

HGMatch: A Match-by-Hyperedge Approach for Subgraph Matching on Hypergraphs

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Graphs vs Hypergraphs





Hypergraph



Subgraph Matching on Hypergraphs



Query Hypergraph



Data Hypergraph



Subgraph Matching on Hypergraphs







Data Hypergraph



Subgraph Matching on Hypergraphs







Data Hypergraph



Applications

- Mining Biological Networks
 - e.g., protein interactions, gene interactions
- Querying Hypergraph Databases
 - e.g., AtomSpace, HyperGraphDB, TypeDB
- Pattern Learning in NLP
 - e.g., semantic hypergraphs (each word is a vertex, and each sentence is a hyperedge)
- Q/A over Hypergraph Knowledge Base
 - e.g., JF17K dataset (a subset of non-binary relations extracted from Freebase)



Example Queries for JF17K Dataset



Which football players represented different teams in different matches?

OActor Season OTV Show OCharacter OSeason OActor Which actors played the same

character in a TV show on different seasons?



Strawman Approach

• Convert the hypergraph to a *bipartite graph* and apply existing *subgraph*

matching algorithms

- by taking the incidence matrix and treating this as the incidence matrix of a bipartite graph
- Directly extend existing subgraph matching <u>algorithms</u> to the case of <u>hypergraphs</u>
 - recursively expand the partial embedding vertex-by-vertex by mapping a query vertex to a data vertex following a given matching order and backtrack when necessary



Motivations

- 1. The *match-by-vertex* approach in the strawman approaches generally underutilise high-order information in hypergraphs
 - hyperedges are used as a verification condition in the match-by-vertex framework, which can lead to a huge search space and large enumeration cost
- 2. It is difficult to compute subgraph matching on *massive hypergraphs* using sequential algorithms
 - none of the existing subhypergraph matching algorithms supports parallel execution



Contributions

1. A match-by-hyperedge framework

- Match the query by hyperedges instead of vertices
- Use set operations to efficiently generate candidates
- Filter out false positives with set comparison

2. A highly optimised parallel execution engine

- Adopt the dataflow model for parallelisation
- Bounded memory consumption with our task-based scheduler
- Load balancing with dynamic work-stealing



HGMatch Overview





Hypergraph Data Layout

- Hypergraphs are stored as *hyperedge tables* with *inverted hyperedge index*
 - Hyperedge Signature: a *multiset* of all vertex labels contained in a hyperedge







Suppose partial result $m = (e_1, e_3)$, we want to match $\{u_0, u_1, u_3, u_4\}$ the next data hyperedge *e*.

((a) Partition 1								
$S(e) - \{A, B\}$			(b) Partition 2						
	(c) = (II, D)			$\mathcal{S}(e) = \{A, A, C\}$					
E	$e_1 = \{v_2, v\}$	4}		-	$e_3 = \{v_0, v_1, v_2\}$				
	$e_2 = \{v_4, v_6\}$			E	$\begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix}$				
	$v_2 \rightarrow [e_1]$				$e_4 = \{v_3, v_5, v_6\}$				
I				τ	$v_0, v_1, v_2 \rightarrow e_3 $				
	$v_4 \rightarrow [e_1, e_2]$				$v_3, v_5, v_6 \rightarrow e_4$				
	$v_6 \rightarrow e_2 $				03,03,00 , [04]				
(c) Partition 3									
$\mathcal{S}(e) = \{A, A, B, C\}$									
		E	$e_5 = \{v_0, v_1, v_4, v_6\}$						
			$e_6 = \{v_2, v_3, v_4, v_5\}$						
			v_0, v_1, v_0	$_6 \rightarrow [$	$[e_5]$				
		Ι	$v_4 ightarrow [e_5, e_6]$						
			v_2, v_3, v_3	$_5 \rightarrow $	$[e_6]$				





(a) Partition 1 (b) Partition 2 $\mathcal{S}(e) = \{A, B\}$ $\mathcal{S}(e) = \{A, A, C\}$ $e_1 = \{v_2, v_4\}$ E $e_3 = \{v_0, v_1, v_2\}$ $e_2 = \{v_4, v_6\}$ $\{v_3, v_5, v_6\}$ $v_2 \rightarrow [e_1]$ $v_0, v_1, v_2 \rightarrow [e_3]$ Ι $v_4 \rightarrow |e_1, e_2|$ $v_3, v_5, v_6 \rightarrow [e_4]$ $v_6 \rightarrow [e_2]$ (c) Partition 3 $\mathcal{S}(e) = \{A, A, B, C\}$ $e_5 = \{v_0, v_1, v_4, v_6\}$ E $e_6 = \{v_2, v_3, v_4, v_5\}$ $v_0, v_1, v_6 \rightarrow |e_5|$ $v_4 \rightarrow [e_5, e_6]$ $v_2, v_3, v_5 \rightarrow [e_6]$

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- *e* must be incident to $v_4 \in e_1$ and $v_0, v_1 \in e_3$







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- *e* must have the same signature with the query hyperedge
- *e* must be incident to $v_4 \in e_1$ and $v_0, v_1 \in e_3$

$$\implies C(e) = \{e_5\} \cap \{e_5\} \cap \{e_5, e_6\} = \{e_5\}$$



Parallel Execution

- Dataflow Model
 - We designed three operators: SCAN, EXPAND, SINK
- Task-based Scheduler
 - Computation are broken down into tasks and scheduled in LIFO order to bound memory
- Dynamic Work Stealing
 - Idle worker will steal tasks from others for load balancing



Example Dataflow Graph and Task Tree



Experimental Setup

- Hardware: a server with two 20-core Xeon E5-2698 V4 CPU and 512G of memory
- **Baselines**: we propose a <u>generic</u> framework to extend existing subgraph matching algorithms to the case of hypergraphs
 - We compared the extended version of *CFL* (SIGMOD16), *DAF* (SIGMOD19), *CECI* (SIGMOD19), and *RapidMatch* (VLDB20)
- **Queries**: randomly sample subhypergraphs from the data hypergraphs with given number of hyperedges and vertices



Datasets

• **Datasets**: we use 10 real-world hypergraphs as data hypergraphs

Dataset	V	E	$ \Sigma $	a_{max}	\bar{a}	Index
HC	1,290	331	2	81	34.8	178KB
MA	73,851	5,444	1,456	1,784	24.2	2.1MB
CH	327	7,818	9	5	2.3	109KB
CP	242	12,704	11	5	2.4	190KB
SB	294	20,584	2	99	8.0	2.1MB
HB	1,494	52,960	2	399	20.5	15.5MB
WT	88,860	65,507	11	25	6.6	6.8MB
TC	172,738	212,483	160	85	4.1	7.8MB
SA	15,211,989	1,103,193	56,502	61,315	23.7	419.7MB
AR	2,268,264	4,239,108	29	9,350	17.1	998.6MB



Index Building





Single-thread Comparisons



Execution Time for each Query Set

UNS

21

Parallel Comparisons



Vary Number of Threads



Task-based Scheduling





Thank you!

