



How to build scalable **SPARQL** engines for Big **RDF** data

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Info: Panos.Kalnis@kaust.edu.sa

- Paid internships for undergrads
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- Big Data, Analytics
- Cloud, Parallel, Distributed, HPC
- Machine Learning, Al
- Visual Computing
- Bio-Informatics
- Cyber-Security

Systems for Big Data & Machine Learning





Systems for Big Data & Machine Learning



Paid Remote Internships

- Final year undergraduates, or Master's
- 3 6 months, start anytime
- US\$ 1000 / month
- Meetings via Zoom
- Can be combined with final year project
 - Διπλωματική / Πτυχιακή εργασία



Klearchos Kosmanos MSc – Aristotle Univ. Thessaloniki



Kelly Kostopoulou PhD – Columbia Univ. New York



Stamatis Anoustis PhD - KAUST

Graphs are Everywhere...



...But processing is expensive

• E.g., subgraph isomorphism, NP

"Big": CPU vs. Big size









Image from: https://aws.amazon.com/blogs/apn/exploring-knowledge-graphs-on-amazon-neptune-using-metaphactory/

11 Billion DBpedia

23 Billion

Pub[©]hem 130 Billion

RDF: Set of triples:

< Subject Predicate Object >

James	gradFrom	MIT
EE	subOrgOf	MIT
James	worksFor	CS
CS	subOrgOf	MIT
Lisa	advisor	Bill
John	advisor	Bill
	•••	
	•••	

RDF: Set of triples:

or

Directed edge-labelled graph



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	•••	
	•••	



RDF: Set of triples:

or

Directed edge-labelled graph





SPARQL: query language for RDF

SELECT	?prof	?stud	WHERE	{
?pro:	f worl	csFor	CS	•
?stu	d advi	lsor	?prof	•
•				

Return all professors who work for CS department, and their students

SPARQL: query language for RDF

SELECT	?prof	?stud	WHERE	{
?prof	work	ksFor	CS	•
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SPARQL: query language for RDF

SELECT	?prof	?stud	WHERE	{
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Return all professors who work for CS department, and their students



RDF: Directed edge-labelled graph



SPARQL: query language for RDF

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RDF: Directed edge-labelled graph



SPARQL: query language for RDF

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•				

Return all professors who work for CS department, and their students



RDF: Directed edge-labelled graph



AdPart: Dynamic Partitioning • In: VLDB Journal, 2016

- Evaluating SPARQL queries on massive RDF datasets, **PVLDB**, 2015
- Survey & experimental comparison of distributed SPARQL engines for very large RDF data, PVLDB, 2017
- Query optimizations over decentralized RDF graphs, ICDE, 2017
- Lusail: a system for querying linked data at scale, PVDLB, 2017
- A demonstration of Lusail: Querying linked data at scale, (demo) SIGMOD, 2017

Classification of RDF systems



Partitioning for Parallel Processing





AdPart – Dynamic Partitioning



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AdPart is at least 10x faster

Table 6: Runtime for LUBM-10240 queries (ms). SM: Single Machine, MR: MapReduce, and SS: Specialized systems. S2X failed to execute all queries; gStore and gStoreD could not preprocess the data within 24 hours.

	T LIDNA 10940	Complex Queries		Simple Queries			Geo-	Query /h		
	LODW-10240	L1	$\mathbf{L2}$	L3	L7	L4	$\mathbf{L5}$	L6	Mean	Query/II
\mathbf{SM}	RDF-3X	1,812,250	101,750	$1,\!898,\!500$	$98,\!250$	38	20	526	10,466	6
	SHARD	413,720	$187,\!310$	N/A	469,340	358,200	$116,\!620$	$209,\!800$	261,362	N/A
	H2RDF+	$285,\!430$	71,720	$264,\!780$	180,320	$24,\!120$	$4,\!760$	$22,\!910$	59,275	30
\mathbf{MR}	CliqueSquare	125,020	$71,\!010$	80,010	$224,\!040$	90,010	$24,\!000$	$37,\!010$	$74,\!488$	39
	S2RDF-VP	217,537	$28,\!917$	$145,\!761$	29,965	46,770	$5,\!233$	$11,\!308$	$35,\!845$	52
	S2RDF-ExtVP	$46,\!552$	$35,\!802$	$21,\!533$	$47,\!343$	9,222	2,718	$4,\!555$	$15,\!275$	150
	AdPart-NA	2,743	120	320	3,203	1	1	40	75	$3,\!920$
	TriAD	6,023	$1,\!519$	$2,\!387$	$17,\!586$	6	4	114	369	912
	\mathbf{TriAD} - \mathbf{SG}	5,392	1,774	$4,\!636$	$21,\!567$	9	5	10	333	755
	Urika-GD	5,835	$2,\!396$	$1,\!871$	$6,\!951$	1,442	720	$1,\!588$	2,259	$1,\!211$
\mathbf{SS}	H-RDF-3X	7,004	$2,\!640$	$7,\!957$	$7,\!175$	$1,\!635$	$1,\!586$	$1,\!965$	3,412	841
	H-RDF-3X (in-memory)	6,841	$2,\!597$	$7,\!948$	$7,\!551$	1,596	$1,\!594$	$1,\!926$	3,397	839
	SHAPE	25,319	$4,\!387$	$25,\!360$	$15,\!026$	1,603	$1,\!574$	$1,\!567$	5,575	337
	DREAM	13,031,410	$98,\!263$	$2,\!358$	4,700,381	18	14	10,755	12,110	1
	DREAM (cached)	$1,\!843,\!376$	$98,\!263$	<1	$83,\!053$	18	14	468	911	12



- Specialized for Graphs
- 1000x of CPU cores, TBs of RAM
- NUMA architecture
 - Global memory address space
 - Specialized network
 - Transparent to programmer

Spartex: RDF meets Graph Analytics

• In: IEEE Trans. On Parallel and Distributed Systems, 2017

RDF Analytics: Drug Repositioning



RDF Analytics: Drug Repositioning



Vertex-Centric Framework: Pregel, ...

















SPARTEX: RDF @ Vertex-centric [Kalnis et al., IEEE-TPDS, 2017]



SPARTEX syntax (1)

PREFIX sptx: <http://www.spartex.com/analytics/> CALL com.sptx.algo.centrality() AS sptx:centrality CALL com.sptx.algo.PageRank(max_iter) AS sptx:pRank SELECT ?s WHERE teaches ?c . ?p ?s takes ?c. ?s advisor ?p . ?p sptx:pRank ?rank . sptx:centrality ?cent . ?c FILTER (?rank > val1 && ?cent > val2)



SPARTEX syntax (2)

```
PREFIX sptx: <http://www.spartex.com/analytics/>
CALL com.sptx.algo.centrality() AS sptx:centrality
CALL com.sptx.algo.PageRank(max_iter) AS sptx:pRank
ADD TRIPLE { ?p sptx:popular "T" . } WHERE {
   ?p teaches ?c .
   ?s takes ?c .
   ?s advisor ?p .
   ?p sptx:pRank ?rank .
   ?c sptx:centrality ?cent .
   FILTER (?rank > val1 && ?cent > val2)
FILTER_VERTEX AS start WHERE {
 ?p sptx:popular "T" .
CALL algo:SSSP() USING start AS sptx:sssp
```


SPARTEX: 10x faster



MAGiQ: Portability and Scalability

- Demo in PVLDB, 2018
- In: Proc. of EuroSys, 2019

Existing Engines and Large Graphs

• Expensive indices

Data loading time (minutes) Memory consumption (GB) ■ Wukong [OSDI '16] This work

Data: LUBM-1B (1.3B edges); Hardware: Linux server, 24 cores@2.4Ghz, 512GB

[almost no indices]

Existing Engines and Data-intensive Queries

- Slow and difficult to port to different HW [effortlessly portable]
 - Distributed AdPart [VLDBJ '16]
 - GPU Wukong+G [ATC '18]



■ Wukong [OSDI '16] ■ This work (CPU) ■ This work (GPU)

Data: LUBM-1B (1.3B edges); Hardware: Linux server, 24 cores@2.4Ghz, 512GB, NVIDIA Quadro P6000

Our Proposal: MAGiQ

- Translate graph queries into matrix algebra programs:
 - Decouple query evaluation logic from particular HW [Portability]
 - Compact sparse matrix representation of input graphs [Scalability]
 - Utilize highly efficient existing matrix algebra libraries



[Efficiency]

Graphs as Matrices... old news?



GraphBLAS



- Represent graphs as sparse matrices
- Define common operations
- Matrix \mathbf{x} Vector \rightarrow BFS

Algorithm (Problem)	Canonical Complexity	LA-Based Complexity
Breadth-first search	<i>Θ</i> (<i>m</i>)	<i>Θ</i> (<i>m</i>)
Betweenness Centrality	Θ(mn)	Θ(mn)
(unweighted)		
All-pairs shortest-paths (dense)	Θ(n ³)	Θ(n ³)
Prim (MST)	$\Theta(m+n \log n)$	Θ(n ²)
Borůvka (MST)	<i>Θ</i> (<i>m</i> log <i>n</i>)	<i>Θ</i> (<i>m</i> log <i>n</i>)
Edmonds-Karp (Max Flow)	Θ(m ² n)	Θ(m²n)
Greedy MIS (MIS)	$\Theta(m+n \log n)$	<i>Θ</i> (<i>mn</i> + <i>n</i> ²)
Luby (MIS)	$\Theta(m+n \log n)$	$\Theta(m \log n)$

MAGIQ – RDF Graph Representation





Α

Pre-processing \rightarrow Matrix operations \rightarrow Post-processing

MAGIQ – RDF Graph Representation



Pre-processing \rightarrow Matrix operations \rightarrow Post-processing

Selection as Matrix Multiplication



• S: 1 at row $i \rightarrow$ select row i from M

Generalized Matrix Selection



- Semi-ring with
 - isEqual instead of multiplication
 - OR instead of addition

MAGIQ – Algebraic Operations

Matrix-matrix multiplication over isEqual , OR semi-ring



MAGIQ – Algebraic Operations

Matrix-matrix multiplication over isEqual , OR semi-ring



MAGIQ - Algebraic Operations

Matrix-matrix multiplication over *isEqual*, OR *semi-ring*

Row selection with predicate:

neighbors connected to **C** and **E** with **e** outgoing edges





MAGIQ – Algebraic Operations

any(**M**): reduction with **OR**



MAGIQ – Algebraic Operations

diag(v): construct diagonal selection matrix



SELECT	?x ?y WHERE	{
?x	<a> ?y .	
}		





SELECT	?x ?y WHERE	{
?x	<a> ?y .	
}		







SELECT	?x ?y WHERE	{
?x	<a> ?y .	
}		







SELECT	?x ?y WHERE	{
?x	<a> ?y .	
}		







Graph query translation



Graph query translation



Graph query translation



Graph query translation



$$\begin{split} \mathbf{M}_{xy} &= \mathbf{I} * a \otimes \mathbf{A} \\ \mathbf{M}_{yz} &= \mathtt{diag}(\mathtt{any}(\mathbf{M}_{xy}')) * c \otimes \mathbf{A} \\ \mathbf{M}_{xy} &= \mathbf{M}_{xy} \times \mathtt{diag}(\mathtt{any}(\mathbf{M}_{yz})) \\ \mathbf{M}_{xw} &= \mathtt{diag}(\mathtt{any}(\mathbf{M}_{xy})) * b \otimes \mathbf{A} \end{split}$$

Graph query translation



$$\begin{split} \mathbf{M}_{xy} &= \mathbf{I} * a \otimes \mathbf{A} \\ \mathbf{M}_{yz} &= \mathtt{diag}(\mathtt{any}(\mathbf{M}'_{xy})) * c \otimes \mathbf{A} \\ \mathbf{M}_{xy} &= \mathbf{M}_{xy} \times \mathtt{diag}(\mathtt{any}(\mathbf{M}_{yz})) \\ \mathbf{M}_{xw} &= \mathtt{diag}(\mathtt{any}(\mathbf{M}_{xy})) * b \otimes \mathbf{A} \end{split}$$

Graph query translation



Graph query translation



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MAGiQ – Evaluation Setup

• Single machine:

2 x 14-core Intel Xeon E5-2680 @ 2.4Gh 512GB NVIDIA Quadro P6000 GPU [Pascal, 24GB GDDR5X]

MAGiQ – Evaluation Setup

- Single machine: 2 x 14-core Intel Xeon E5-2680 @ 2.4Gh
 512GB
 NVIDIA Quadro P6000 GPU [Pascal, 24GB GDDR5X]
- Distributed-memory: Cray XC40



[6,174 Compute Nodes: 12,348 CPUs] 2 x 16-core Intel Xeon E5-2698 @ 2.3 GHz 128GB per Compute Node
MAGIQ - Datasets

Dataset	#Triples (M)	#Nodes (M)	# P
WatDiv-100M	109.23	10.28	85
YAGO2	284.30	60.70	98
WatDiv-1B	1,092.16	97.39	86
LUBM-1B	1,366.71	336,51	18
Bio2RDF	4,287.59	1,135.93	1,714
LUBM-10B	10,677.83	2,628.99	18
LUBM-512B	512,527.41	126,188.23	18

MAGIQ – Competing Engines

- Research:
 - **RDF-3X** [VLDB'08] Relational, single machine, serial
 - gStore [VLDB'11] Graph-based, single machine, serial
 - AdPart [VLDBJ'16] Relational, distributed
 - Wukong[OSDI'16] Graph-based, distributed, multithreaded
- Commercial:
 - UrikaGD
 - Virtuoso

- Specialized hardware appliance
- Relational, single machine, multithreaded

MAGIQ – Data-intensive Queries^{*}

LUBM-1B (1.3B edges)

		Loading time	Dat	ta-intensiv (seco	ve query 1 onds)	ime	
			L1	L2	L3	L7	
RDF-3X	[VLDB'08]		901	116	898	426	
Wukong	[OSDI'16]		11	10	11	42	
MAGiQ(S	uiteSparse)						
MAGiQ(M	atlab-CPU)						
MAGiQ(Matlab-GPU)							

*MAGiQ is slower for selective queries

MAGIQ – Data-intensive Queries^{*}

LUBM-1B (1.3B edges)

		Loading time	Dai	ta-intensiv (seco			
		(minutes)	L1	L2	L3	L7	
RDF-3X	[VLDB'08]	447	901	116	898	426	
Wukong	[OSDI'16]	57	11	10	11	42	
MAGiQ(S	uiteSparse)	16					
MAGiQ(M	atlab-CPU)	16					
MAGiQ(M	atlab-GPU)	16					

*MAGiQ is slower for selective queries

MAGIQ – Data-intensive Queries^{*}

LUBM-1B (1.3B edges)

		Loading time	Dat	a-intensiv (seco	Query time GeoMean			
		(minutes)	L1	L2	L3	L7	(seconds)	
RDF-3X	[VLDB'08]	447	901	116	898	426	308	E
Wukong	[OSDI'16]	57	11	10	11	42	15	
MAGiQ(S	uiteSparse)	16	173	38	108	155	102	S
MAGiQ(M	atlab-CPU)	16	25	14	6	38	17	
MAGiQ(M	atlab-GPU)	16	3	2	2	5	3	

*MAGiQ is slower for selective queries

MAGIQ – Scalability on Cray XC40 Supercomputer







Matrix algebra for RDF: it's MAGIQ



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Extra slides

Extra:

- Main limitations:
 - No support for queries with variable predicates.
 - No support property path queries.
 - Slow performance for selective queries compared to index-based engines.

Extra: Slow for selective queries

LUBM-1B [data-intensive] query times (seconds)

	L1	L2	L3	L7	GeoMean
RDF-3X	901.4	115.6	898.2	426.2	307.6
Virtuoso	25.0	1,268.2	11.7	308.1	103.3
UrikaGD	5.8	2.4	1.9	7.0	3.7
Wukong	11.1	10.3	10.5	42.0	15.0
MAGiQ (SuiteSparse)	173.2	38.0	107.7	155.0	102.4
MAGiQ (Matlab-CPU)	24.9	14.3	6.1	38.2	17.0
MAGiQ (Matlab-GPU)	3.2	2.1	1.5	5.4	2.7



Cyclic queries





Query planning



13B Triples - Shaheen



- CombBLAS
 - Scales with sqrt(p), where p: number of cores



Workload evaluation





LUBM-10B query times (seconds)

		L1	L2	L3	L4	L5	L6	L7
	AdPart	5.12	0.12	0.24	0.07	0.08	3.51	4.84
× .	MAGiQ (CombBLAS)	3.08	0.93	0.67	1.66	0.61	1.36	3.79



Loading time (minutes)

Dataset	RDF-3X	GSTORE	Virtuoso	Wukong	MAGiQ
WatDiv-100M	18	40	9	4	1
YAGO2	78	63	50	9	3
LUBM-1B	447	n/a	191	57	16
Bio2RDF	n/a	n/a	331	n/a	92