

CSC 522 - Automated Learning and Data Analysis

Graph Mining

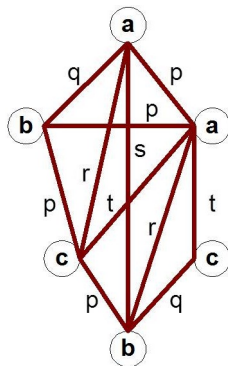
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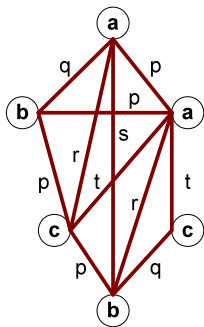
- 1 Graph Theory
 - What is a Graph
 - Some basic Concepts
- 2 Graph Mining
 - Why Mine Graphs
 - Flavors of Graph Mining
- 3 Frequent Subgraph Mining
 - Introduction
 - Challenges
 - Apriori Based Approach
 - Issues

Graphs - Brief Introduction

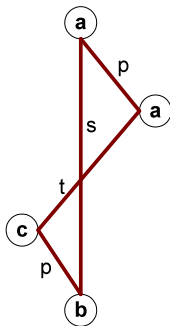
- A graph is an ordered pair $G = (V, E)$ comprising a set V of vertices or nodes together with a set E of edges or lines that connect the vertices.
- The size of a graph is the number of vertices $= |V|$



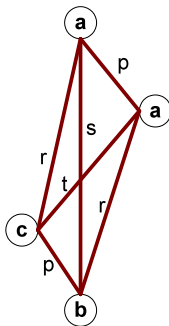
Graph Definitions



(a) Labeled Graph



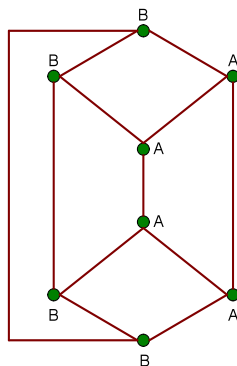
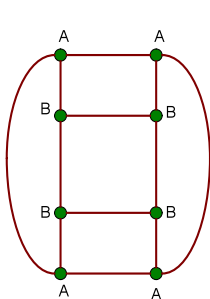
(b) Subgraph

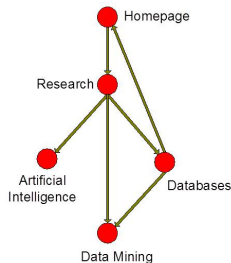
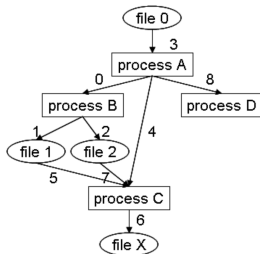
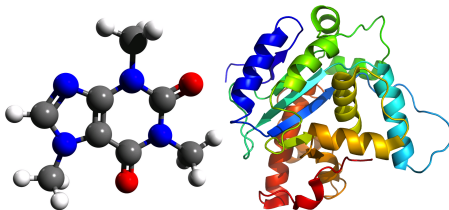


(c) Induced Subgraph

Graph Isomorphism

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





PS. You may be interested in this paper:

The NFL Coaching Network: Analysis of the Social Network Among Professional Football Coaches, Fast and David Jensen, AAAI 2006

http://sports.espn.go.com/nfl/columns/story?columnist=wickersham_seth&id=4781314

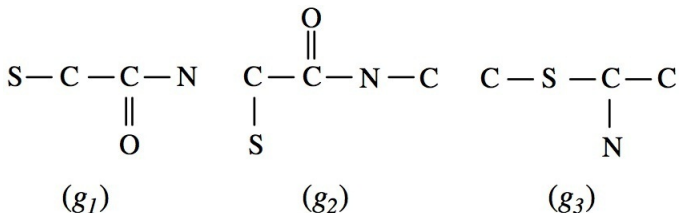
So, what can we do with these graphs?

- Mining Frequent Subgraphs
- Graph Classification
- Graph Clustering

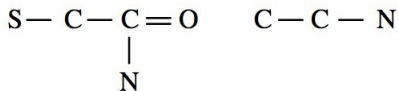
Frequent Subgraph Mining

- A (sub)graph is frequent if its support (occurrence frequency) in a given dataset is no less than a minimum support threshold
- Applications
 - 1 Mining biomolecular/ Chemical structures - to identify the most common cores in active compounds
 - 2 Program control flow analysis
 - 3 Mining XML structures or Web communities
 - 4 Building blocks for graph classification, clustering, compression, comparison, and correlation analysis

Example



Sample graph dataset.



Frequency:2

Frequency:3

Source: Mining Graph Data, Diane Cook and Larry Holder, Wiley, 2007.

What are the Challenges?

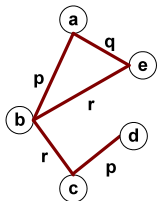
What are the Challenges?

- How do we represent the graphs?
- How do we generate candidates of size $(k + 1)$ given a structure of size k ?
- What is support and how do we count support?
- Assumption: frequent subgraphs must be connected
- Oh wait! aren't most of these computationally complex?

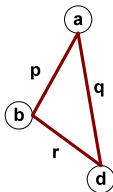
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- Oh wait! aren't most of these computationally complex? An n -edge frequent graph may have 2^n subgraphs!

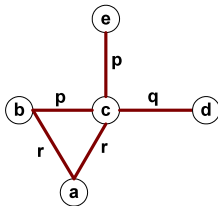
Representing Graphs as Transactions



G1



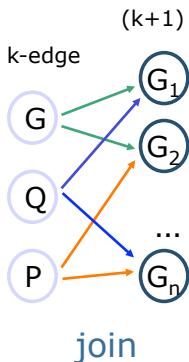
G2



G3

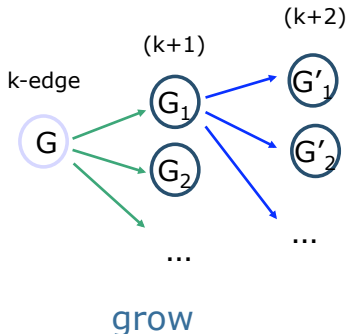
	(a,b,p)	(a,b,q)	(a,b,r)	(b,c,p)	(b,c,q)	(b,c,r)	...	(d,e,r)
G1	1	0	0	0	0	1	...	0
G2	1	0	0	0	0	0	...	0
G3	0	0	1	1	0	0	...	0
G3

Generation of Candidate Patterns



Apriori-Based Approach

VS.



Pattern-Growth Approach

Apriori Based Approach

- Apriori-like approach: Use frequent k -subgraphs to generate frequent $(k+1)$ subgraphs
- That's fine... but does Apriori Principle hold?

Apriori Based Approach

- Apriori-like approach: Use frequent k -subgraphs to generate frequent $(k+1)$ subgraphs
- That's fine... but does Apriori Principle hold? YES !!!!!!!!!!!!!!!!!!!!!
If a graph is frequent, all of its subgraphs are frequent
- Support: number of graphs that contain a particular subgraph

Apriori-like Algorithm

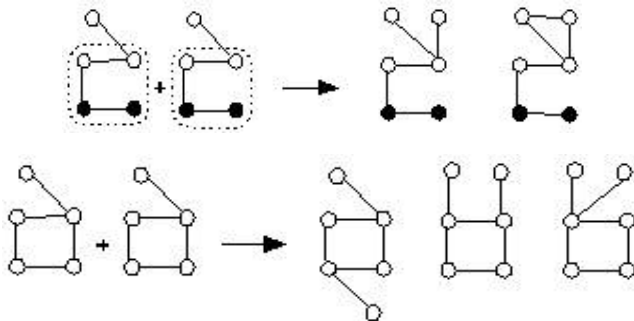
- Find frequent 1-subgraphs
- Repeat
 - Candidate generation
 - ◆ Use frequent $(k-1)$ -subgraphs to generate candidate k -subgraph
 - Candidate pruning
 - ◆ Prune candidate subgraphs that contain infrequent $(k-1)$ -subgraphs
 - Support counting
 - ◆ Count the support of each remaining candidate
 -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

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

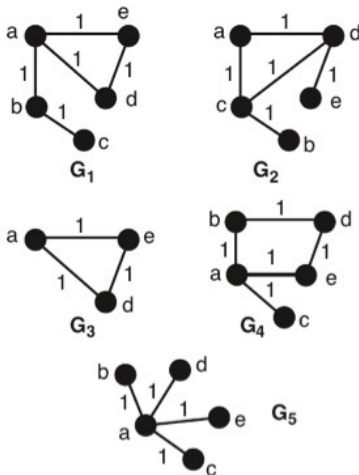
Candidate Generation

There are 2 ways to generate a candidate k -graph from two given $k - 1$ -subgraphs.

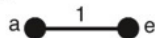
- ① Vertex Growing: Iteratively expanding the graph by adding one vertex at a time
- ② Edge Growing: Iteratively expanding the graph by adding one edge at a time



Support Counting



Graph Data Set

Subgraph g_1 

support = 80%

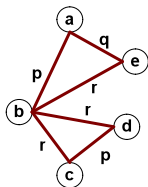
Subgraph g_2 

support = 60%

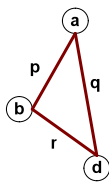
Subgraph g_3 

support = 40%

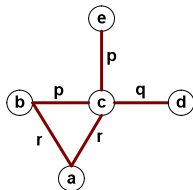
Example: Dataset



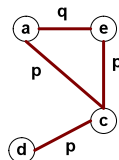
G1



G2

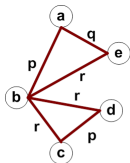


G3

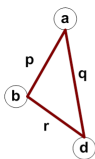


G4

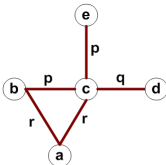
	(a,b,p)	(a,b,q)	(a,b,r)	(b,c,p)	(b,c,q)	(b,c,r)	...	(d,e,r)
G1	1	0	0	0	0	1	...	0
G2	1	0	0	0	0	0	...	0
G3	0	0	1	1	0	0	...	0
G4	0	0	0	0	0	0	...	0



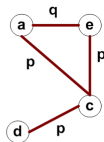
G1



G2



G3



G4

Minimum support count = 2

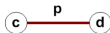
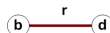
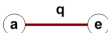
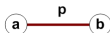
k=1

Frequent
Subgraphs



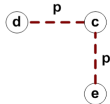
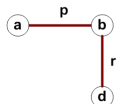
k=2

Frequent
Subgraphs



k=3

Candidate
Subgraphs



(Pruned candidate)

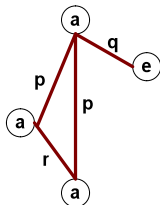
Issues

Apriori-based algorithms have two kinds of considerable overheads:

- ① Joining two size- k frequent graphs to generate size- $(k + 1)$ graph candidates - This produces an exponential number of candidates.
- ② Checking the frequency of these candidates separately - Some graphs are isomorphic

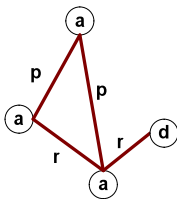
These overheads constitute the performance bottleneck of Apriori-based algorithms.

Multiplicity of Candidates (Vertex Growing)

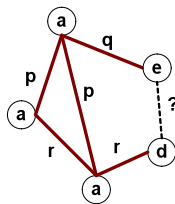


G1

+



G2



G3 = join(G1, G2)

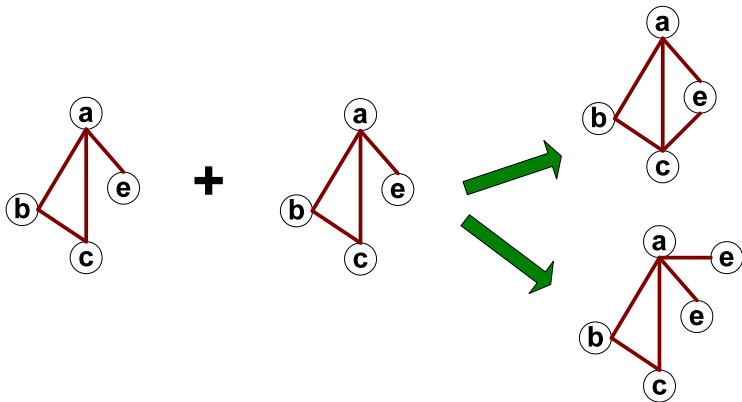
$$M_{G_1} = \begin{pmatrix} 0 & p & p & q \\ p & 0 & r & 0 \\ p & r & 0 & 0 \\ q & 0 & 0 & 0 \end{pmatrix}$$

$$M_{G_2} = \begin{pmatrix} 0 & p & p & 0 \\ p & 0 & r & 0 \\ p & r & 0 & r \\ 0 & 0 & r & 0 \end{pmatrix}$$

$$M_{G_3} = \begin{pmatrix} 0 & p & p & 0 & q \\ p & 0 & r & 0 & 0 \\ p & r & 0 & r & 0 \\ 0 & 0 & r & 0 & ? \\ q & 0 & 0 & ? & 0 \end{pmatrix}$$

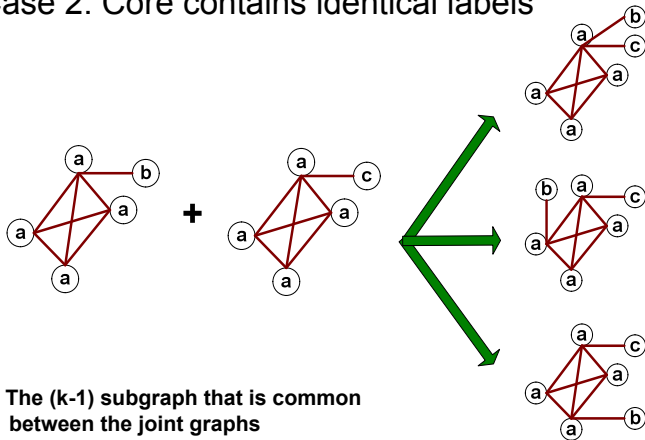
Multiplicity of Candidates (Edge growing)

- Case 1: identical vertex labels



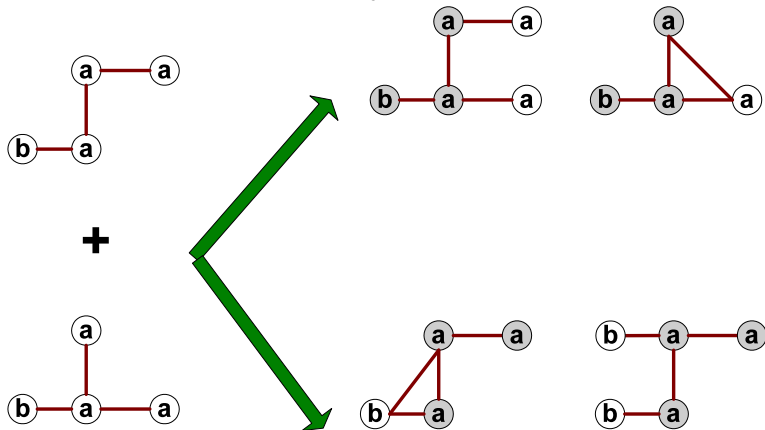
Multiplicity of Candidates (Edge growing)

- Case 2: Core contains identical labels



Multiplicity of Candidates (Edge growing)

- Case 3: Core multiplicity



Graph Isomorphism

- 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

