

# Graph Mining

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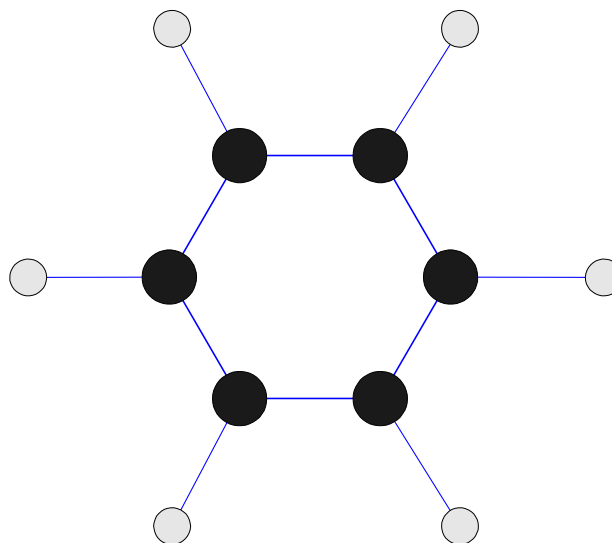
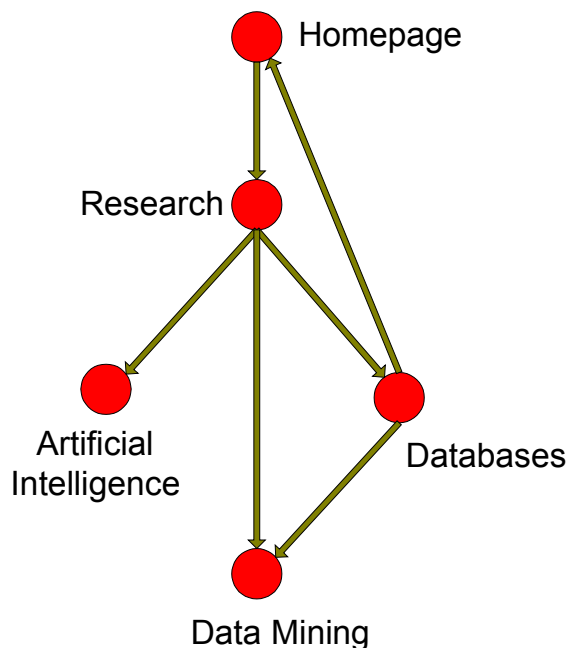
Pisa KDD Lab, ISTI-CNR & Univ. Pisa

<http://kdd.isti.cnr.it/>

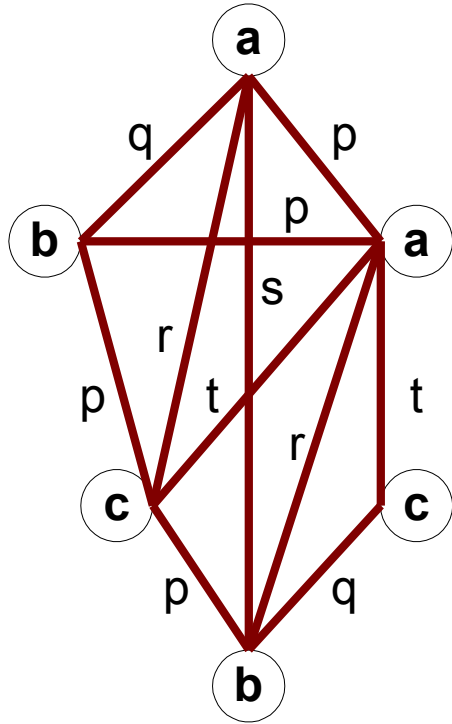
Slides from “Introduction to Data Mining” (Tan, Steinbach, Kumar)

# Frequent Subgraph Mining

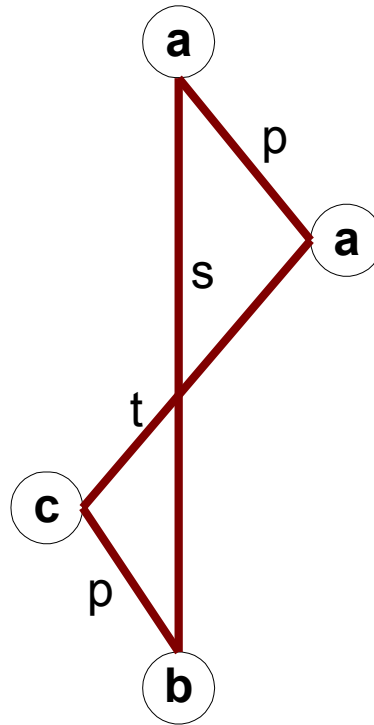
- Extend frequent itemset mining to finding frequent subgraphs
- Useful for Web Mining, computational chemistry, bioinformatics, spatial data sets, etc



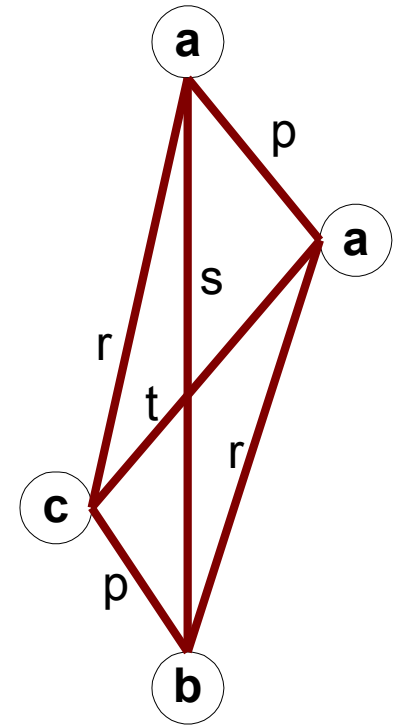
# Graph Definitions



(a) Labeled Graph

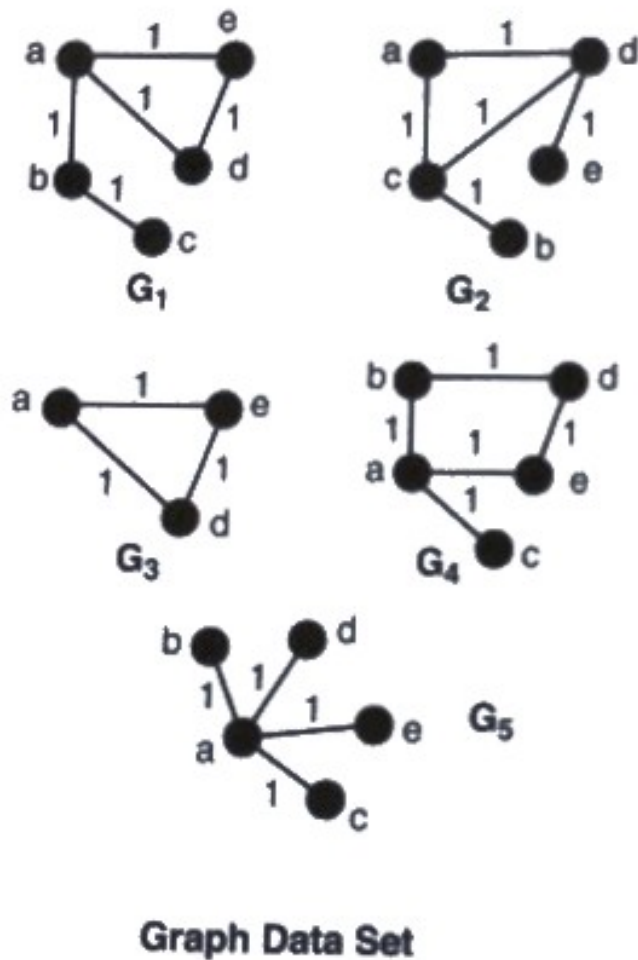


(b) Subgraph



(c) Induced Subgraph

# Examples of sub-graph containment

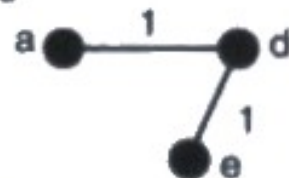


**Subgraph  $g_1$**



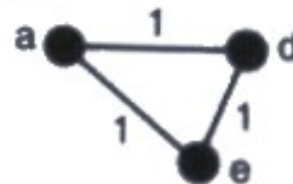
support = 80%

**Subgraph  $g_2$**



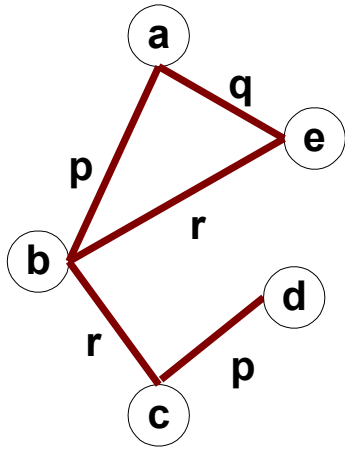
support = 60%

**Subgraph  $g_3$**

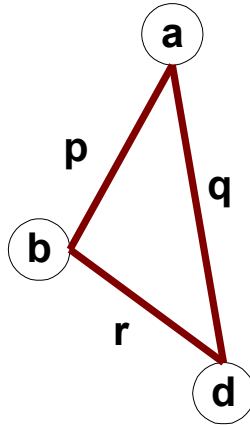


support = 40%

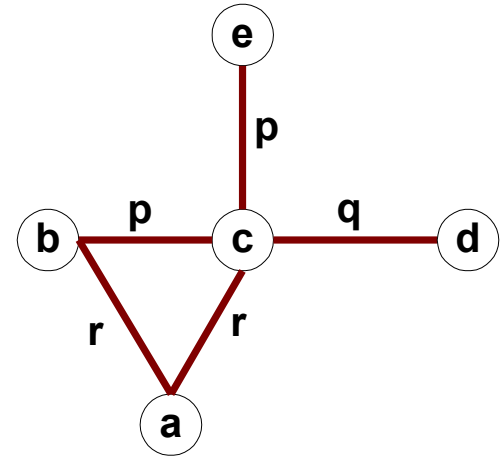
# Representing Graphs as Transactions



G1



G2

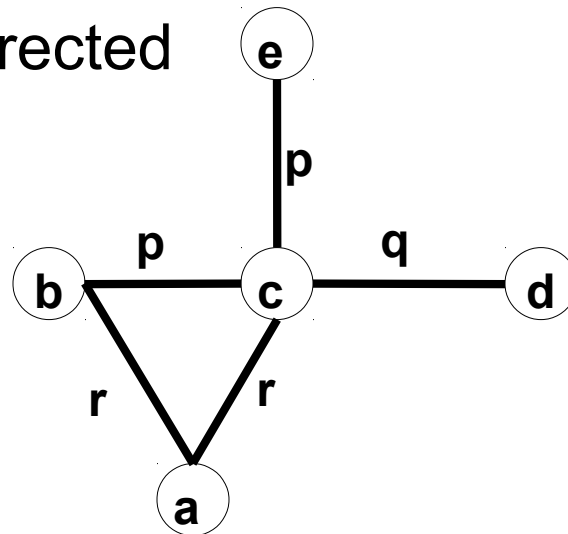


G3

	(a,b,p)	(a,b,q)	(a,b,r)	(b,c,p)	(b,c,q)	(b,c,r)	...	(d,e,r)
G1	1	0	0	0	0	1	...	0
G2	1	0	0	0	0	0	...	0
G3	0	0	1	1	0	0	...	0
G3	...	...	...	...	...	...	...	...

# Challenges

- Node may contain duplicate labels
- Support
  - How to define it?
- Assumptions
  - Frequent subgraphs must be connected
  - Edges are undirected



# Mining frequent sub-graphs

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- Support:
  - number of graphs that contain a particular subgraph
  
- Apriori principle still holds
  
- Apriori-like approach: Use frequent  $k$ -subgraphs to generate frequent  $(k+1)$  subgraphs
  - Vertex growing:  $k$  is the number of vertices
  - Edge growing:  $k$  is the number of edges

# Vertex Growing

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- Follow same strategy as Apriori:
  - Find pairs of frequent, overlapping  $k$ -graphs
  - Merge them to form a  $(k+1)$ -graph



# Edge Growing

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# Apriori-like Algorithm

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- Find frequent 1-subgraphs
- Repeat
  - Candidate generation
    - ◆ Use frequent  $(k-1)$ -subgraphs to generate candidate  $k$ -subgraph
  - Candidate pruning
    - ◆ Prune candidate subgraphs that contain infrequent  $(k-1)$ -subgraphs
  - Support counting
    - ◆ Count the support of each remaining candidate
  - Eliminate candidate  $k$ -subgraphs that are infrequent

**In practice, it is not as easy. There are many other issues**

# Example: Dataset

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# Example

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# Candidate Generation

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- In Apriori:
  - Merging two frequent  $k$ -itemsets will produce a candidate  $(k+1)$ -itemset
  
- In frequent subgraph mining (vertex/edge growing)
  - Merging two frequent  $k$ -subgraphs may produce more than one candidate  $(k+1)$ -subgraph

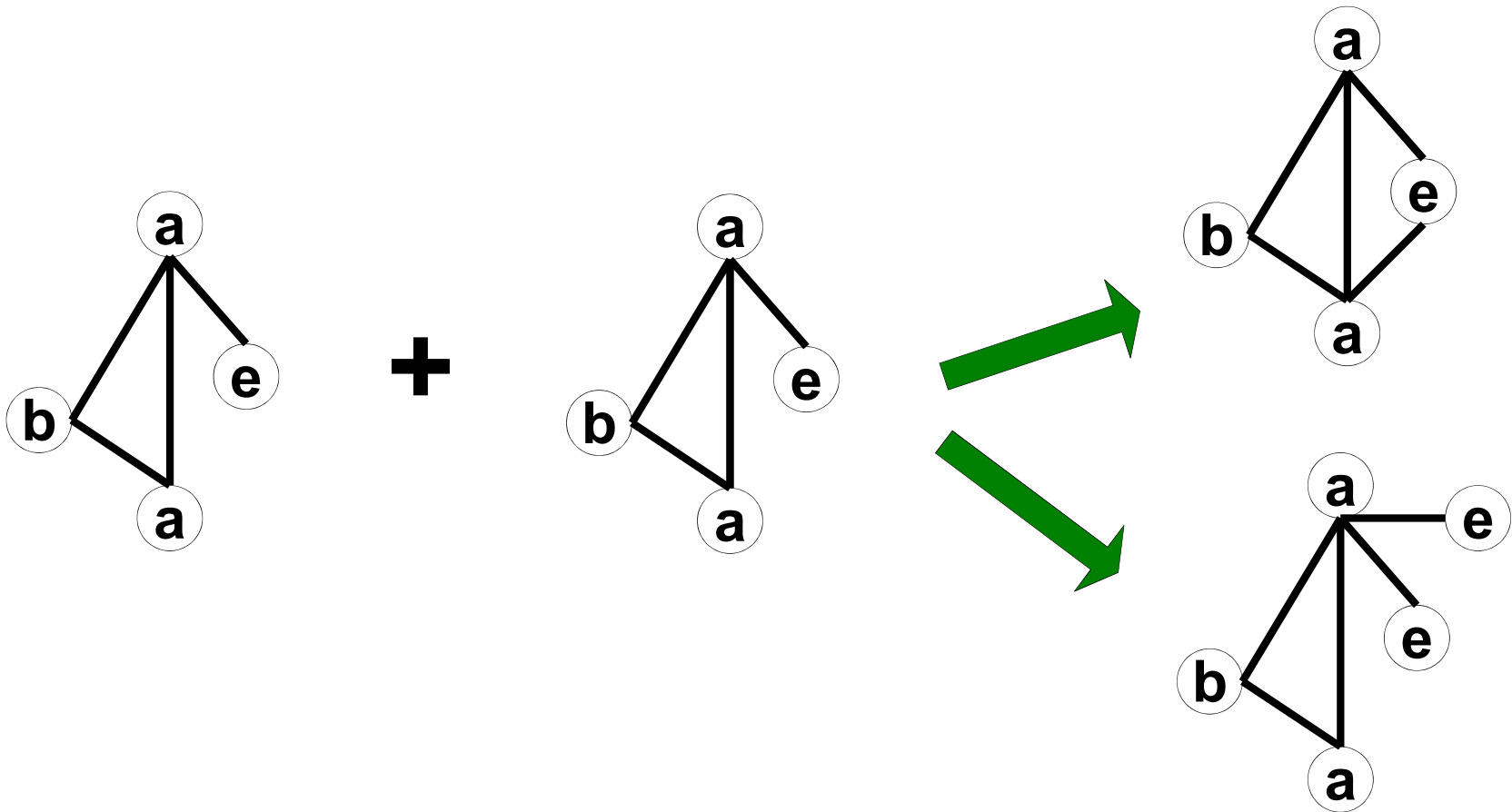
# Multiplicity of Candidates (Vertex Growing)

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# Multiplicity of Candidates (Edge growing)

- Case 1: identical vertex labels



# Multiplicity of Candidates (Edge growing)

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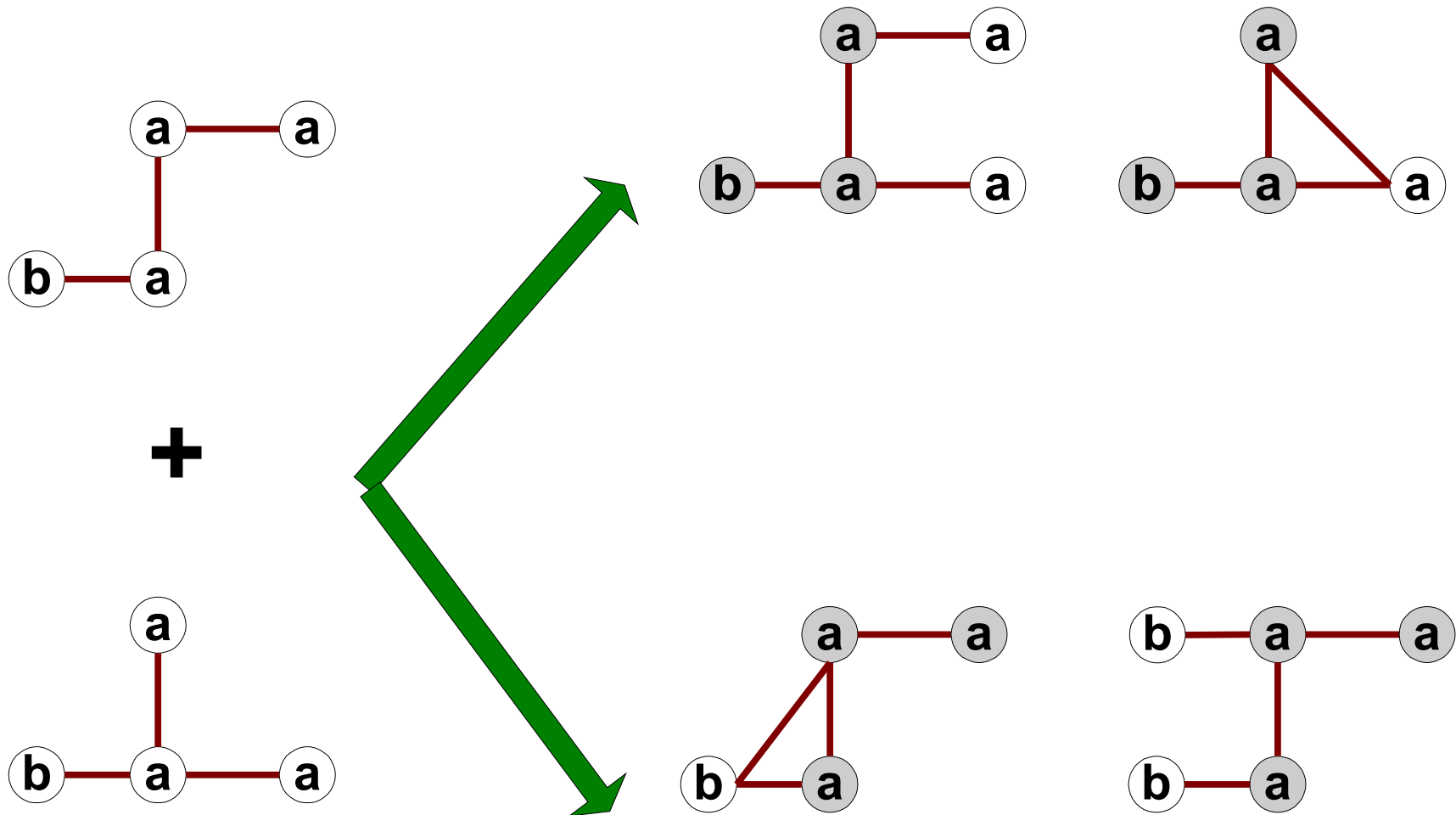
- Case 2: Core contains identical labels

**Core: The  $(k-1)$  subgraph that is common between the joint graphs**

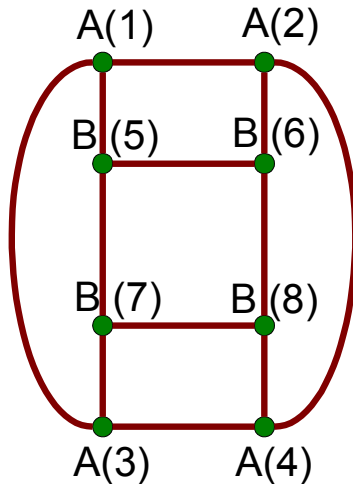


# Multiplicity of Candidates (Edge growing)

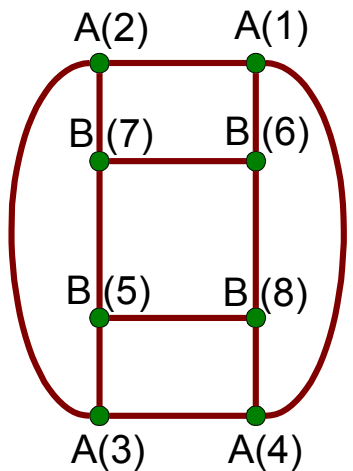
## Case 3: Core multiplicity



# Adjacency Matrix Representation



	A(1)	A(2)	A(3)	A(4)	B(5)	B(6)	B(7)	B(8)
A(1)	1	1	1	0	1	0	0	0
A(2)	1	1	0	1	0	1	0	0
A(3)	1	0	1	1	0	0	1	0
A(4)	0	1	1	1	0	0	0	1
B(5)	1	0	0	0	1	1	1	0
B(6)	0	1	0	0	1	1	0	1
B(7)	0	0	1	0	1	0	1	1
B(8)	0	0	0	1	0	1	1	1



	A(1)	A(2)	A(3)	A(4)	B(5)	B(6)	B(7)	B(8)
A(1)	1	1	1	0	1	0	0	0
A(2)	1	1	0	1	0	1	0	0
A(3)	1	0	1	1	0	0	1	0
A(4)	0	1	1	1	0	0	0	1
B(5)	1	0	0	0	1	1	1	0
B(6)	0	1	0	0	1	1	0	1
B(7)	0	0	1	0	1	0	1	1
B(8)	0	0	0	1	0	1	1	1

- The same graph can be represented in many ways

# Graph Isomorphism

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- A graph is isomorphic if it is topologically equivalent to another graph

# Graph Isomorphism

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- Test for graph isomorphism is needed:
  - During candidate generation step, to determine whether a candidate has been generated
  - During candidate pruning step, to check whether its  $(k-1)$ -subgraphs are frequent
  - During candidate counting, to check whether a candidate is contained within another graph

# Graph Isomorphism

- Use canonical labeling to handle isomorphism
  - Map each graph into an ordered string representation (known as its code) such that two isomorphic graphs will be mapped to the same canonical encoding
  - Example:
    - ◆ Lexicographically largest adjacency matrix

