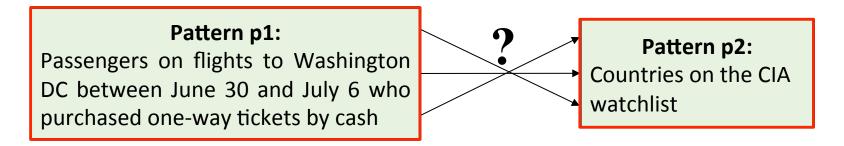
Outline

- Problem Statement and Motivation
 - Generalized Path Queries
 - Algebraic Problem Interpretation
- Background
 - Algebraic Path Problem Solving
- Approach
 - Integrating of graph pattern matching with algebraic path problem solving
- Evaluation
- Conclusion



Motivating Example

Query: Find <u>relationships</u> between passengers on any flights to Washington DC between June 30 and July 6 who purchased one-way tickets by cash, and countries on the CIA watchlist where there is at least one financial link through any bank.



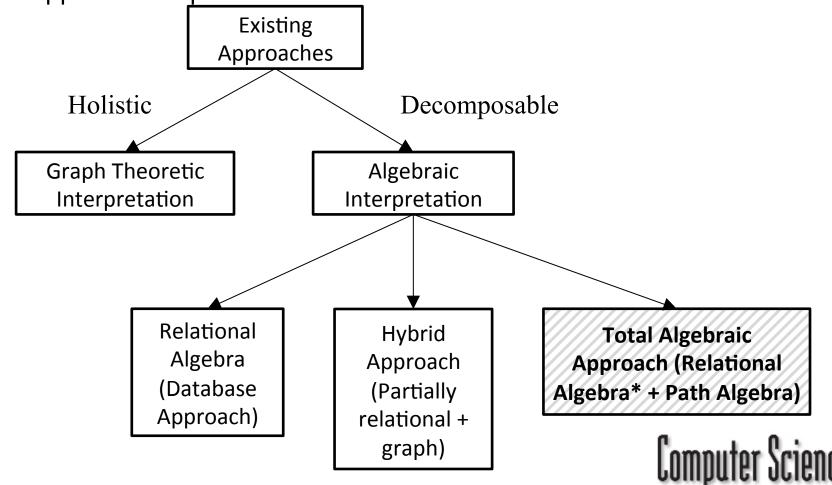
1. Relationships are paths that must be extracted not merely matched!!!

- e.g. different from path expression/property path queries
- 2. Participating entities are not explicitly stated



Existing Problem Interpretation Approaches

• For graph data models like RDF there are multiple ways to approach the problem



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Comparison of Approaches

Graph Theoretic

- Different problems translate to different graph problems i.e. different algorithms
 - Ex. is sub-graph homeomorphism problem (NP hard).
 - Others: Subgraph Isomorphism,
 Shortest Paths, Disjoint Paths
- Often difficult to parallelize or optimize
- Cant deal with declarative specifications

Algebraic

- Decompose into smaller operators
 - Reuse is possible
 - Adapt optimization and composition of smaller operators
- Relational algebra not ideal
 - Arbitrary path length requires iteration and fixpoint semantics
- Hybrid approaches exist
 - Pattern matching (algebraic), traversal (graph theoretic)
 - Emphasis on shortest paths for traversals



Our Proposal: A Total Algebraic Approach

Query: Find relationships between passengers on any flights to Washington DC between June 30 and July 6 who purchased one-way tickets by cash, and countries on the CIA watchlist where there is at least one financial link through any bank.

Problem interpretation is as a Generalized Path Query – gpqs with

- 1. Two entity sets declaratively specified as patterns P1, P2
- 2. A connection set linking p1, p2 instances
- 3. A connection constraint on the connection set (edge type membership)
- 1: Solvable with algebraic graph pattern matching
- 2, 3: Solve with algebraic path finding (plus extension)



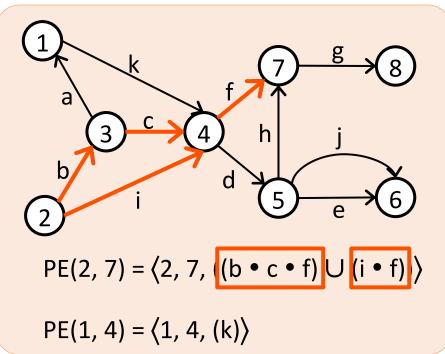
Algebraic Path Problem Solving Framework

- An efficient algebraic path problem solving approach introduced by Tarjan[23, 24].
- Basic Definitions:
 - An edge *e* in a directed labeled graph G = (V, E) is denoted as $e = (v_1, v_2)$ with label $\lambda(e) = l_e$ where $v_1, v_2 \in V$ and $e \in E$.
 - A path p in such a graph G = (V,E) is an alternating sequence of nodes and labeled edges terminating in a node p
 - = { v_1 , l_{e1} , v_2 , l_{e2} , ..., v_n , l_{en} , v_{n+1} } where v_1 , v_2 ,..., v_n , $v_{n+1} \in V$ and e_1 , e_2 ,..., $e_n \in E$.



Path Encoding as Path Expressions

- A Path Expression [23, 24] of type (*s*, *d*), *PE(s*, *d*), is a 3-tuple (*s*, *d*, *R*), where
 - *R* is a regular expression over the set of edges defined using union(∪), concatenation(•) and closure (*).
 - The language L(R) of R represents paths from s to d where the graph contains nodes s and d.

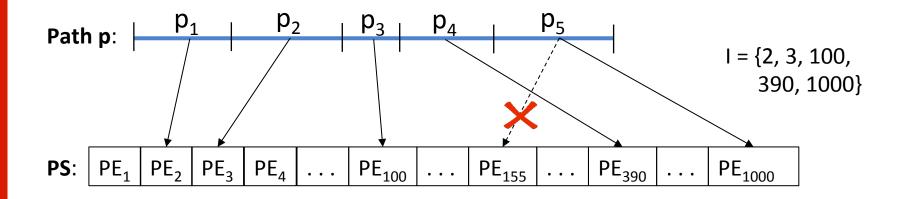




Graph Path Information Representation: A Sequence of Path Expressions

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- A Path Sequence (PS) [23,25] is a unique ordering of path expressions that represent all path information in a graph, such that for any path *p*,
 - there is a unique partition of p into non empty subpaths, and
 - a unique sequences of indices *I of PS*, such that
 - the *ith* subpath of *p* is represented by the path expression in PS at the *ith* index in *I*.



• The path sequence representation of a graph allows for path problems to be solved by single forward scan.

Path Computation using Path Sequence

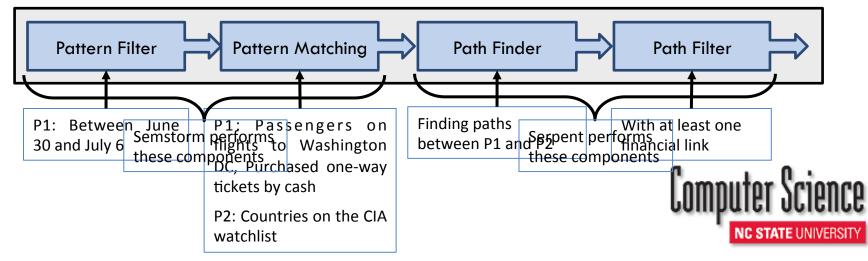
- A simple propagation SOLVE algorithm [23,25] can be used to solve path problems.
- The SOLVE algorithm assembles path information while scanning the path-sequence from left to right.
- At every iteration of the SOLVE algorithm the following step is performed

 $PE(s,w\downarrow i) \cup (PE(s,v\downarrow i) ? PE(v\downarrow i,w\downarrow i)) \rightarrow SA[w\downarrow i]$



Overview of Approach (1)

- We built a prototype by integrating
 - SemStorm [31]:
 - a Hadoop-based file organization storage system
 - supports efficient graph pattern matching query execution using an algebraic query evaluation technique
 - uses Apache Tez as the execution environment.
 - Serpent [25,27]:
 - platform for finding all paths between a set of sources and destinations.
 - ^o builds on the path algebraic technique using path-sequences.



Overview of Approach (2)

1. Query Expression

- *Goal:* Minimize disruption to existing infrastructure, e.g. parser.
- Solution: Use syntactic sugar to represent path operator.

2. Query Planning

- *Goal:* Integrate graph pattern matching with path problem solving
- *Solution:* Modify graph pattern matching query plan by adding algebraic path querying operators to produce a gpqs query plan.

3. Query Execution

- Goal: Execute gpqs.
- *Solution:* Translate gpq logical query plan into physical query plan by introducing required physical query operators.



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Introduction of Syntactic Sugar – ?pathVar as a special property variable

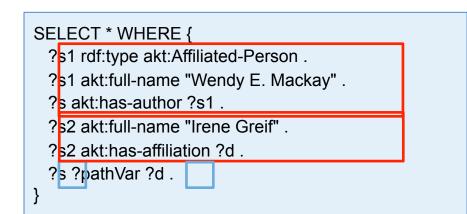
- Avoids change to SPARQL's query syntax.
- For triple pattern (?s ?pathVar ?d),
 - ?pathVar is actually a path variable
 - removed and handled specially while rest of query is compiled normally as graph pattern query.

SELECT * WHERE { ?s1 rdf:type akt:Affiliated-Person . ?s1 akt:full-name "Wendy E. Mackay" . ?s akt:has-author ?s1 . ?s2 akt:full-name "Irene Greif" . ?s2 akt:has-affiliation ?d . ?s ?pathVar ?d .

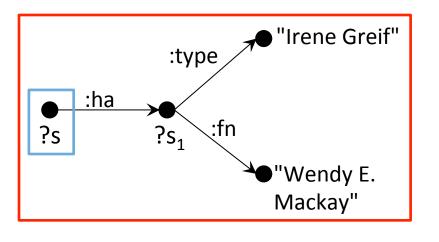
}

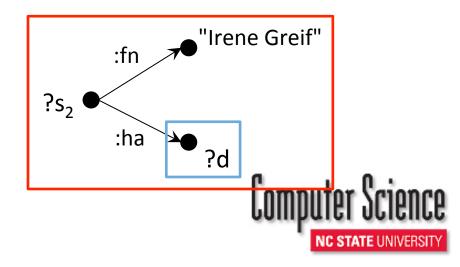


Introduction of Syntactic sugar – ?pathVar as a Property Variable



- Challenge: Need to track the path source and destination variables in the graph pattern
- Solution: Use SemStorm's datastructures for tracking variables.





Overview of Approach

- 1. Query Expression
 - *Goal:* Minimize disruption to existing infrastructure, e.g. parser.
 - *Solution:* Use syntactic sugar to represent path operator.
- 2. Query Planning
 - Goal: Integrate graph pattern matching with path problem solving
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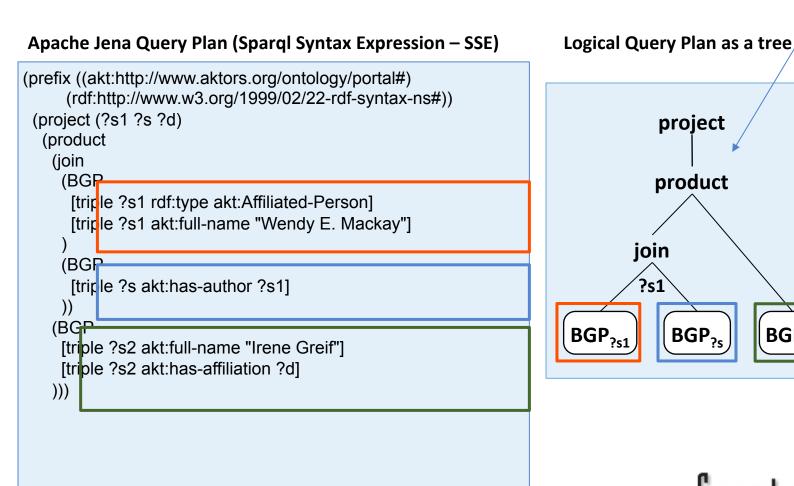
Logical Plan Example as a tree

Disconnected sub-graph patterns leads to cross-product

project

product

BGP₂

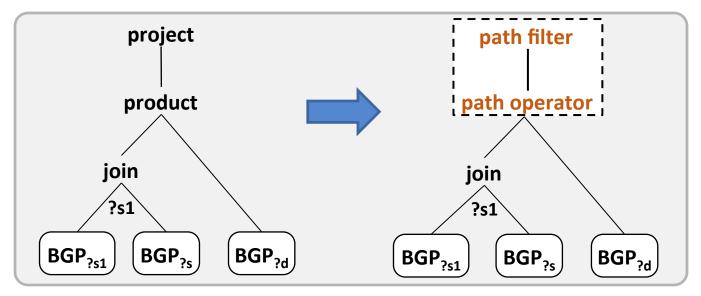




BGP₂

Logical Plan Transformation Example

 Remove cross-product and projection operators and introduce path query operators.





Overview of Approach

- 1. Query Expression
 - *Goal:* Minimize disruption to existing infrastructure, e.g. parser.
 - *Solution:* Use syntactic sugar to represent path operator.

2. Query Planning

- *Goal:* Integrate graph pattern matching with path problem solving
- *Solution:* Modify graph pattern matching query plan by adding algebraic path querying operators to produce a gpqs query plan.

3. Query Execution

- Goal: Execute gpqs.
- *Solution:* Translate gpq logical query plan into physical query plan by introducing required physical query operators.

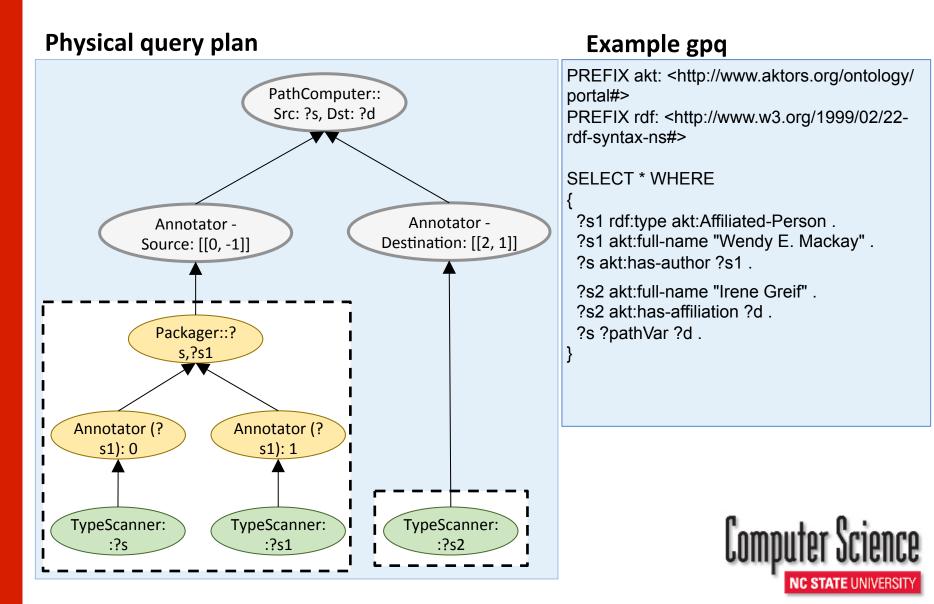


Implementation Strategy

- Physical query operators for our platform are Tez vertices
- Physical query plan is represented by the Tez DAG.
- The following physical query operators were introduced
 - Annotator Vertex for source, destination and constraint variables identify the source, destination or constraint variables, allowing only the bindings for that variable to pass through.
 - PathComputer Vertex is the path operator which performs the final path computation.



Example Query & DAG



Evaluation

Test Setup:

- We compared our integrated system with an existing platform on
 - 1. Expressiveness.
 - 2. Query compilation time comparison with and without path operator.
 - 3. Performance.
 - 4. Completeness of results.
- Evaluation was conducted on single node server
 - running HDFS
 - with Xeon octa core x86 64 CPU (2.33 GHz),
 - 40GB RAM,
 - two HDDs (3.6TB and 445GB).



Issues with Existing Platforms

Neo4j:

- The fast BFS algorithm is only for **finding shortest path**.
- For finding all paths the **slower exhaustive DFS** is used.
- Gpqs could not be run on Neo4j as it was running out of resources and crashing.

Stardog:

- Uses algebraic operators but **applies path filter first** and then joins with graph pattern.
- This is efficient only if the path filter is highly restrictive.
- Limited support for path constraints.
- Hence, could not compare constrained queries.



Dataset and Queries

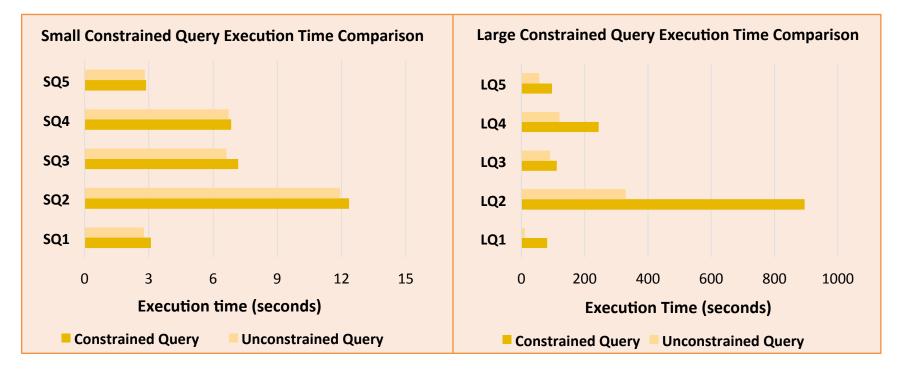
- Our queries were evaluated on the BTC500M dataset (size 0.5GB, 2.5 million triples).
- The queries were formulated to find paths that are at least three hops long.

Number of sources and Destinations								
Queries	Sources	Destinations	Queries	Sources	Destinations			
SmallQuery ₁	25	2	LargeQuery ₁	13641	907			
SmallQuery ₂	4	6	LargeQuery ₂	29974	32583			
SmallQuery ₃	4	3	LargeQuery ₃	11793	6			
SmallQuery ₄	29	7	LargeQuery ₄	29974	2290			
SmallQuery ₅	26	31	LargeQuery ₅	2290	32582			

• The queries vary from small set of sources and destinations to very large set of sources and destinations.



Constrained vs. Unconstrained GPQs

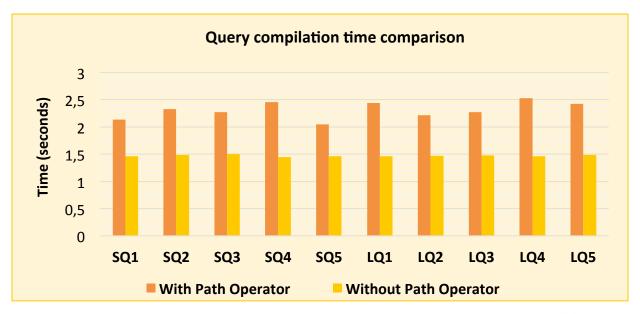


- Stardog has limited support for path constraints.
- Neo4j has predicate functions (all, any, exists, none, single) similar to constraints.
- The constrained queries took longer time to complete since these include an extra filtering step.



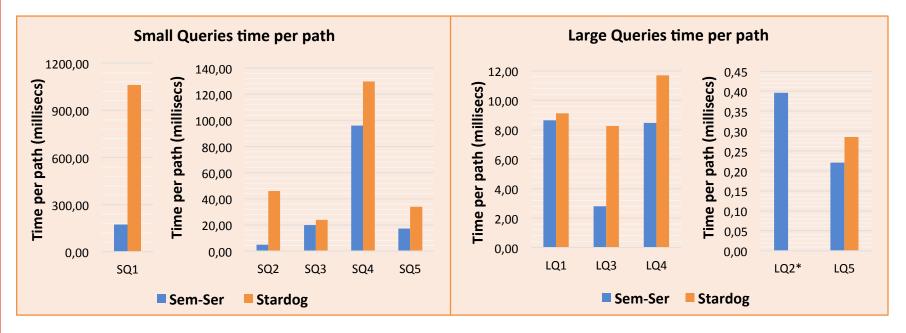
Query Compilation Time Comparison

- The path operator does not have much effect on the query compilation time.
- In most cases the compilation time increased by less than one second.





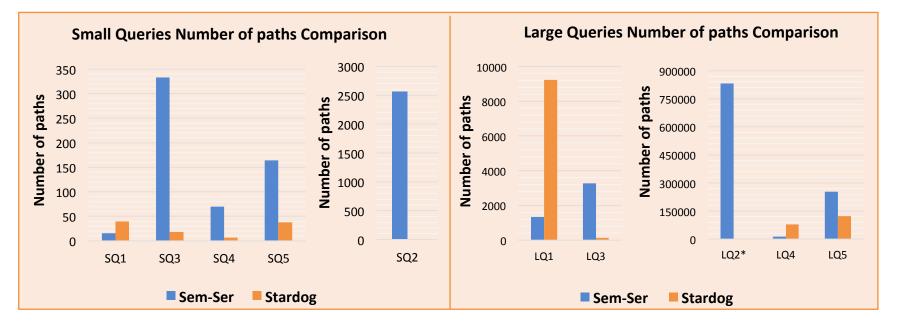
Performance Evaluation



- Stardog performs better in terms of absolute time taken.
- However, for most queries the number of paths found by Stardog is much less.
- Hence, we plotted the time taken per path identified.

Algebraic path evaluation is also more MQO amenable

Completeness of Results



- Stardog produced incomplete results.
- BTC has a lot of self-loops: triples like (acm:58567 akt:has-publication-reference acm:58567).
- Stardog does not consider these triples in its paths.
- Stardog results also contain duplicate paths.



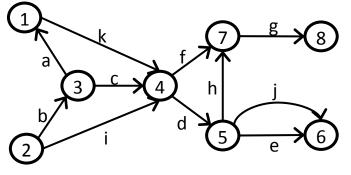
Conclusion

- An algebraic query evaluation strategy for generalized path queries with declaratively defined sources, destinations and constraints.
- A general framework to integrate any graph pattern matching platform with a path computation platform.
- An example implementation of an integrated platform.
- Performance comparison of integrated platform with a popular existing platform.
- The work presented here is partially funded by NSF grant IIS-1218277 and CNS-1526113.

Thank You!



Example Path Sequence and Solve Algorithm



1:	(1, 4, <mark>k</mark>)		2:	(2, 3, <mark>b</mark>)
3:	(2, 4, <mark>i</mark>)		4:	(3, 4, <i>a</i> • <i>k</i> ∪ <i>c</i>)
5:	(4, 5, <mark>d</mark>)		6:	(4, 7, <u>f</u>)
7:	(5, 6, <mark>e</mark> U	ן ו	8:	(5, 7, <mark>h</mark>)
9:	(7, 8, <mark>g</mark>)		10:	(3, 1, <i>a</i>)

Solving(s =1, d): Initialize: PE(s, s) = $\lambda \rightarrow SA[s]$, PE(s, d) = Ø for d ≠S → SA[d] Step i (iteration i): PE(s, w_i) U (PE(s,v_i) • PE(v_i,w_i)) → SA[w_i] Step 1 (s=1, v₁=1, w₁=4):PE(1, 4) U (PE(1,1) • PE(1, 4)) = SA[4] U (SA[1] • PE(1,4)) = Ø U ($\lambda \cdot k$) = k → SA[4] Step 5 (s=1, v₅=4, w₅=5):PE(1, 5) U (PE(1,4) • PE(4, 5)) = SA[5] U (SA[4] • PE(4,5)) = Ø U (k • d) = k • d → SA[5] Step 7 (s=1, v₇=4, w₇=5):PE(1, 6) U (PE(1,5) • PE(5, 6)) = SA[6] U (SA[5] • PE(5, 6)) = Ø U ((k • d) • (e U j)

