Data Summarization with Hierarchical Taxonomy

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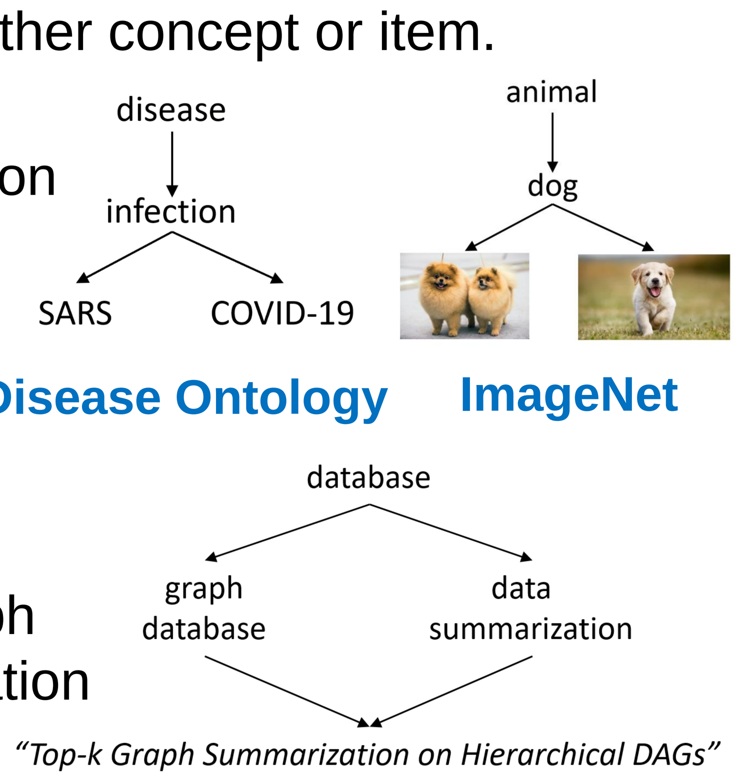
Motivations

Hierarchical DAGs (HDAG) are everywhere

Vertices are general concepts or certain items.

Directed Edges are the relationships that a general concept can summarize another concept or item.

- **Disease Ontology**
  Concepts: disease, infection
  Items: SARS, COVID-19
- **ImageNet**
  Concepts: animal, dog
  Items: images
- **ACM CCS**
  Concepts: database, graph database, data summarization
  Items: papers



HSD Problem

HSD Problem

Input: A hierarchical DAG, a query set of popular items Q, an integer k;

Output: A set S with at most k concepts;

Summary Score: $f(S) = \frac{|cov(S) \cap Q|}{|cov(S) \cup Q|}$

The larger summary score, the better selection!

S: The selection set.
cov(S): The items that set S cover.
Q: The query item set.

Objective: Find the set $S^* = \arg \max_{S \subseteq V, |S|=k} f(S)$

NP-hard: Reduction from set cover problem.

Applications: attributes filter, image set labeling, personalized recommendation

Algorithms

Transformation

Score function:

$$f(S) = \frac{|cov(S) \cap Q|}{|cov(S) \cup Q|} \geq \alpha$$
$$|cov(S) \cap Q| - \alpha \cdot |cov(S) \cup Q| \geq 0$$
$$|cov(S) \cap Q| - \alpha \cdot |cov(S) \setminus Q| \geq \alpha \cdot |Q|$$

Maximum weighted coverage:

$$g(S) = \sum_{x \in cov(S)} w(x) \geq \alpha \cdot |Q| \text{ ,where } w(x) = \begin{cases} 1 & , x \in Q \\ -\alpha & , x \notin Q \end{cases}$$

Binary search α, and then transform to the maximum weighted coverage problem.

DP on tree

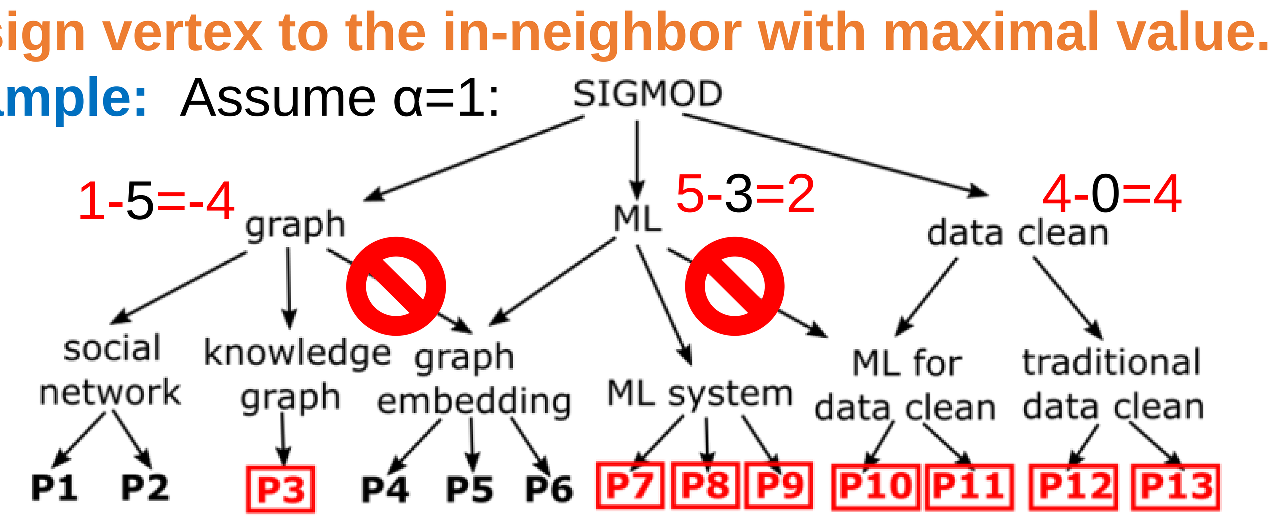
DP(v, k) the maximal weighted coverage with selecting no more than k vertices in subtree T_v.

$$DP(v,k) = \max\{DP_Y(v,k), DP_N(v,k)\}$$
$$DP_Y(v,k) = \sum_{u \in cov(v)} w(u), \text{ subject to } k \geq 1.$$
$$DP_N(v,k) = \max_{\{k_1,k_2,\ldots,k_u\}} \{\sum_{u \in N^-(v)} DP(u,k_u)\}, \text{ s.t. } \sum_{u \in N^-(v)} k_u \leq k.$$

Algorithm on HDAG

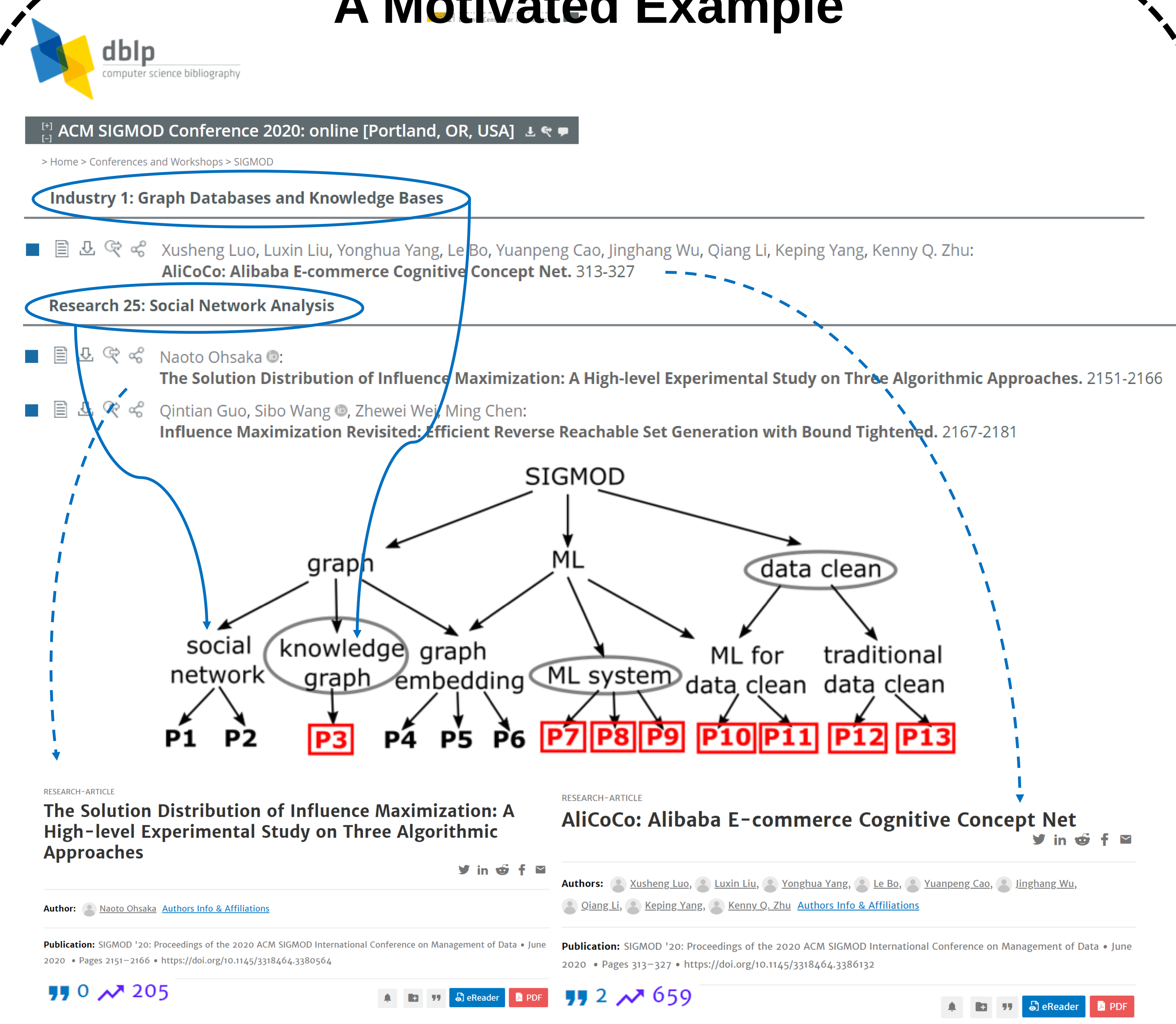
Assign vertex to the in-neighbor with maximal value.

Example: Assume α=1:



Then, apply tree algorithm.

A Motivated Example



P1: paper downloads less than 500

P3: paper downloads more than 500

Popular papers summarization in SIGMOD:

Some papers are popular and others are unpopular.
Select k topics to summarize popular papers.
Cover more popular papers, cover less unpopular papers.

An example selection (k=3):

data clean: P10, P11, P12, P13
ML system: P7, P8, P9
knowledge graph: P3

Cover all popular papers and cover no unpopular papers!

Related work

Aggregate Method [X Jing et al. 2014]

Method: Select top-k topics with maximum aggregate popular papers.
Selection (example): ML, data clean, ML system
Limitation: Lack diversity (ML & ML system)
Summary Score: $f(S) = \frac{|\{P7,P8,P9,P10,P11,P12,P13\}|}{|\{P3,P4,P5,P6,P7,P8,P9,P10,P11,P12,P13\}|} = \frac{7}{11}$

K-PCGS Method [X Zhu et al. CIKM 2020]

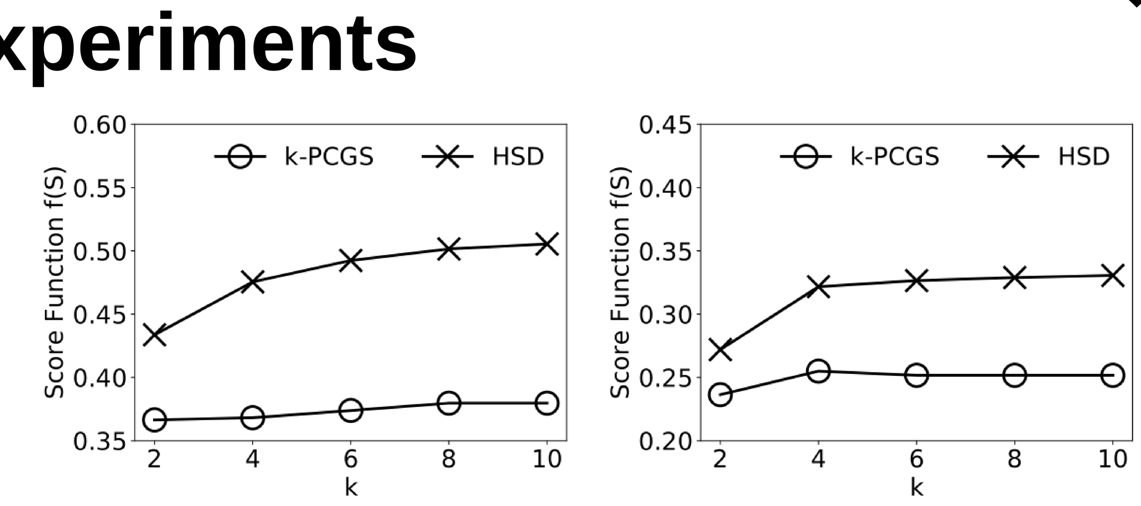
Method: Select k diverse topics with maximum summary score greedily.
Selection (example): ML, traditional data clean, knowledge graph
Limitation: Cover several unpopular papers (P4, P5, P6)
Summary Score: $f(S) = \frac{|\{P3,P7,P8,P9,P10,P11,P12,P13\}|}{|\{P3,P4,P5,P6,P7,P8,P9,P10,P11,P12,P13\}|} = \frac{8}{11}$

Our Method

Selection (example): data clean, ML system, knowledge graph
Summary Score: $f(S) = \frac{|\{P3,P7,P8,P9,P10,P11,P12,P13\}|}{|\{P3,P7,P8,P9,P10,P11,P12,P13\}|} = \frac{8}{8} = 1$

Experiments

Datasets: Disease Ontology
4,227 vertices, 8,190 edges
Evaluation metrics: f(S)
Method compare: k-PCGS



(a) Tree Dataset (b) HDAG Dataset