Efficient Aggregation for Graph Summarization

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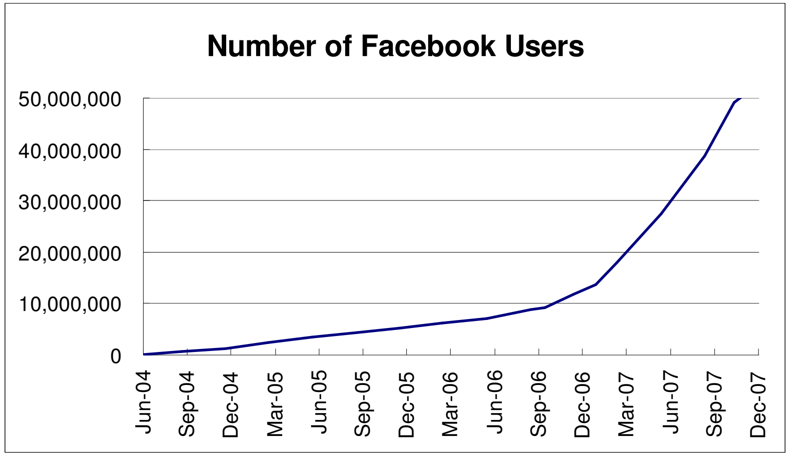
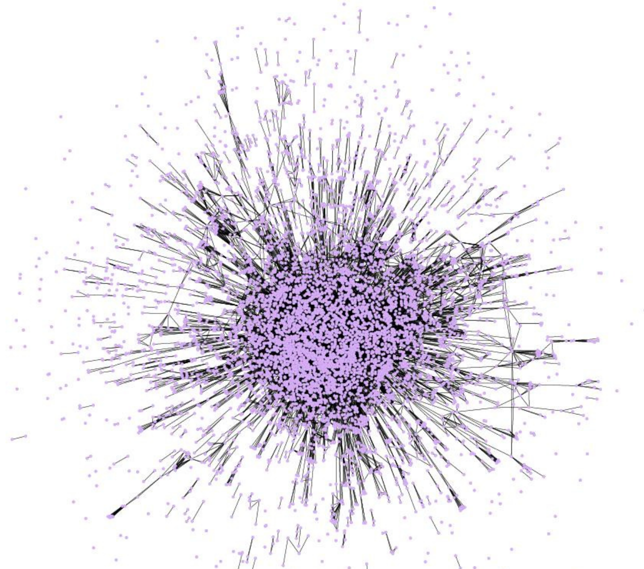
Motivation

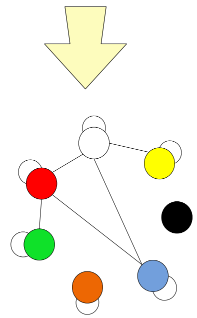
- Graphs are everywhere
  - Social networks, biological networks
- Graph datasets growing rapidly in size.





DB Coauthorship

7,445 nodes, 19,971 edges



- Impossible to understand by mere visual inspection.
- Need: Graph Summarization

Existing Methods

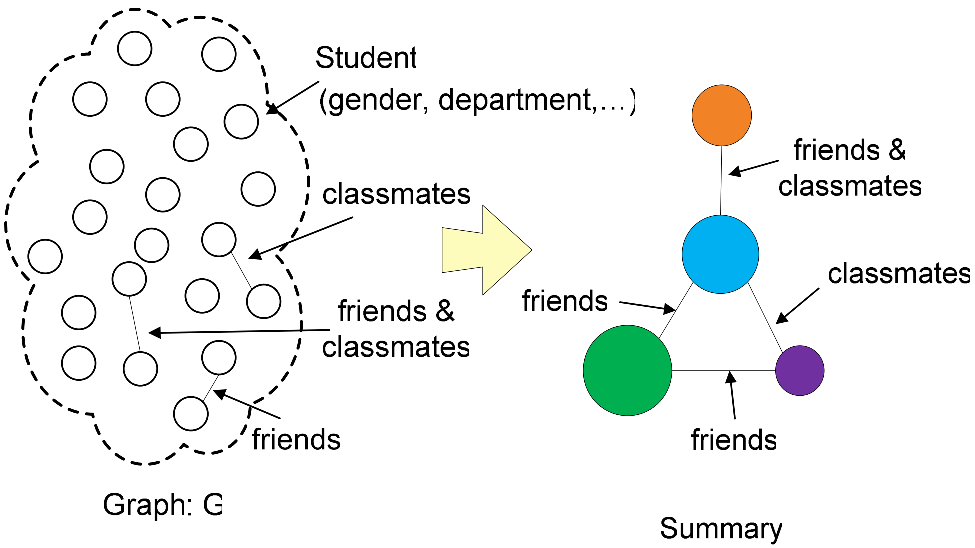
- Statistical methods
  - Limited information, hard to interpret & manipulate.
- Frequent subgraph mining methods
  - Produce a large number of results.
- Graph partitioning methods
  - Largely ignore node attributes.
- Graph compression
  - Compact storage.
- Graph visualization
  - Ben’s keynote talk.
- MDL-based graph summarization (Nisheeth’s talk)

Solution: **Graph Aggregation**

- Two well-defined novel graph aggregation operations: SNAP & k-SNAP
  - Summarization based on user-selected node attributes and relationships.
  - Produce summaries with controllable resolutions.
  - Provide “drill-down” and “roll-up” abilities to navigate multi-resolution summaries.
- Efficient algorithms
  - Produce meaningful summaries for real applications.
  - Efficient and scalable for very large graphs.

SNAP Operation

- Group nodes by user-selected node attributes & relationships
- Nodes in each group are homogenous w.r.t. attributes and relationships
- The grouping with the minimum # groups



For example:

- All students in the blue group have the same gender and are in the same dept
- Every student in the blue group has:
  - at least one "friend" in the green group
  - at least one "classmate" in the purple group
  - at least one "friend" in the orange group
  - at least one "classmate" in the orange group

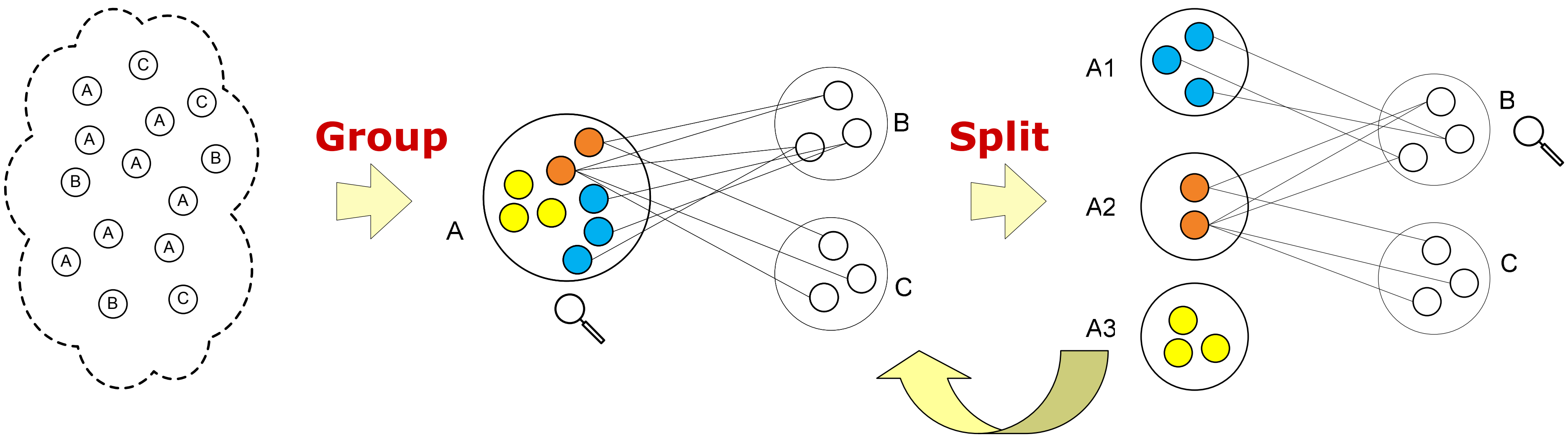
Evaluating SNAP Operation

Top-Down Approach

- **Step 1:** group nodes just based on user-selected attributes.
- **Iterative Step:**

  while a group breaks homogeneity requirement for relationships

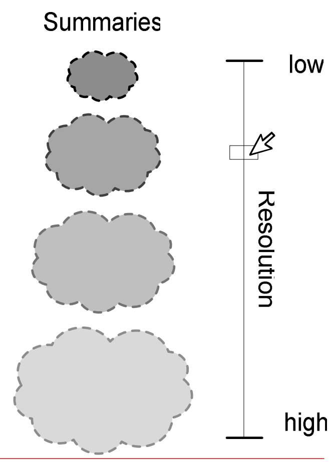
  split the group based on its relationships with other groups



Limitations of SNAP Operation

- Problems with the SNAP operation
  - Homogeneity requirement for relationships
    - Noise and uncertainty

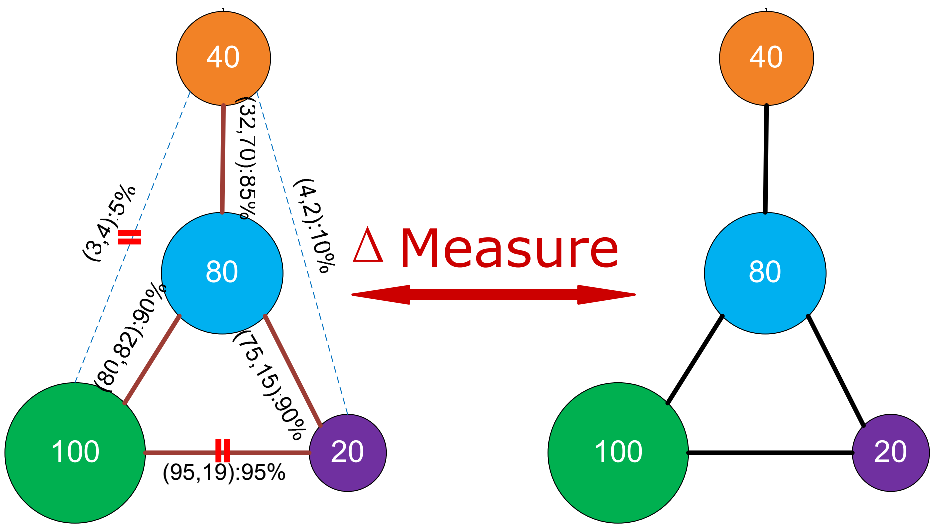
  - Users have no control over the resolutions of summaries
    - SNAP operation can result in a large number of small groups



- **k-SNAP** operation:
  - Relax the homogeneity requirement for relationships
  - Let users control the resolutions of summaries
  - Provide “drill-down” and “roll-up” abilities to navigate summaries with different resolutions.

k-SNAP Operation

- Users control # groups in the resulting summary: k
  - Maintain homogeneity requirement for attributes.
  - Relax homogeneity requirement for relationships.
- Assess the quality of a summary



$$\Delta = \sum_{g_i, g_j} \{ \delta_{g_i, g_j}(g_i) + \delta_{g_i, g_j}(g_j) \}$$

$$\delta_{g_i, g_j}(g_i) = \begin{cases} |P_{g_i, g_j}(g_i)| & \text{if } p_{i,j} \leq 0.5 \\ |g_i| - |P_{g_i, g_j}(g_i)| & \text{otherwise} \end{cases}$$

$\Delta = 0$

➢5% ≤ 50% (weak)

Δ += 3+4 ← extra participants

➢95% > 50% (strong)

Δ += (100-95)+(20-19) ← missing participants

……

Evaluating k-SNAP Operation

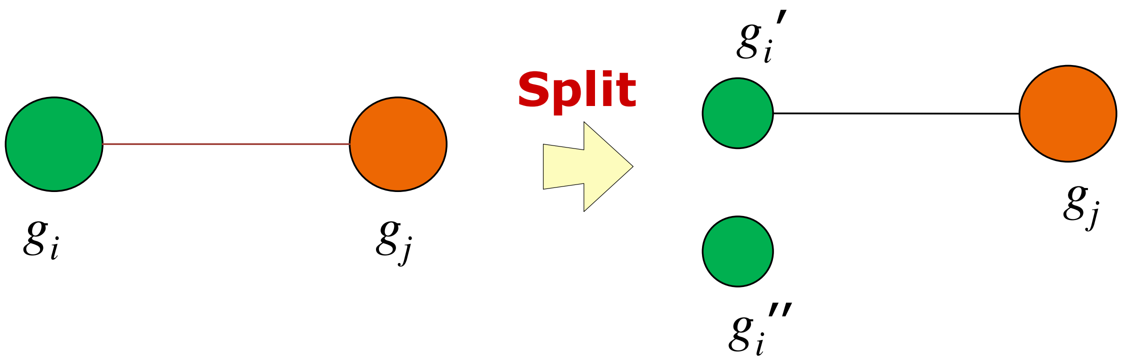
- **Goal:** Find the summary of size k with the minimum Δ value (best quality)
  - Proved to be **NP-Complete!**
    - Infeasible to produce exact k-SNAP summaries.
  - Alternative: **heuristics**
    - Top-Down Approach
    - Bottom-Up Approach

Top-Down Approach

- Similar to the SNAP evaluation algorithm (coarse → fine)
- (Difference) At each iteration, it needs to decide:
  - which group to split?
  - how to split the group?
- Heuristics:
  - Split a group into two subgroups at each iteration
  - Find g_i with the maximum $\delta_{g_i, g_j}(g_i)$ (the most contribution to Δ)
  - Split group g_i based on whether the nodes in g_i connect to g_j.

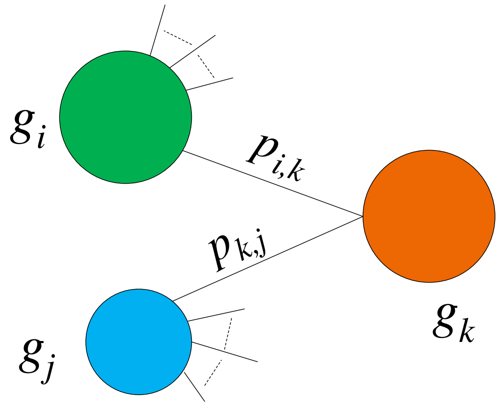
max

$$\Delta = \sum_{g_i, g_j} \{ \boxed{\delta_{g_i, g_j}(g_i)} + \delta_{g_i, g_j}(g_j) \}$$



Bottom-Up Approach

- Compute the SNAP summary first (fine → coarse)
- Iteratively merge two groups until the # groups is k
  - Which two groups to merge?
  - Heuristics:
    - Same attribute values
    - Similar neighbors
    - Similar participation ratio



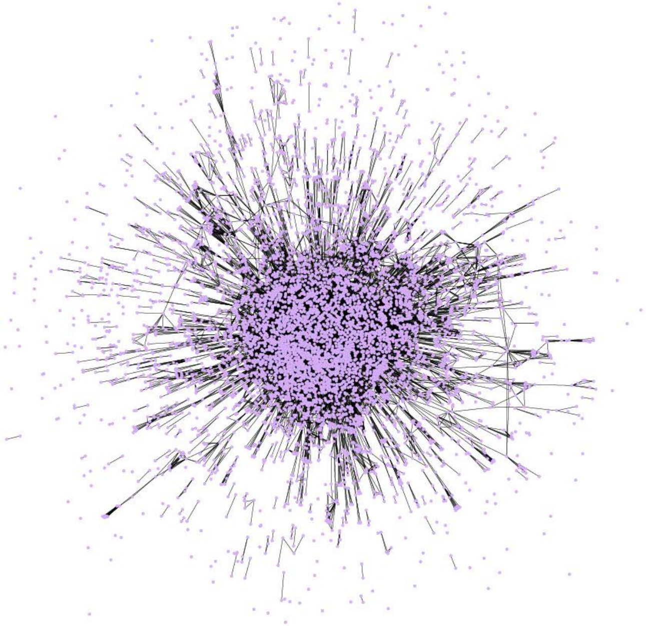
$$MergeDist(g_i, g_j) = \sum_{k \neq i,j} | p_{i,k} - p_{k,j} |$$

Merge two groups with the minimum *MergeDist*.

Experimental Evaluation

- Implementation
  - C++ on top of PostgreSQL
- Evaluation Platform
  - 2.8GHz P4, 2GB RAM, 250GB SATA disk, FC2
  - PostgreSQL: version 8.1.3, 512 MB buffer pool
- Evaluation Measures:
  - Effectiveness & Efficiency
  - Verified by the SIGMOD repeatability committee.

Effectiveness: DB Coauthorship



DBLP Database Coauthorship Graph

(7,445 nodes, 19,971 edges)

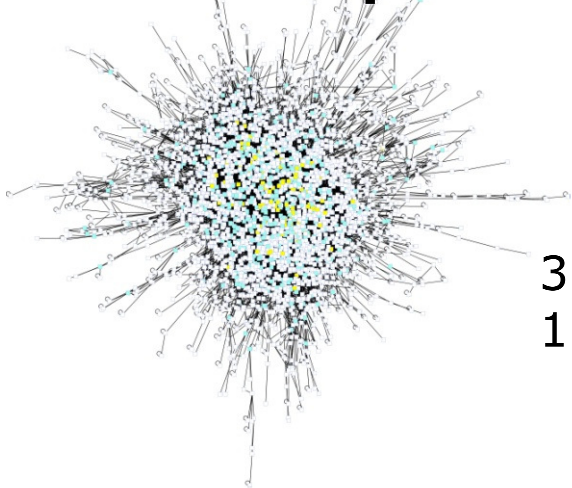
Node Attributes:

name (string), numPub (int), prolific (LP, P, HP)

LP:[1, 5], P:[6, 20], HP:[21, -]

Relationship: coauthorship

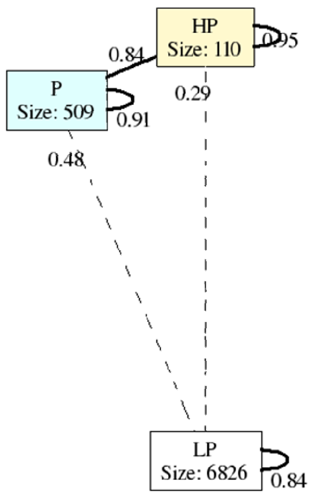
SNAP
Attribute: prolific
Relationship: coauthorship



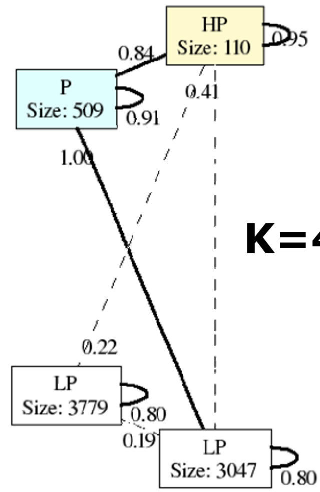
3,569 groups,
11,293 group relationships

Effectiveness: DB Coauthorship

SNAP
Attribute: prolific

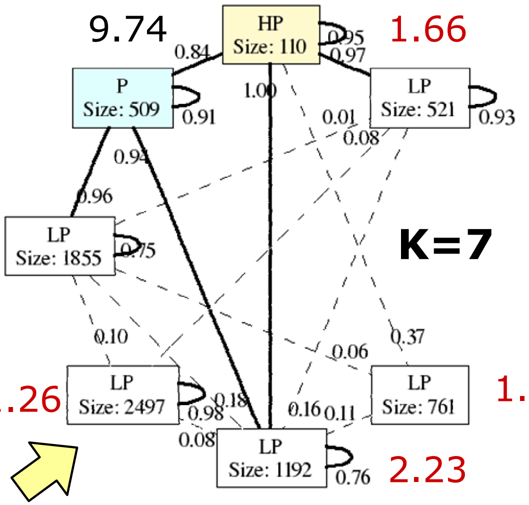


k-SNAP
Attribute: prolific
Relationship: coauthorship

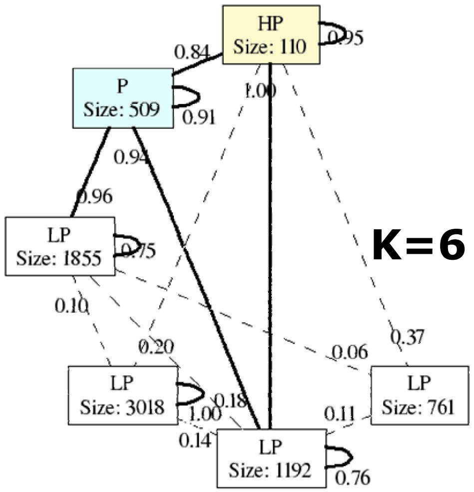


K=4

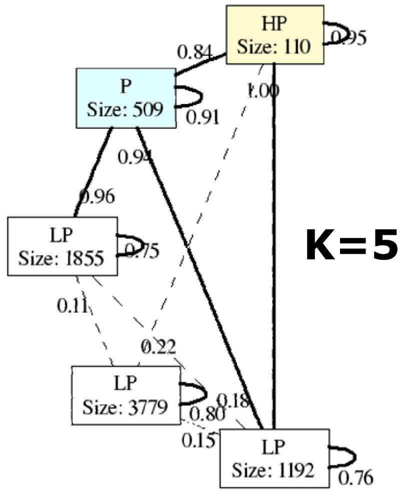
36
9.74
1.66
1.55
1.26
1.23
2.23



K=7



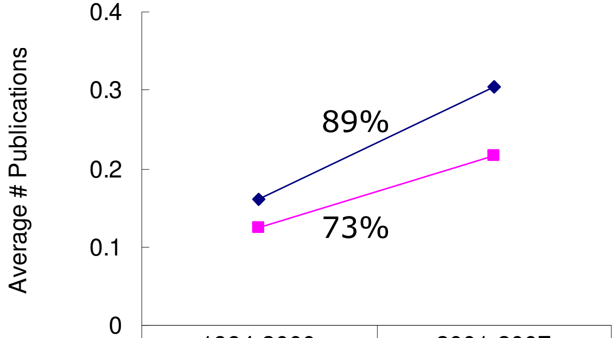
K=6



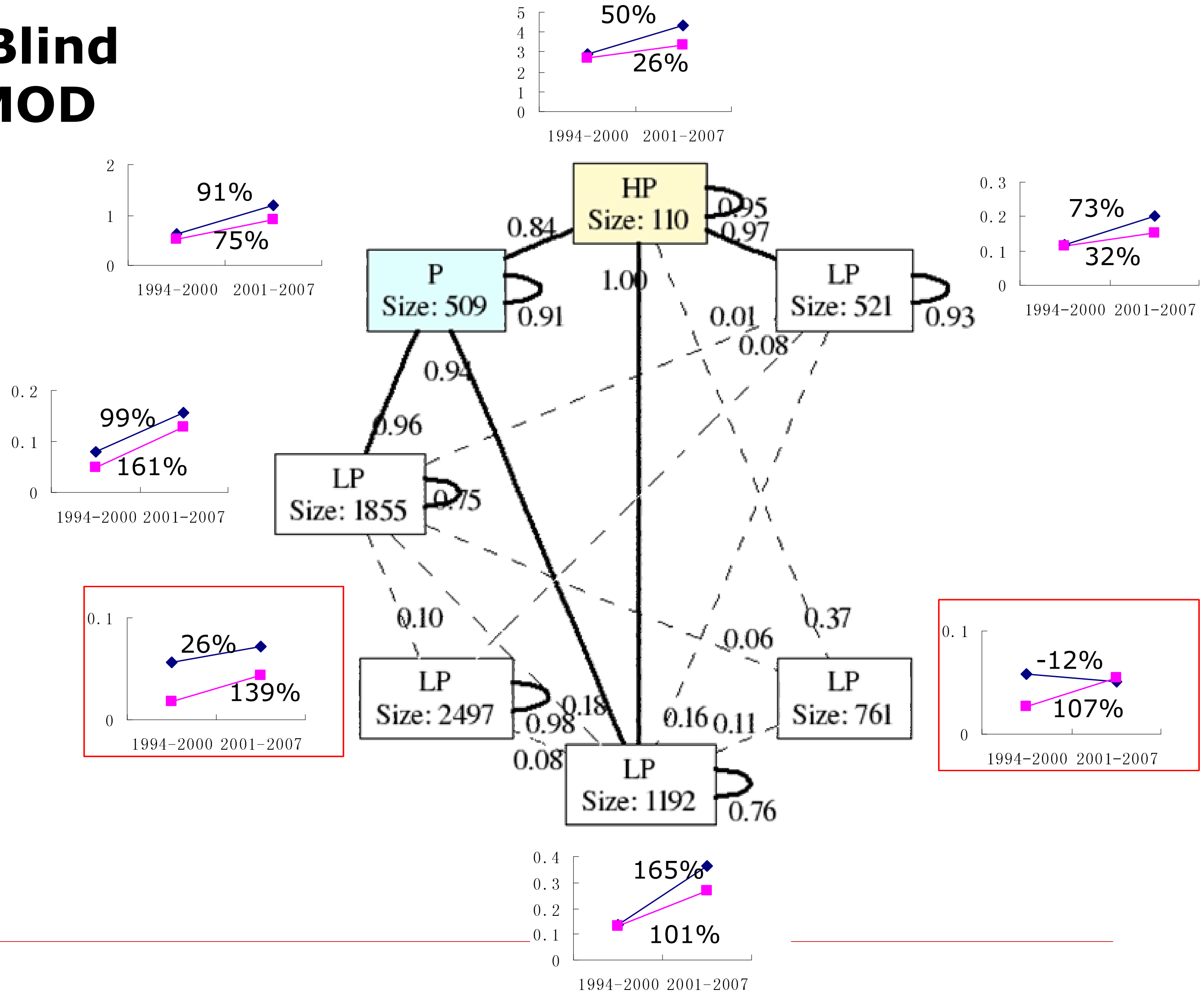
K=5

Effectiveness: DB Coauthorship

Impact of Double-Blind Reviewing on SIGMOD



	1994-2000	2001-2007
VLDB	0.161	0.305
SIGMOD	0.125	0.217

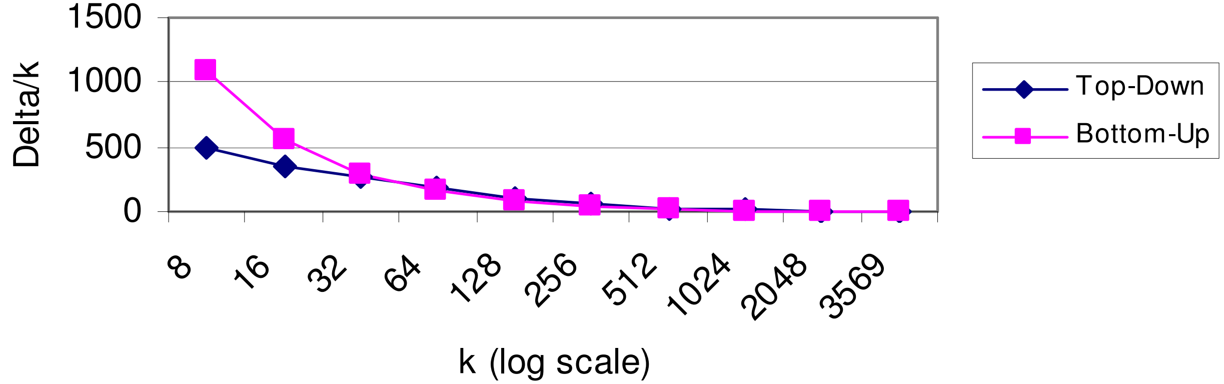


k-SNAP: Top-Down vs. Bottom-Up

Dataset: DBLP DB Coauthorship Graph

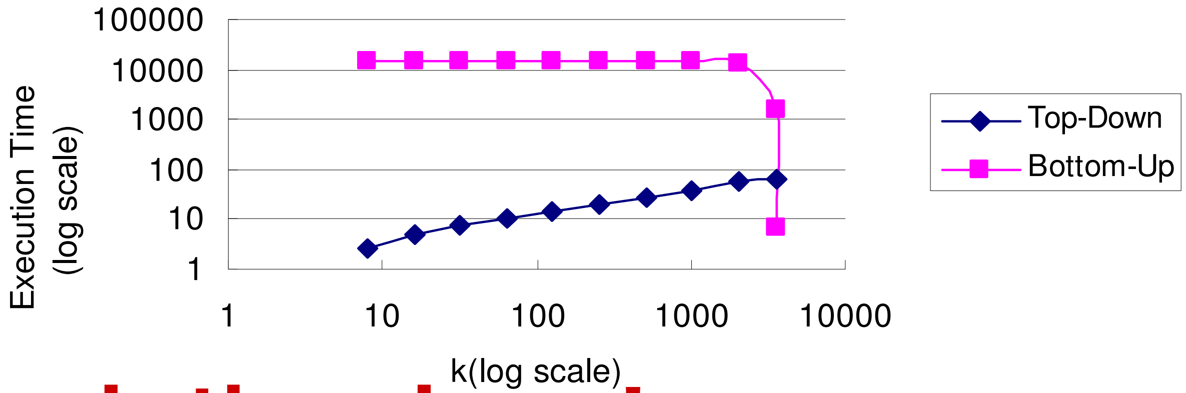
Quality

- Measure: Δ/k
- Top-down beats bottom-up for small k values



Execution Time

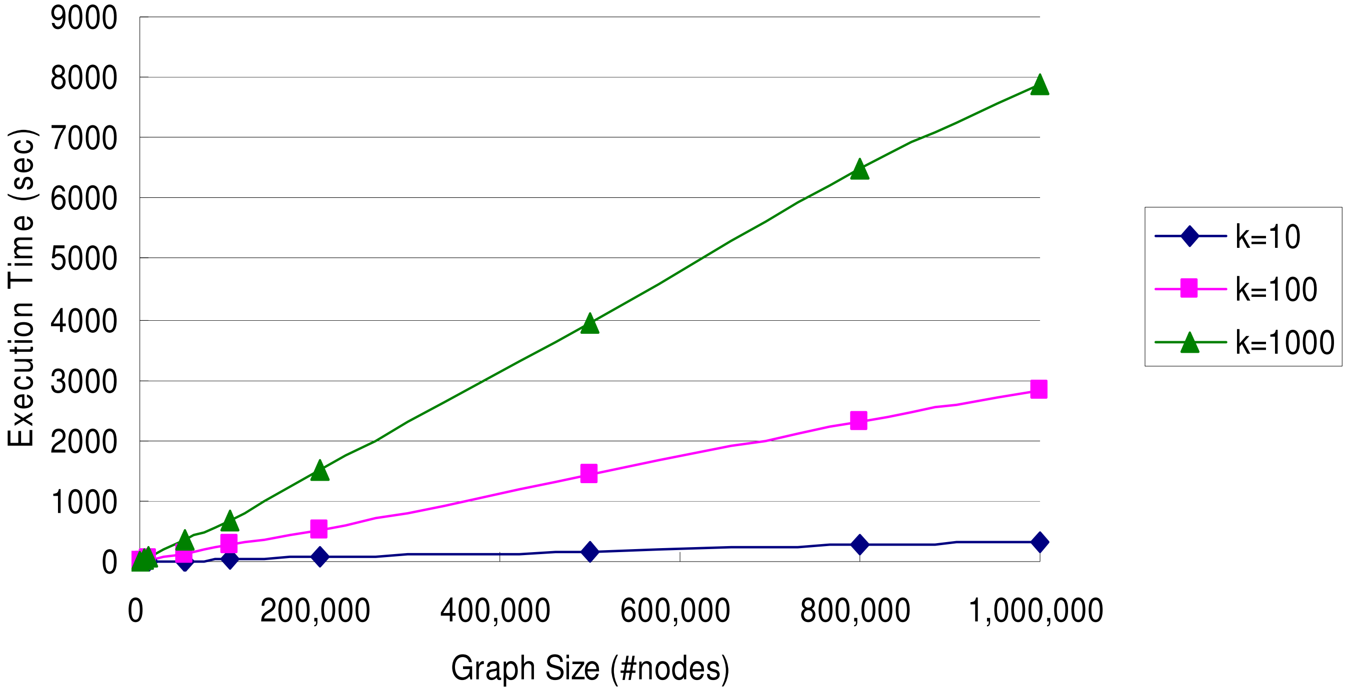
- Top-down is much faster than bottom-up



Overall, top-down is the winner!

Efficiency: Synthetic Graphs

Dataset: Synthetic Power-Law Graphs (by GTgraph)
(avg degree:5)



Conclusion

- Database-style aggregation for graph summarization
  - Customized summaries
  - Controllable resolutions
  - “drill-down” and “roll-up” abilities
  - Meaningful summaries for real applications
  - Efficient and scalable for very large graphs
- Incorporated in Periscope/GQ graph querying system
  - Combined with other graph operations to perform complex analysis on graphs (VLDB’08 Demo)

Questions?

Suggestions?

Thanks! ☺