TriAD: A Distributed Shared-Nothing RDF Engine based on Asynchronous Message Passing

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RDF is a data model for representing information on the Web

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Honolulu

Hawaiian: hono'lulu

State Capital

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Scale of RDF Data Published – Linked Open Data Cloud



Source: http://linkeddata.org

Indexing and Querying RDF Data

- RDF triples are stored and indexed in a relational table (relational approach)
- SPARQL is the language suggested by W3C for querying RDF data
- SPARQL has many similarities with standard SQL
- SELECT-PROJECT-JOIN forms the main building blocks of SPARQL

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SPANQL Query.	NDI Data.				
Find persons who are born in USA and won a prize	Subject	Predicate	Object		
OFLEGT Service LUEDE	Barack Obama	bornIn	Honolulu		
SELECT (person, (City, (prize where {	Barack Obama	won	Nobel Peace Prize		
<pre>(R1) ?person <bornin> ?city .</bornin></pre>	Barack Obama	won	Grammy Award		
(R2) ?city <locatedin> USA .</locatedin>	Barack Obama	memberOf	Republican Party		
	Honolulu	locatedIn	United States		
(RS) (person (Won> (prize .)	Barack Obama	isA	Singer		
bornIn locatedIn	John F. Kennedy	bornIn	Brookline		
?person $\xrightarrow{\text{Dormin}}$?city $\xrightarrow{\text{Docatedin}}$ USA	John F. Kennedy	memberOf	Republican Party		
	John F. Kennedy	diedIn	Dallas		
?prize	Dallas	locatedIn	United States		
	Brookline	locatedIn	United States		

PDE Data

SPARQL Query:

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DDE Data

Results: $(R1 \bowtie R2 \bowtie R3)$

CDADOL Outern

?person?city?prizeBarack_ObamaHonoluluPeace_Nobel_PrizeBarack_ObamaHonoluluGrammy_Award

Efficiency – thoroughly investigated in single-node setting

- crucial factors Join-order optimization, Join-ahead pruning, indexing layout, choice of operators
- Eg. Jena, Sesame, HexaStore, MonetDB-RDF, SW-Store, RDF-3X, TripleBit, BitMat, gStore, ...

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Scalability - recently a line of distributed systems has been proposed

► SHARD, H-RDF-3X, Relational-based Graph-based ...

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Relational-based

Graph-based

Relational-based (Joins) vs Graph-based (Exploration) [distributed setting]

- ▶ SPARQL 1.0 requires a row-oriented output \rightarrow joins are inevitable
- Relational approaches suffer from "large intermediate relations" (inaccurate/insufficient statistics resulting in poor query plans)

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Problems with existing distributed relational-based RDF engines

- 1. Synchronous processing of joins
- ▶ 2. Dangling triples occur in intermediate relations but not in final results

Consider a query with four relations R_1 , R_2 , R_3 , R_4 with join order:



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$$(R_1 \bowtie_2 R_2) \bowtie_1 (R_3 \bowtie_3 R_4)$$



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Synchronous case 1 : $MR.job1 \rightarrow MR.job2 \rightarrow MR.job3$ Synchronous case 2 : $MR.job1 \rightarrow MR.job2$ $MR.job1 \rightarrow MR.job2$ $MR.job1 | M_2 | M_3 | M_3 | M_3$

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Sideways Information Passing (SIP) of RDF-3X1

- Powerful runtime pruning technique
- Shares information across join operators
- Requires synchronization



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Our approach: Join-ahead pruning

- Pre-partition the triples (into groups)
- Query over groups to find the ones which are relevant to the query

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- Pre-partition the triples (into groups)
- Query over groups to find the ones which are relevant to the query
- Scan & Join only triples from the relevant groups

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Locality-based grouping (using METIS)



Locality-based grouping (using METIS) isA isA Singer Lady Gaga Barack Obama bornIn/ memOf won won Democratic Party bornIn Honolulu Grammy Award JocIn USA won New York ocli locim locir memQf Texas New Haven won governo bornIn Plains Nobel Peace prize George W Bush boxnin wor memOf Jimmy Carter Republican Party

Summary Graph







SPARQL Query:

SELECT ?city, ?prize WHERE {
Barack Obama <bornIn> ?city .
?city <locatedIn> USA .
Barack Obama <won> ?prize .
}

Supernode Bindings:

?city	:	P_1	
?prize	:	Ρ2,	P_4

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SELECT ?city, ?prize WHERE {
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Supernode Bindings: !!! Empty Result

?city	:	
?prize	:	

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False postives may occur but no false negatives!!!

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Asynchronous Processing of Joins via MPICH2 communication protocol

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Join-ahead pruning via Graph Summarization

Asynchronous Processing of Joins via MPICH2 communication protocol

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Two-stage Query Optimization (distributed, multi-threading, and join-ahead pruning into account)

Join-ahead pruning via Graph Summarization

Asynchronous Processing of Joins via MPICH2 communication protocol











10/19



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RDF graph partitioning

- using a locality-based non-overlapping partitioning algorithm
- ▶ i.e Each s (or o) of RDF triple $\langle s, p, o \rangle$ mapped to one supernode P_s (or P_o)

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Triple encoding

- Each triple $\langle s, p, o \rangle$ is encoded into two triples: data triple, summary triple
- $\label{eq:constraints} \begin{array}{l} \blacktriangleright \mbox{ Dictionary encoding: Each entity is assigned a globally unique id is computed by concatenating (supernode id) P_s and a (local id) id_s Eg. (Barack_Obama, won, Nobel_Prize) Data triple: $\langle 1||1,6,4||3 \rangle$ Summary triple $\langle 1,6,4 \rangle$ } \end{array}$

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 Data triple: (1|1,6,4||3)
 Summary triple (1,6,4)

Locality-aware sharding and distributed indexing of data triples

Each data triple is hash partitioned onto atmost two slaves and indexed in six permutations (in total)
 Eg. triple (1||1, 6, 4||3) is hashed on to slaves 1 mod n and 4 mod n (for n-slaves)

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Summary graph index

Summary triples are indexed in two-permutation adjacency list for efficient graph exploration

Query Processing

In TriAD, query processing is performed in two stages

Stage 1: Summary graph query processing (join-ahead pruning)

Performed using graph exploration at master node to generate supernode bindings

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Stage 1: Summary graph query processing (join-ahead pruning)

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Stage 2: Data graph query processing

- Done using relational joins in a distributed setup
- Inspired by the RISC style processing, we employ three physical operators: Distributed Index Scan (DIS): Invokes a parallel scan over a permutation list that is sharded across all slaves
 Distributed Merge Join (DMJ): If both input (or intermediate) relations are sorted according to the join key(s) in the query plan
 Distributed Hash Join (DHJ): If the input (or intermediate) relations are not sorted according to their join key(s)

Global Statistics & Query Optimization

Precomputed statistics

- Computed in parallel at slaves and sent to master node
- Statistics:

Individual cardinalities: s, p, o of SPO triples Pair cardinalities: (s, o), (s, p), (p, o)Join selectivities of predicate pairs (p_1, p_2)

Similar statistics are computed over summary graph

For a given query with patterns Q $\{R_1, R_2, ...R_n\}$

Stage 1: Exploration Optimization

We compute the exploration plan by using a bottom-up dynamic programming and the following cost model:

$$Cost(R_1, \dots, R_n) \propto Card(R_1) + \sum_{i=2}^n \left(Card(R_i) \prod_{j=1}^i Sel(R_i, R_j) \right)$$
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Re-estimating cardinalities of a relations R_i

New cardinalities are re-estimated from the Stage 1 supernode bindings

$$\begin{array}{l} \blacktriangleright \quad Card(R_i) := \frac{|C_s^Q|}{|C_s|} \cdot \frac{|C_o^Q|}{|C_o|} \cdot Card(R_i) \text{ (on the fly computation)} \\ & \text{where } |C_s|, |C_o| \text{ are the supernode bindings of } R_i \\ & \text{and } |C_s^Q|, |C_o^Q| \text{ are the supernode bindings of } Q \ (R_i \in Q) \end{array}$$

Stage 2: Global plan optimization

A global plan is computed for stage 2 using re-estimated cardinalities and the following cost model

$$Cost(Q) := \begin{cases} Cost(R_i^k) & \text{if } R_i \text{ denotes a DIS over permutation } k;\\ max(Cost(Q^{left}), Cost(Q^{right})) \\ +Cost(Q^{left} \Join^{op} Q^{right}) \\ +Cost(Q^{left} \rightleftharpoons^{op} Q^{right}) & \text{otherwise.} \end{cases}$$

The cost model captures the multi-threaded and distributed execution framework

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Querying Optimization & Processing - Example

SPARQL Query:

Find persons who are born in USA and won a prize.. SELECT ?person, ?city, ?prize WHERE { R_1 ?person <bornIn> ?city . R_2 ?city <locatedIn> USA . R_3 ?person <won> ?prize . R_4 ?prize <hasName> ?name . }

Querying Optimization & Processing - Example



Querying Optimization & Processing - Example



Query Optimization & Processing – Example (2)



Stage 2: Distributed query execution

Evaluation

We compared performance of TriAD with the following state-of-the-art systems

- Centralized systems RDF-3X, MonetDB-RDF, BitMat
- Distributed systems H-RDF-3X, Trinity.RDF, 4store, SHARD, Spark

Datasets:

- (Synthetic) LUBM 160 28 Million triples, 16GB raw data
- ▶ (Synthetic) LUBM 10240 1.8 Billion triples, 730GB raw data
- (Real world) BTC 2012 1.4 Billion triples, 231 GB raw data
- (Synthetic) WSDTS 109 Million triples, 15 GB raw data
- Benchmark queries for LUBM, BTC, & WSDTS datasets

System Setup:

- ► TriAD, TriAD-SG is implemented in C++
- Cluster setup: 12-nodes, 48GB RAM, 2 quad-core CPUs of 2.4GHz (HT enabled)

Evaluation - Large datasets





Queries	Characteristics	TriAD	TriAD-SG	Trinity.RDF	H-RDF-3X		RDF-3X	
Q1	Selective (6 joins)	7,631	2,146	12,648	2.3e6	1.7E5	1.9e6	1.8e6
Q2	Non-Selective(1 join)	1,663	2,025	6,018	5.3E5	4,095	$2.4 \mathrm{E5}$	1.8E5
Q4	Selective (5 joins)	2.1	1.3	5	166	1	243	3
Q7	Selective (6 joins)	14,895	16,863	31,214	2.3e6	$2.1\mathrm{E5}$	$6.5\mathrm{E5}$	46,262

Summary

TriAD is a fast distributed RDF engine built on top of **asynchronous communication layer** and **multi-threaded execution** framework

- efficient distributed and parallel join executions
- join-ahead pruning technique via graph summarization helps in pruning dangling triples and making query processing efficient
- distributed- and join-ahead pruning aware query optimizer
- so far reported fastest runtimes over three benchmark datasets: LUBM, BTC, WSDTS

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Questions & Thank You!!