

GraphGen: Adaptive Graph Processing using Relational Databases

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Graph + Relational Design

Graph Analysis Tasks Vary Widely

- Different types of Graph Queries
- Continuous Queries / Real-Time Analysis
- Batch Graph Analytics
- Machine Learning

GraphGenDL

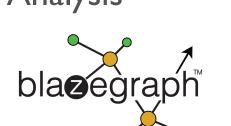
AuthorPub(ID1, pub),

AuthorPub(ID2, pub).

over the database

CoAuthors GraphView

CREATE GRAPHVIEW CoAuthorsWeighted AS



©neo4j

→OrientDB^o

Dgraph

GraphLab

GraphX

Many different ways to deal with graph data

- Graph Databases (Neo4j, OrientDB, RDF stores)
- (Giraph, GraphX, GraphLab)
- In-Memory Systems(Ligra, Green-Marl, X-Stream)
- Many research prototypes/custom indexes

I. Graph Frontend, Graph **Backend**

- RDF, Property Graph databases
- Focus on **graph queries**

• Using a **graph engine** to

long series of joins.

over relational data

efficiently process **SQL** queries

Mostly to tackle queries involving

• Issue: Requires a complete buy-in

2. Graph Frontend, **Relational Backend**

- Some XML/RDF/ Property Graph Database (e.g., SQLGraph, Titan)
- Graph analytics frameworks (Vertexica, Grail)
- **Issue:** Requires complete buy-in; limited expressivity for analytics

3. Relational Frontend, 4. Graph+Relational Relational Backend, Graph Frontend, Relational Backend (GraphGen)

- Aster Graph, SAP Graph Engine
- **Enterprises** have existing relational databases with *rigid schemas*
- Need to enable analysis of the hidden graphs within them
- While continuing to support SQL queries/analytics

- A P A C H E G I R A P H
- Distributed Batch Analysis Frameworks

GraphGen

Declarative specification of **GraphViews**

Nodes(ID, name) :- Author(ID, name).

Edges(ID1, ID2, wt=\$COUNT(pub)) :-

Ego-Graphs Multi-GraphView

• User specifies **Nodes** and **Edges**

GraphGenQL

Support for subgraph pattern matching query languages like SPARQL etc.

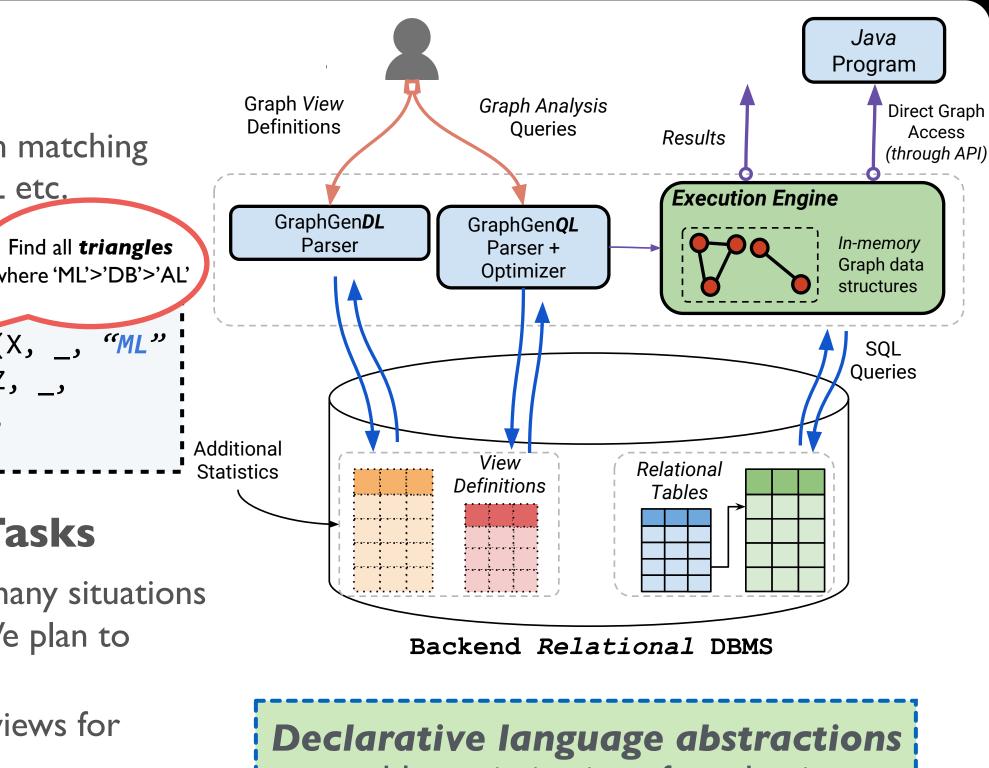
Engine

Datalog is a natural fit!

where 'ML'>'DB'>'AL' **USING GRAPHVIEW** CoAuthors Triangle(X, Y, Z) :- Nodes(X, _, "ML")), Nodes(Y, _, "DB"), Nodes(Z, _, "AL"), Edges(X, Y), Edges(Y, Z), Edges (X, Z).

Specifying Analysis Tasks

- **Vertex-centric** works for many situations but **not very expressive**. We plan to support:
 - **Direct access** to graph views for complex programs
 - Datalog-based DSL (build upon languages like **Socialite**)



enable optimizations for adaptive processing

CREATE GRAPHVIEW AuthorEgoNetworks(X) WHERE Author(X) AS

Nodes(X, name) :- Author(X, name).

Nodes(ID, name) :- AuthorPub(X,pub), AuthorPub(ID,pub), Author(ID, name). Edges(ID1, ID2) :- AuthorPub(ID1, pub),;

Opportunities and Challenges

Where to Execute Tasks?

AuthorPub(ID2, pub).

- Dependent on workload, rate of updates, rate of queries...
- Usually in-memory is faster, but ETL may not be worth it
- Other issues: Large-output joins, and selectivity estimation errors associated with them.

Key Challenge: Develop accurate cost models, workload monitoring tools, and **optimization** techniques

- How much of the graph do we pre-compute / materialize?
- Incremental view maintenance for graph-views may prove challenging

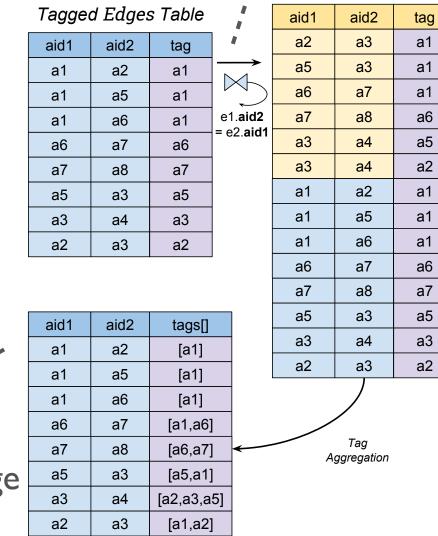
Query Rewriting

- Auto-generated SQL can consist of many blocks
- Many ways of writing equivalent SQL queries, optimization can be challenging
 - Could define edges using the WITH clause, or as a VIEW

Optimizing the Extraction of Multi-Graph Views

Tagged Edges Table Typically one would need to generate a separate query for each graph

We employ a technique called result-tagging



Find edges I-hop

away from source

(tag) & union with

Key Challenge: Optimizing SQL for graph analytics exposes gaps in query optimizers

DISTINCT WITH Nodes as (...) WITH Edges as (...) (SQL for answering query)

Create VIEW Nodes as (...) Create VIEW Edges as (...) DISTINCT (SQL for answering query)

Tag-list: which egographs include edg

Key Challenge:

Develop a systematic

approach towards

execution over

collections of graphs

	a1	a5	a1		a6	а7	a'	
	a1	a6	a1	e1.aid2	а7	a8	а	
	a6	а7	а6	= e2. aid1	a3	a4	a!	
	а7	a8	а7		a3	a4	aź	
	a5	а3	a5		a1	a2	a'	
	а3	a4	a3		a1	a5	a'	
	a2	а3	a2		a1	a6	a'	
!				•	a6	а7	a	
					а7	a8	a	
1	aid1	aid2	tags[]		a5	а3	a!	
	a1	a2	[a1]		a3	a4	a:	
	a1	a5	[a1]		a2	a3	aź	
	a1	a6	[a1]					
	a6	a7	[a1,a6]					
	а7	a8	[a6,a7]	<u> </u>	Tag Aggregation			
ge	a5	а3	[a5,a1]					
8	а3	a4	[a2,a3,a5]					
	a2	а3	[a1,a2]					
				-				

Preliminary Experiments

Query	DBS1	DBS2	MySQL	PostgreSQL	
With (at edges)	1	1.62	NA	13.8	
With (at the end)	53.028	2.99	NA	37.8	
View (at edges)	1.054	2.07	3.01	15.6	
View (at the end)	51.92	77.13	538.19	35.991	
On Base Table	46.45	74.878	678.87	36.160	
Triangle Counting (small); time in seconds					

Query	DBS1	MySql	PostgreSql
Using With (in edge)	48.05	NA	477.56
Using With (at the end)	2404	NA	1499.33
Using View (in edges)	44.72	357.59	811
Using View (at the end)	2377.61	>3600	1774.54
Directly On Base Table	2348	> 3600	1790

Triangle Counting (large); time in seconds

Triangle Counting Triangle Pattern Dataset ETL small 0.169 0.001 2.049 large 6.723 0.015 17.52 In-memory execution; time in seconds

DBS2 DBS1 PostgreSQL MySQL With (at edges) NA 14.765 0.749 4.59 NA 0.704

With (at the end) View (at edges) 15.557 4.26 2.193 View (at the end) 4.25 20 11.063 On Base Table 8.612 3.089 22.69

Pattern Matching where area='ML' (large); time in seconds

 Query rewrites lead to significant differences in performance

Query

In-memory execution is usually faster but when its warranted

dataset	#rows	nodes	edges		
small	100,000	1,639	55,436		
large	500,000	15,741	529,434		
Dataset sizes					