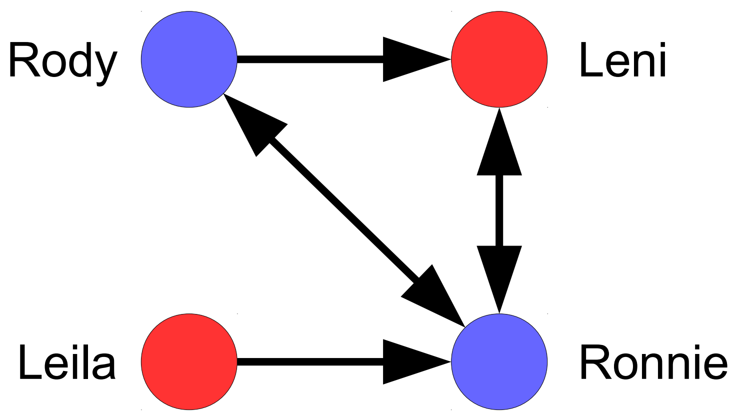
    - Line *n*+2:
      - If Undirected: `*Edges`
      - If Directed: `*Arcs`
    - Line *n*+3 and onward: <integer> <integer>

Network Metrics

- Workshop #1: Example data set: *perception of close friendship*
  - Line 1:
  - Line 2:
  - Line 3:
  - Line 4:
  - Line 5:
  - Line 6:
  - Line 7:
  - Line 8:
  - Line 9:
  - Line 10:
  - Line 11:
  - Line 12:

```
*Vertices 4
1 "Rody"
2 "Leni"
3 "Ronnie"
4 "Leila"
*Arcs
1 2
1 3
2 3
3 1
3 2
4 3
```



*

Network Metrics

- Workshop #1: Example data set: *perception of close friendship*
  - Line 1: `*Vertices 4`
  - Line 2: `1 “Rody”   x_fact 1 y_fact 1 ic Blue`
  - Line 3: `2 “Leni”   x_fact 1 y_fact 1 ic Red`
  - Line 4: `3 “Ronnie” x_fact 1 y_fact 1 ic Blue`
  - Line 5: `4 “Leila”  x_fact 1 y_fact 1 ic Red`
  - Line 6: `*Arcs`
  - Line 7: `1 2`
  - Line 8: `1 3`
  - Line 9: `2 3`
  - Line 10: `3 1`
  - Line 11: `3 2`
  - Line 12: `4 3`

Add these to Lines 2 through 5, respectively

*

Network Metrics

- Workshop #1: Example data set: *perception of close friendship*
  - Draw the Network and explore the drawing options
  - Compute for the following centralities:
    - Degree
    - Closeness
    - Betweenness
  - Identify the Hubs and Authorities

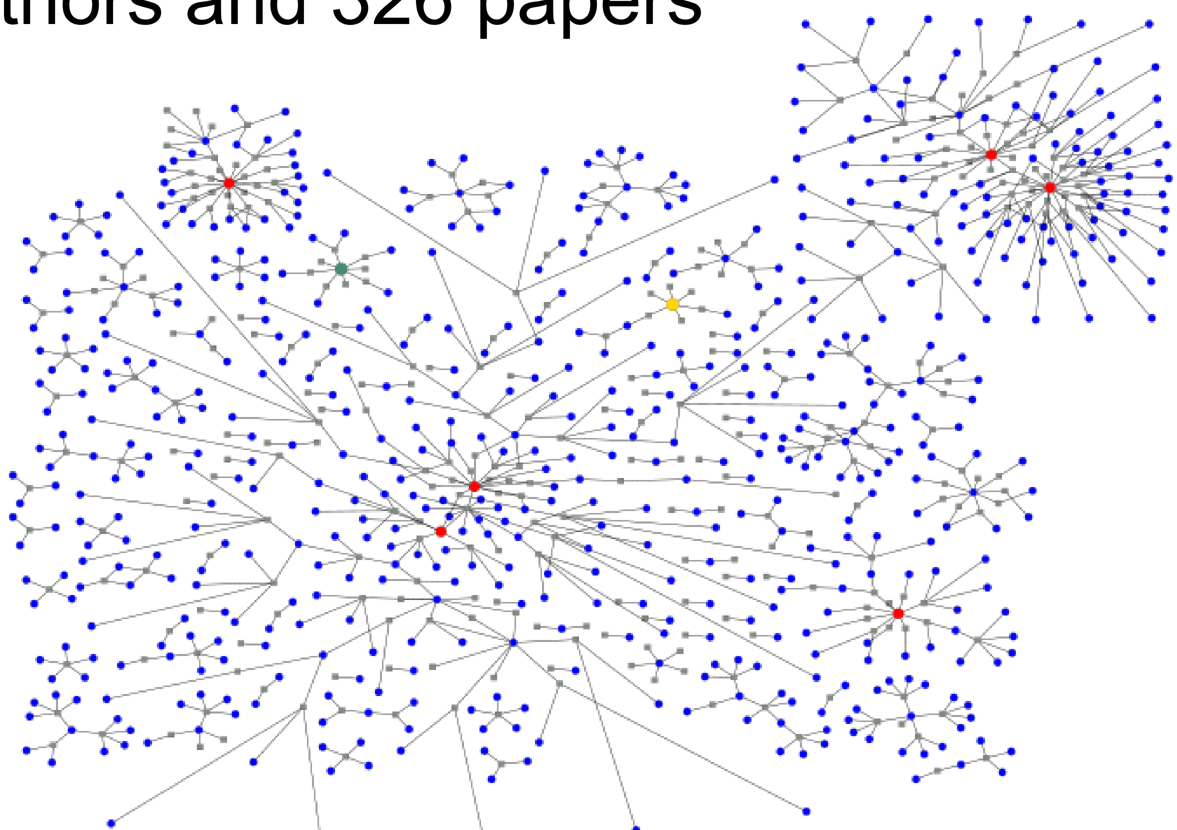
Network Metrics

- Workshop #2: Scientific Collaboration Network
  - Copy the Pajek dataset for the Collaboration Network of Filipino Computer Scientists*
  - Inspect, using your word or text processor (preferably notepad or better), if the data file follows the Pajek input format
    - 542 nodes/authors
    - 969 edges/co-authorship

* *Pabico JP. 2010. Authorship patterns in computer science research in the Philippines.* ***Philippine Computing Journal*** *5(1):1-13*

Network Metrics

- Workshop #2: Scientific Collaboration Network
  - Started out as a paper-author bipartite network with 542 authors and 326 papers



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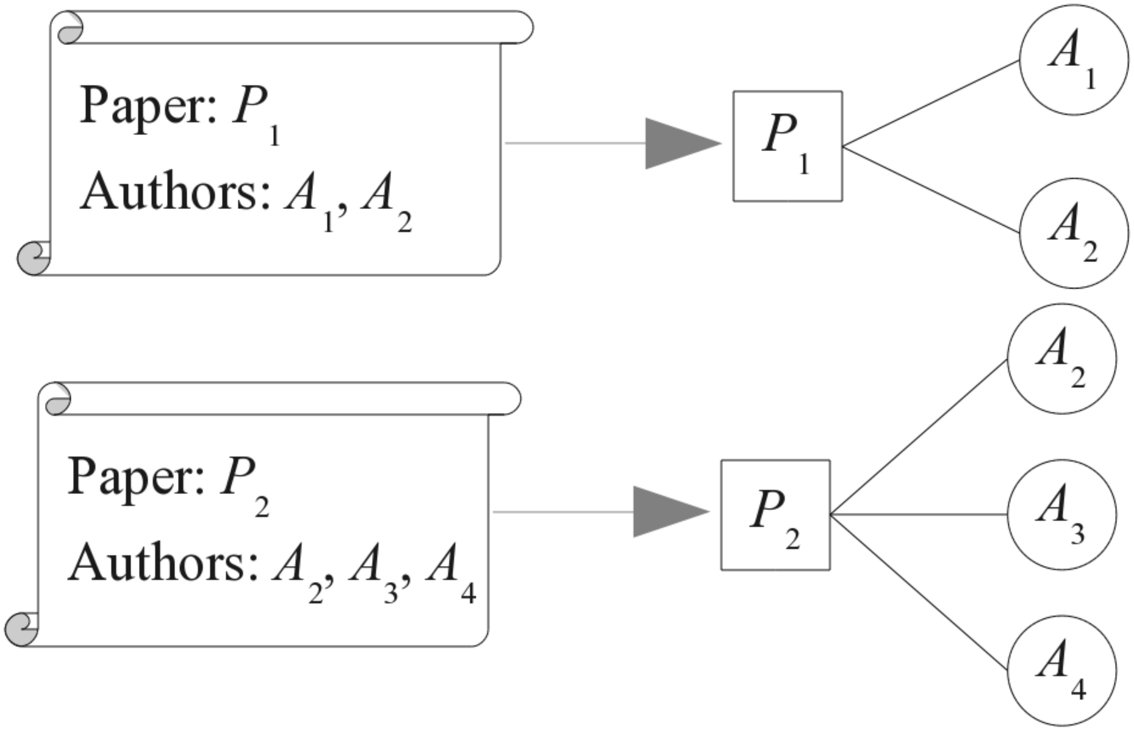
Network Metrics

- Workshop #2: Scientific Collaboration Network
  - Idea:



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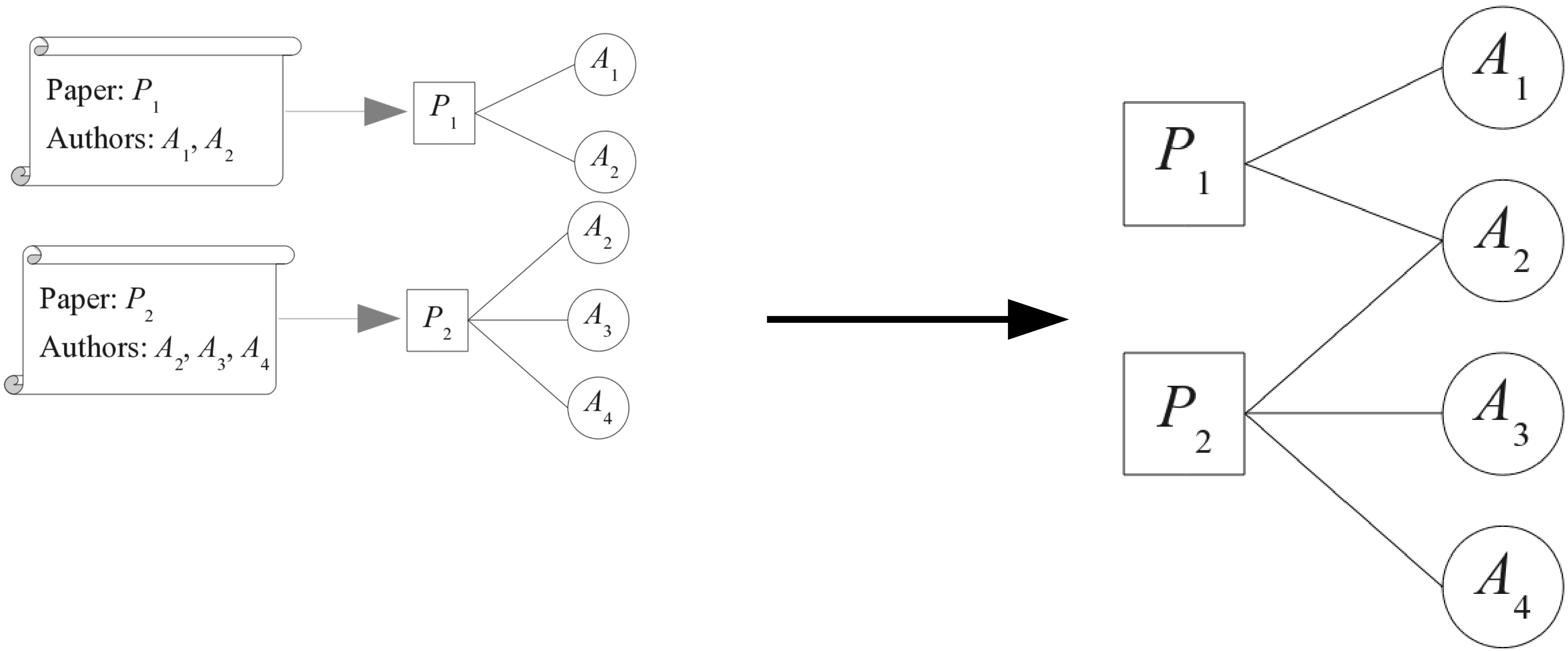

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Network Metrics

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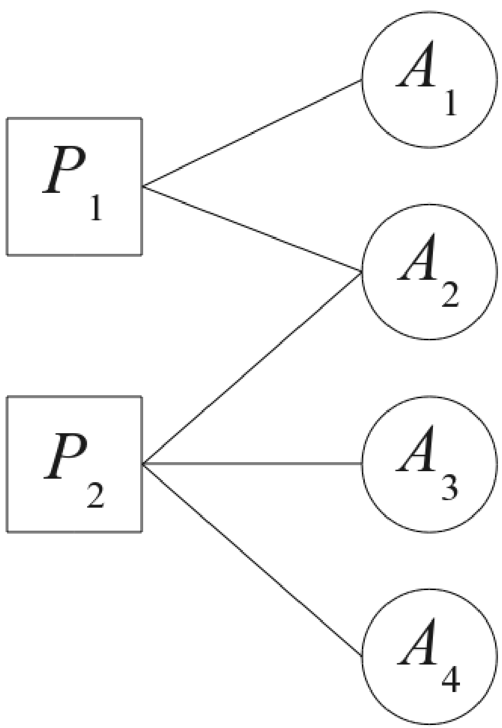


$$
\begin{array}{cc}
 & \begin{array}{cccccc} P_1 & P_2 & A_1 & A_2 & A_3 & A_4 \end{array} \\
\begin{array}{c} P_1 \\ P_2 \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} &
\begin{bmatrix}
0 & 0 & 1 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 \\
1 & 0 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0
\end{bmatrix}
\end{array}
$$

* *Pabico JP. 2010. Authorship patterns in computer science research in the Philippines.* ***Philippine Computing Journal*** *5(1):1-13*

Network Metrics

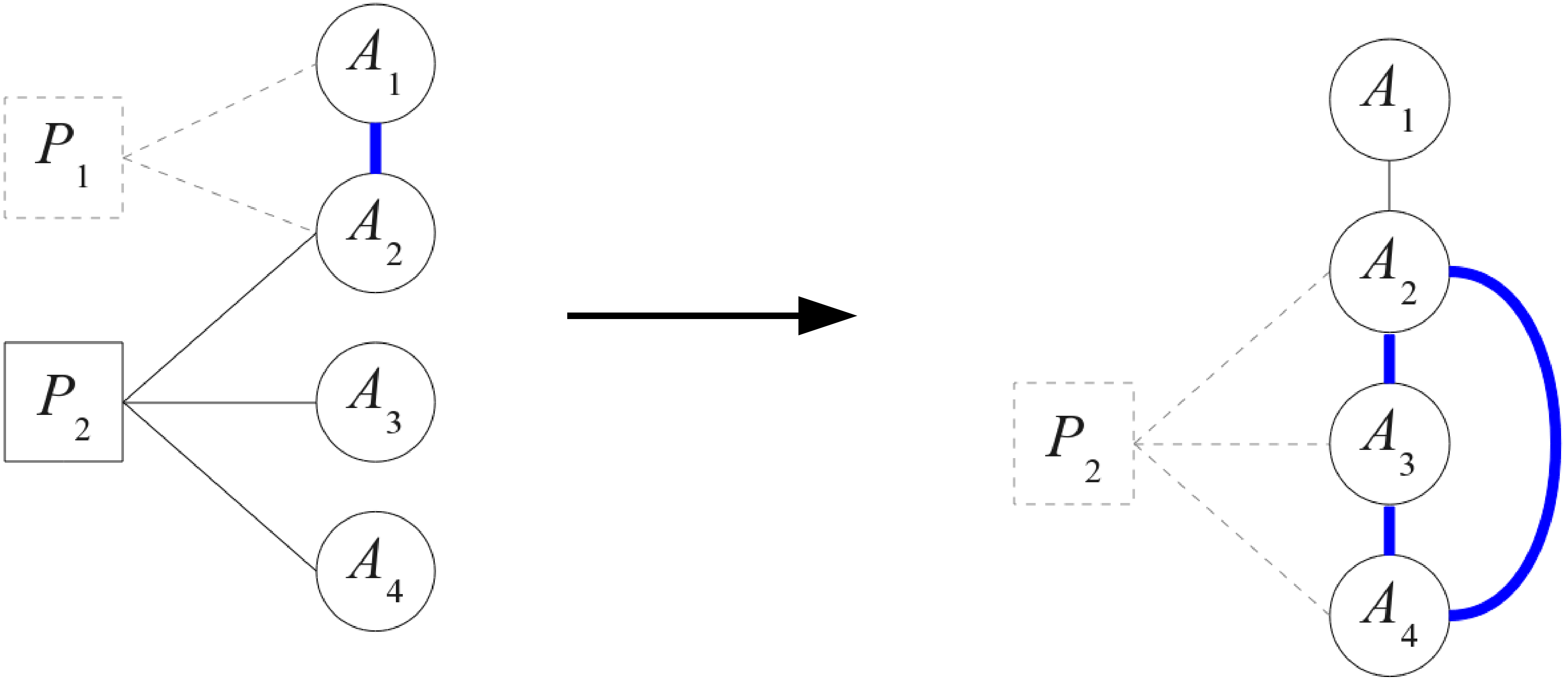
- Workshop #2: Scientific Collaboration Network
  - Idea:

$$\begin{array}{c|cccccc|} & P_1 & P_2 & A_1 & A_2 & A_3 & A_4 \\ \hline P_1 & 0 & 0 & 1 & 1 & 0 & 0 \\ P_2 & 0 & 0 & 0 & 1 & 1 & 1 \\ A_1 & 1 & 0 & 0 & 0 & 0 & 0 \\ A_2 & 1 & 1 & 0 & 0 & 0 & 0 \\ A_3 & 0 & 1 & 0 & 0 & 0 & 0 \\ A_4 & 0 & 1 & 0 & 0 & 0 & 0 \\ \hline \end{array} \longrightarrow \begin{array}{c|cccc|} & A_1 & A_2 & A_3 & A_4 \\ \hline P_1 & 1 & 1 & 0 & 0 \\ P_2 & 0 & 1 & 1 & 1 \\ \hline \end{array}$$

* *Pabico JP. 2010. Authorship patterns in computer science research in the Philippines.* ***Philippine Computing Journal*** *5(1):1-13*

Network Metrics

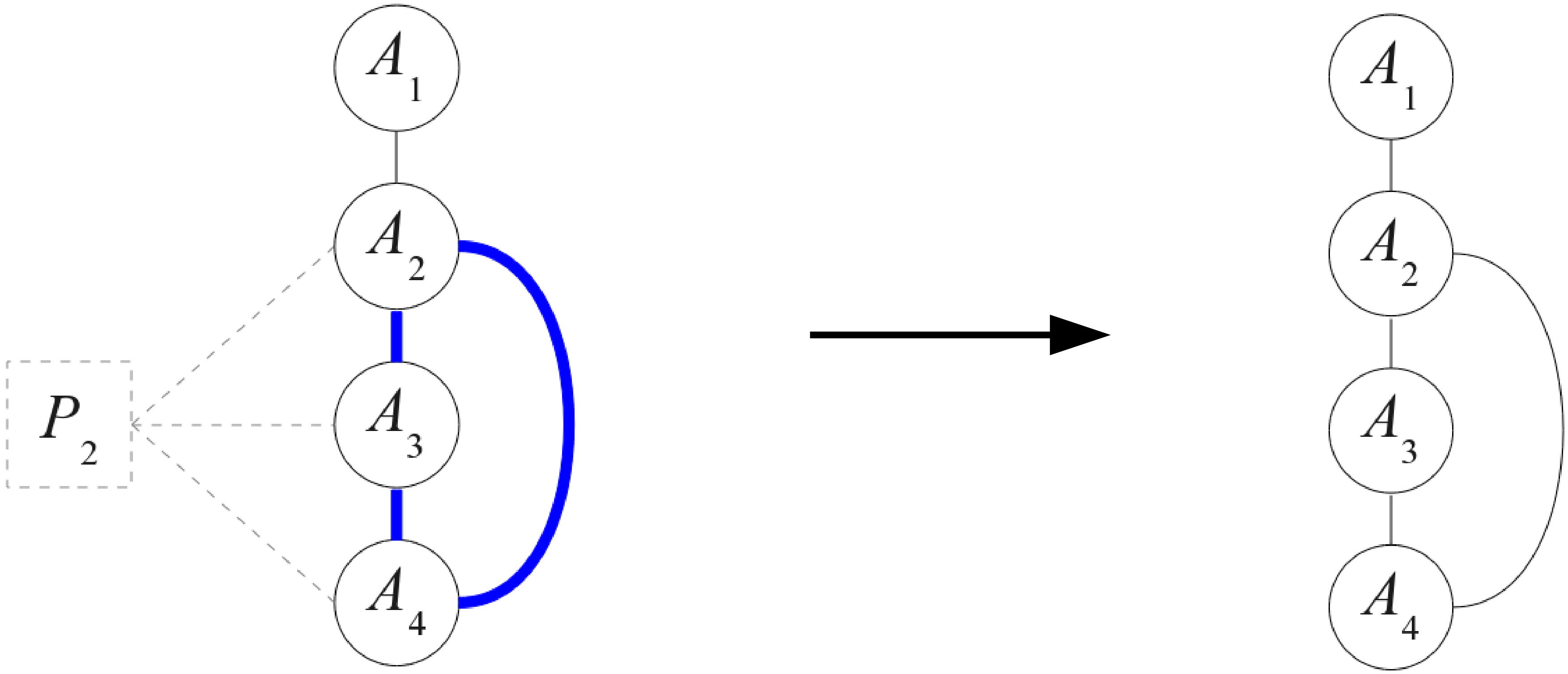
- Workshop #2: Scientific Collaboration Network
  - Idea:



* *Pabico JP. 2010. Authorship patterns in computer science research in the Philippines.* ***Philippine Computing Journal*** *5(1):1-13*

Network Metrics

- Workshop #2: Scientific Collaboration Network
  - Idea:



* *Pabico JP. 2010. Authorship patterns in computer science research in the Philippines.* ***Philippine Computing Journal*** *5(1):1-13*

Network Metrics

- Workshop #2: Scientific Collaboration Network
  - Load the dataset
  - Draw the network using various drawing techniques
  - Compute for the centralities
    - Degree
    - Closeness
    - Betweenness
  - Characterize the nodes
    - Hubs and authorities

Network Metrics

- Workshop #3: Sex Network*
  - Load the dataset Sex Network
    - Vertices: 16,730
    - Edges: 50,632
  - The data is composed of two types of nodes:
    - Male who are escort service seeker; and
    - Female who are escort service provider.
  - Modify the data so that it can be accepted by Pajek
    - Can we just use your word/text processor?

* *Rocha LEC, Liljeros F and Holme P. 2010. Information dynamics shape the sexual networks of Internet-mediated prostitution.* ***Proceedings of the National Academy of Sciences of USA*** *107(13):5706--5711.*

Network Metrics

- Workshop #3: Sex Network
  - Draw the network using various drawing techniques
  - Compute for the centralities
    - Degree
    - Closeness
    - Betweenness
  - Can we find who are the hubs and the authorities?

Network Metrics

- Workshop #4: Doctors Network*
  - 241 vertices, 1098 edges
  - Draw the network using various drawing techniques
  - Compute for the centralities
    - Degree
    - Closeness
    - Betweenness
  - Can we find who are the hubs and the authorities?

* *Coleman J, Katz E and Menzel H. 1957. The diffusion of an innovation among physicians.* ***Sociometry*** *20(4):253-270.*

Questions?

- Email to <jppabico@uplb.edu.ph> for:
  - Questions requiring detailed answers
  - Proposals for research collaboration
    - Soft computing and machine learning
    - HPC/scheduling and dynamic load balancing
    - Wireless adhoc networks
    - Computer security and forensics
    - Information visualization
- http://www.ics.uplb.edu.ph/jppabico