CS423: Data Mining Introduction to Graph Mining

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- Motivation
- Graph Theory Refresher
- Apriori-based Frequent Subgraph Mining Algorithm

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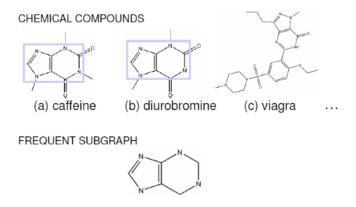
- Graph is a useful modelling tool for representing entities and their relationships.
- Example
 - Internet
 - ★ Vertices: computers, smartphones, routers
 - ★ Edges: communication links
 - Social Network:
 - ★ Vertices: users
 - ★ Edges: friendship
 - Chemical molecule:
 - ★ Vertices: atoms
 - ★ Edges: chemical bonds

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- What are the characteristics of these graphs?
- Are there any interesting patterns in these graphs?
- How to differentiate abnormal social network from a normal one?
- How do these graph evolve over time?
- And so on ...

Patterns mining from graph

• In this class, we will learn about frequent subgraph mining



K. Borgwardt and X. Yan (KDD'08)

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- Program control flow analysis
 - Detection of malware/virus
- Network intrusion detection
- Anomaly detection
- Graph compression

Graph theory refresher

• A graph G(V, E) is a structure which comprised of two set

- V is a set of vertices
- E is a set of edges
- A labelled graph $G(V, E, L_V, L_E)$ is a graph where vertices and edges have names.
 - L_V is a set of vertex labels
 - L_E is a set of edge labels
- Labels need not be unique
 - ► For example, labels may represent chemical elements

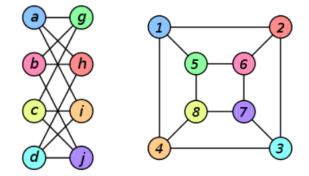
- A graph is said to be **connected** if there is path between every pair of vertices
- A graph $G_s(V_s,E_s)$ is a **subgraph** of another graph G(V,E) iff

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$$V_s \subseteq V$$
 and $E_s \subseteq E$

- Two graphs $G_1(V_1, E_1)$ and $G_2(V_2, E_2)$ are **isomorphic** if they are topologically identical
 - one can be transformed into the other simply by renaming vertices

Graph Isomophism

• The transformation is f(a) = 1, f(b) = 6, f(c) = 8, f(d) = 3, ...,



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- Given two graphs $G_1(V_1, E_1)$ and $G_2(V_2, E_2)$: find an isomorphism between G_2 and a subgraph of G_1
- NP-complete problem

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Given

- D: a set of undirected, labelled graphs
- σ : support threshold, $0 < \sigma \leq 1$

Goal:

 \blacktriangleright Find all connected, undirected graphs that are sub-graphs in at least $\sigma |D|$ of input graphs

- Apriori-based approach (in this class)
- Pattern-growth approach

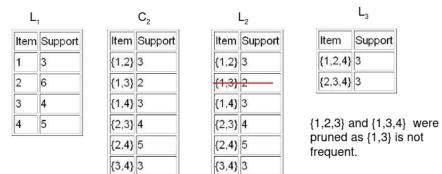
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 $C_k = {\sf candidate \ itemset \ of \ size \ } k$, $L_k = {\sf frequent \ itemset \ of \ size \ } k$

- 1 Find frequent set L_{k-1}
- 2 Joining step
 - C_k is generated from joining member in L_{k-1}
- 3 Pruning step
 - ▶ k-itemset which one of its (k 1)-item(sub)set is not frequent cannot be frequent, and should be removed
- 4 Repeat until C_k is empty.

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Set of transactions : { {1,2,3,4}, {2,3,4}, {2,3}, {1,2,4}, {1,2,3,4}, {2,4} } min_support: 3



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FSG: Frequent Subgraph Mining Algorithm

Proposed by Kumarochi & Karypis in 2001 and revised in 2004
Notation: k-subgraph is a subgraph with k edges.

Init: Scan the transactions to find L_1 and L_2 , the set of all frequent 1-subgraphs and 2-subgraphs, together with their counts;

For(k=3; $L_{k-1} \neq \emptyset$, k++)

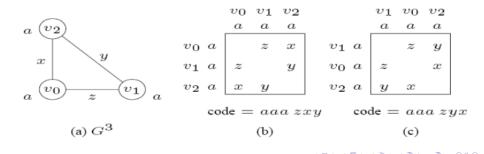
- 1 Candidates generation: C_k from the set of frequent k-1-subgraphs
- 2 **Candidates pruning**: Requires that each of k 1-subgraphs of the candidate is also frequent
- 3 Frequency counting: Scan the database to count the occurrences of $c \in C_k$
- 4 $L_k = \{c \in C_k | c \text{ has counts no less than } \sigma \}$
- 5 Return $L_1 \cup L_2 \cup L_3 \cup \ldots L_k$

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- Follows apriori algorithm by joining two frequent k-subgraph that has common (k-1)-subgraph
 - ▶ Need to check if (*k*-1)-subgraphs are isomorphic (time consuming)
- To avoid that FSG uses canonical labelling to encode graph structure into string.
 - Comparing two subgraphs is just string comparison

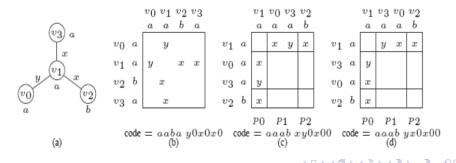
Canonical label of graph

- Lexicographically largest (or smallest) string obtained by concatenating upper triangular entries of adjacency matrix in column-wise manner (after symmetric permutation).
- Uniquely identifies a graph and its isomorphs
 - Two isomorphic graphs will get same canonical label



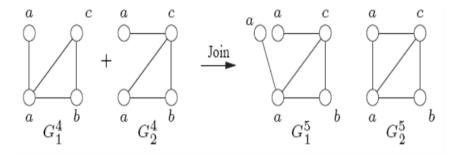
Canonical label of graph

- Canonical labelling is also difficult problem. There are |V|! permutations to try.
- FSG uses inherent properties of vertices that don't change across isomorphic mappings to reduce the size of canonical label set.
 - It groups vertices by degree and label and only permute within the groups.

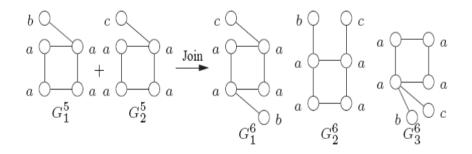


FSG: subgraph joining

• Two k-subgraphs which have (k-1)-subgraph are combined to form (k+1)-subgraph



FSG: subgraph joining [2]

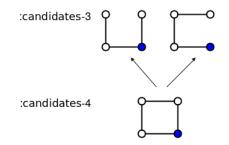


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FSG: Candidate pruning

- Every (k-1)-subgraph must be frequent (downward closure property)
- For all the (k-1)-subgraphs of a given k-candidate, check if downward closure property holds
- FSG also uses canonical labels to remove duplicate candidates



- Subgraph isomorphism check for each candidate against each graph transaction in database
 - naive and so computationally expensive
- FSG uses transaction identifier (TID) lists
 - For each frequent subgraph, keep a list of TID that support it
- To compute frequency for G^{k+1}
 - Find intersection of TID lists of its subgraphs
 - If size of intersection < minsup: prune G^{k+1}
 - Else: Subgraph isomorphism check only for graphs in the intersection

FSG: Frequency counting

 $\begin{tabular}{|c|c|c|c|} \hline Transactions \\ \hline g^{k\cdot 1_1}, g^{k\cdot 1_2} \subset T1 \\ \hline g^{k\cdot 1_1} & \subset T2 \\ \hline g^{k\cdot 1_1}, g^{k\cdot 1_2} \subset T3 \\ \hline g^{k\cdot 1_2} \subset T6 \\ \hline g^{k\cdot 1_1} & \subset T8 \\ \hline g^{k\cdot 1_1}, g^{k\cdot 1_2} \subset T9 \\ \hline \end{tabular}$

$$\label{eq:Frequent subgraphs} \begin{split} & \underline{\mathsf{Frequent subgraphs}} \\ & \mathsf{TID}(\mathsf{g}^{k\cdot 1}_1) = \{ \ 1, \ 2, \ 3, \ 8, \ 9 \ \} \\ & \mathsf{TID}(\mathsf{g}^{k\cdot 1}_2) = \{ \ 1, \ 3, \ 6, \ 9 \ \} \end{split}$$

$$\label{eq:candidate} \begin{split} & \underline{Candidate} \\ c^k = join(g^{k\cdot 1}_1, \ g^{k\cdot 1}_2) \\ & \text{TID}(c^k) \subset \text{TID}(g^{k\cdot 1}_1) \ \cap \ \text{TID}(g^{k\cdot 1}_2) \\ & \downarrow \\ & \text{TID}(c^k) \subset \{ \ 1, \ 3, \ 9 \} \end{split}$$

- Perform subgraph-iso to T1, T3 and T9 with c^k and determine $\mathsf{TID}(c^k)$
- Note, TID lists require a lot of memory.

- Introduction to Graph Mining by Sangameshwar Patil. Systems Research Lab. TRDDC, TCS, Pune. http://www.iiserpune.ac. in/~pgoel/Sangam-Intro2GraphMining.ppt
- Graph Mining by Ehud Gudes. https://www.cs.bgu.ac.il/ ~orlovn/presentations/graph_mining_seminar_2009.ppt