

PhD. Dissertation Presentation

Performance-based Ontology Matching

An Effectiveness-independent Approach for Performance-gain

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Background.(1/2)

• Semantic Heterogeneity

- The progress of information and communication technologies have created abundance of dissimilar information ^[1]
- Semantic Heterogeneity, handling of information variation in meanings and ambiguity is an open challenge ^[2]

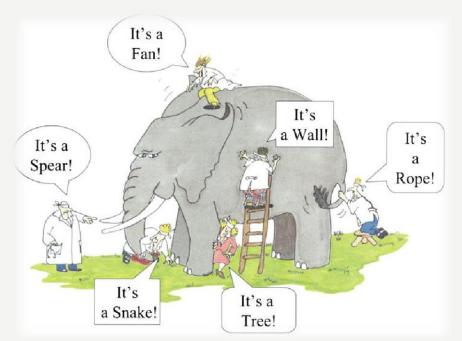


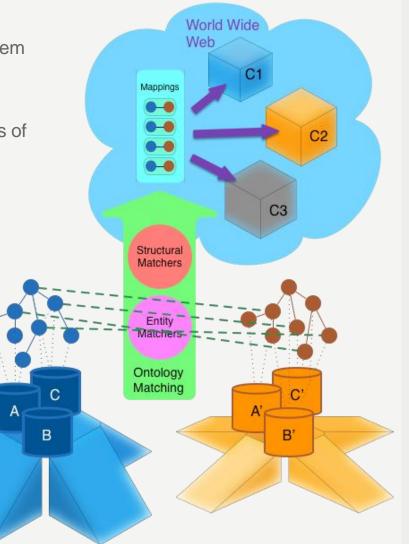
Image from: André Freitas,

Crossing the Vocabulary Gap for Querying Complex and Heterogeneous Databases http://www.slideshare.net/andrenfreitas/crossing-the-vocabulary-gap-for-querying-complex-and-heterogeneous-databases

Background.(2/2)

Ontology Matching

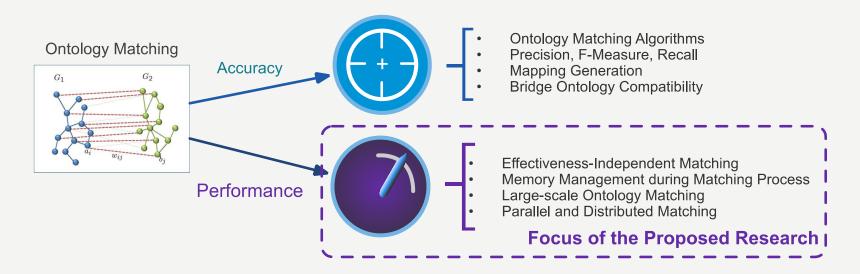
- Primary solution to the heterogeneity resolution problem heterogeneity resolution problem ^[1]
- Resources are annotated by ontologies and correspondence between semantically related entities of these ontologies is determined by library of complex ontology matching algorithms ^[3]
- Correspondences are further used for ^{[5][6]}
 - Information and e-Commerce systems,
 - Database integration,
 - Semantic-web services,
 - Medical knowledge-bases,
 - Clinical guidelines and Decision making,
 - Medical data formats and Standardization
 - Social networks,
 - Data interoperability,
 - Information translation.



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Motivation.

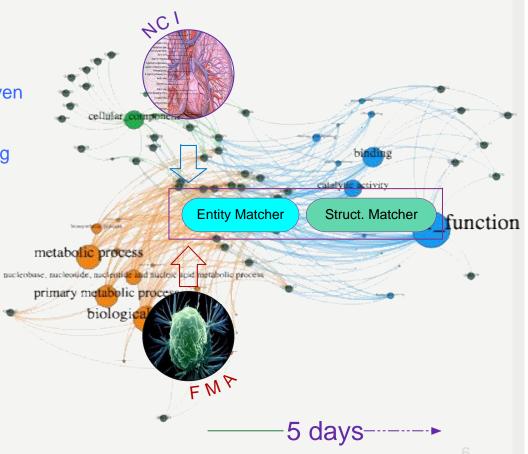
- Due to excess of data, size of the Ontologies have grown and become complex; Consequently, the Ontology Matching has become a computationally intensive task with complexity quadratic or higher ^[4]
- Shvaiko et. al, "Ontology Matching: State of the Art and Future Challenges". *IEEE Transaction on Knowledge and Data Engineering (2013)*, for the first time discussed ontology matching as two-fold problem which requires explicit performance efficiency resolutions for in-time results
- The core techniques for achieving better performance are either related to the optimization of matching algorithms or the fragmentation of ontologies, Parallel and distributed ontology matching is largely unaddressed so far ^[1]
- Design time nature and delay caused by current monolithic matching techniques makes ontology matching ill-equipped for dynamic systems with in-time result needs ^{[1][6][9]}



Motivation.(example)

• FMA, NCI Matching problem

- Two large-scale ontologies with 78 Mb, and 66 Mb owl file size
- Two matching algorithms
- Quad-core commodity machine, 8 Gb Memory
- Impulsive shut-down due to no result even after 5 days
- Java Heap blow up errors during parsing



Problem Statement.

- Ontology matching is the most efficient and used methodology for Semantic Heterogeneity resolution
- Abundance of data has caused Ontologies to grow and become complex; Consequently, matching algorithms have become complex (> $O(n^2)$). As a result, ontology matching is now a computationally intensive task
- Current state-of-the-art resolutions talk about performance in regards with optimization of matching algorithms (effectiveness-dependent resolution), They fail to engage approaches where performance-gain can be achieved without compromising the accuracy (effectiveness-independent performance-gain)
 - For high accuracy, compromise on performance, delay in results making current techniques illequipped for clients and systems with in-time requirements
- Current approaches are monolithic, with no collaboration and sharing at service and platform level
- Goal

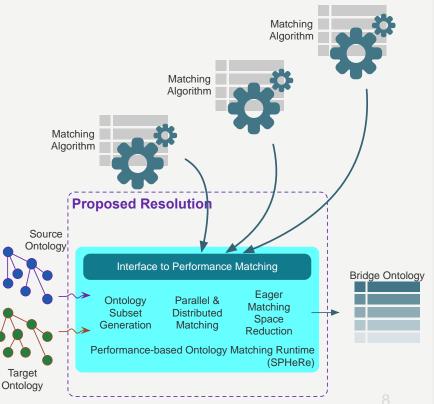
"To devise one such methodology that identifies the possible bottlenecks of the ontology matching process from end-to-end and provides explicit performance measures for the matching process in a shareable environment such that through out the performance gain, accuracy of the matching process is preserved, thus achieving an effectiveness-independent performance-gain resolution"

Objectives.

- A performance-efficient solution for accessing ontology resources in the memory without memory stress
- Optimal exploitation of available computational resources for the matching process
- Avoid redundant computationally expensive matching operations through out the matching process
- Presented resolution must be sharable for mapping generation and decoupled matching library execution
- <u>Challenges</u>
 - Completion of whole matching process with-in

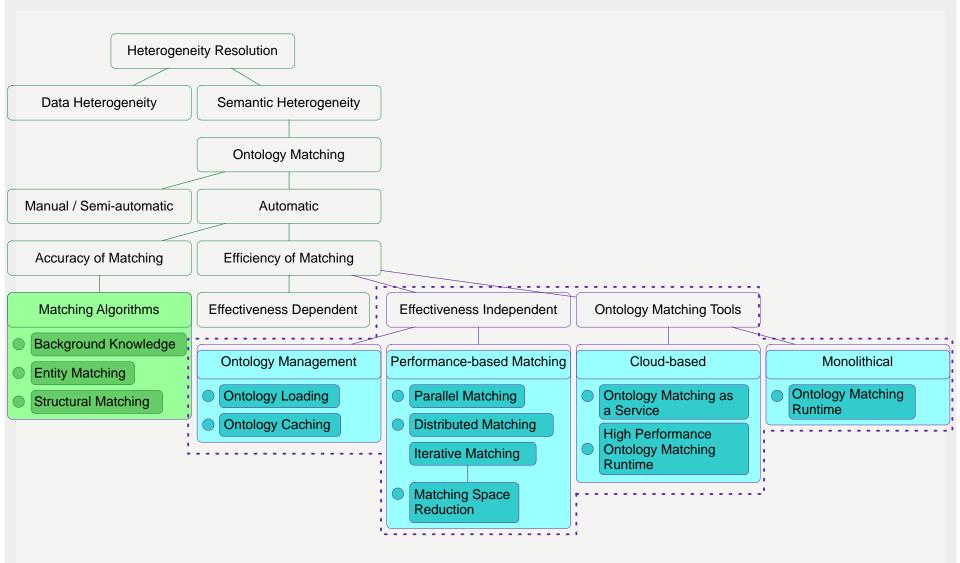
optimal Heap size

- Scalability over available computing cores
- Large-scale ontology matching problems
- Accuracy Preservance through-out the performance-gain (Effectiveness-Independent Resolution)



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Research Taxonomy.



Related Work.(1/2)

Performance-Requirement <u>Matrix</u> Proposed Methodology in comparison with OAEI Ranked System (2006-2014)	1. Domain Independent	2. Accuracy Preservance	3. Design Time Support	4. Soft-real-time Support	5. Matching Library	6. Large-scale Ontology Matching Support	7. Monolithic Runtime	8. Shareable as a Service	9. Parallel and Distributed Matching	10. Scalability	11. Memory Stress and Footprint Reduction
1. AgrMaker ^[10]		8		\otimes	coupled			8	8		8
2. AROMA ^[11]		8		8	Coupled	?		•	8	•	8
3. ASMOV ^[12]	8	8		8	coupled	8		$\mathbf{\otimes}$	8		\mathbf{S}
4. CODI ^[13]		8		8	Coupled	?		\mathbf{S}	8		8
5. CSA ^[14]		\otimes		8	Coupled	2		⊗	8		8
6. Falcon-AO ^[15]	\checkmark	8	\checkmark	8	coupled	S		8	8		8
7. GOMMA ^[16]	\checkmark	\mathbf{S}		\odot	✓ coupled			8		\bigcirc	8
8. Hadoop-MapReduce	\checkmark		\checkmark	8	8		8	platform		\bigcirc	
9. Lily ^[17]	\checkmark	8		⊗	coupled	8		•	8		•
10. LogMap ^[18]	\checkmark	8		8	coupled			\odot	8	•	\odot
11. MAPSSS ^[19]	\checkmark	8		8	coupled	?		\odot	8		8
12. MassMtch ^[20]	\checkmark	8		8	coupled	?		\odot	8	•	\odot
13. SAMBO ^[21]	8	8		8	coupled			\odot	8		8
14. ServOMap ^[22]	8	⊗	v	8	coupled			platform	8		8
Proposed Methodology ^[5]			O		decoupled		Ø	✓ software✓ platform		0	

*the sequence numbers do not reflect the chronological order of ranking

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Related Work.(2/2)

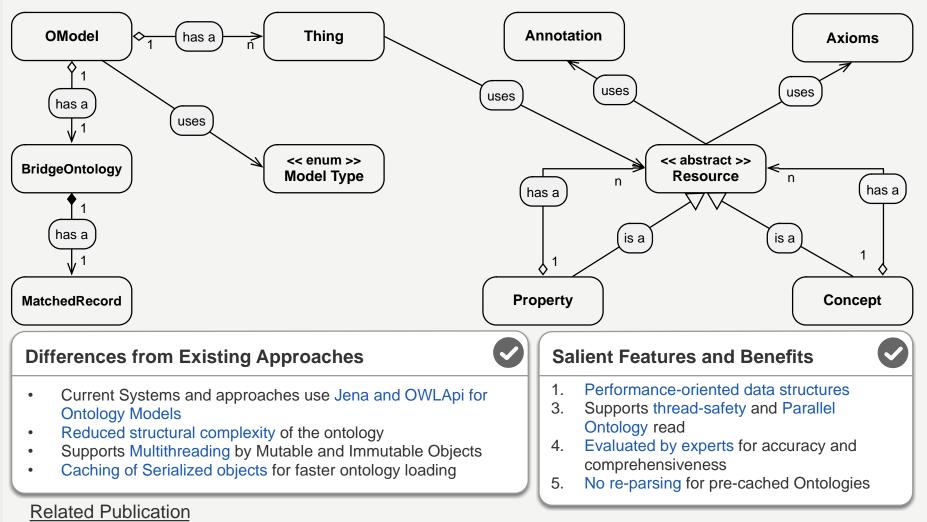
- The performance aspect of the current ontology matching systems is tightly coupled with the accuracy and complexity of matching algorithms
- Their implemented resolutions are more focused on optimization of the matching algorithms and partitioning of larger ontologies into smaller chunks for performance benefits
- Increase the Heap-Memory for Large-scale matching problems
- A clear distinction between the resolutions for accuracy and performance does not exist
- Redundant matching operations with no workflow-based execution
- An explicit and decoupled runtime has not been proposed yet which can improve the performance factors without inflicting any changes in the effectiveness of matching algorithms
- These resolutions fall into the category of effectiveness-dependent solutions where a tradeoff between matching effectiveness (accuracy measures, precision, recall, and F-Measure) and execution time (performance) exists
- The performance improvement based-on exploitation of newer hardware technologies has largely been missed

Proposed Methodology.

	Limitations	Proposed Solution	<u>Objectives</u>
1.	 Lack of Performance-efficient Ontology Model, (Jena and OWLApi are used) Whole Ontology Load with Memory stress and Heap Blowups 	 Generic, yet concise Ontology Model with Caching, re-usability, and multi-threading support Matching Algorithm-based Ontology Subsets Creation and Loading for Parallel Matching 	A performance-efficient solution for accessing ontology resources in the
2.	 Subtle increase in performance with better hardware Ill-equipped to perform Parallel and Distributed Matching for effectiveness independent performance-gain 	 Parallel and Distributed Ontology Matching platform with abstractions defined from grainer to finer level of Matching Process 	Optimal exploitation of available computational resources for the matching process
3.	Late checking for redundant bridge instances	 Aligned execution workflow for Eager Matching Space Reduction 	Avoid redundant computationally expensive matching operations through out the matching process
4.	 Monolithic implementations with no sharing at service or platform level Effectiveness-dependent solutions 	 Cloud-based runtime, Ontology Matching as a Service, as a Platform Effectiveness-independent resolution 	• Presented resolution must be sharable for mapping generation and decoupled matching library execution

Solution $1_{(1/4)}$: Matching Algorithm-based Ontology Subset generation.

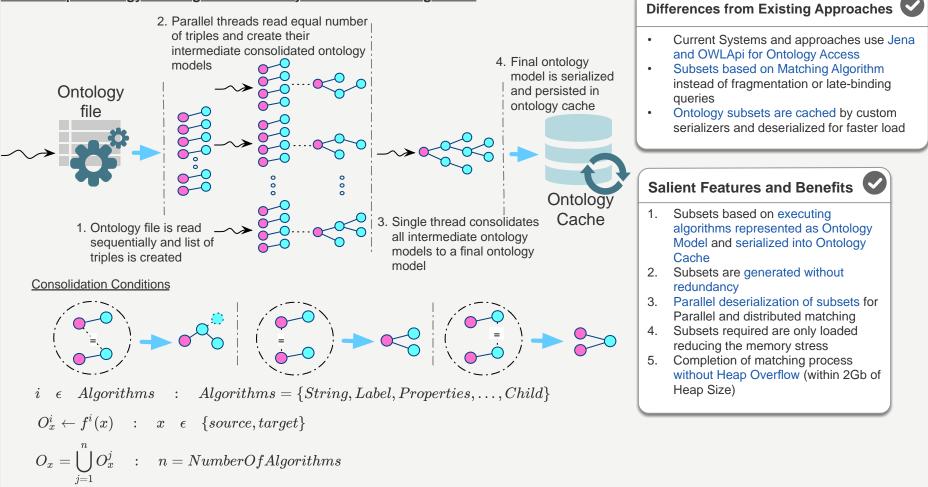
UML Conceptual Representation of Ontology Model



Muhammad Bilal Amin, Rabia Batool, Wajahat Ali Khan, Sungyoung Lee, Eui-Nam Huh. (2014). SPHeRe: A Performance • Initiative Towards Ontology Matching by Implementing Parallelism over Cloud Platform, Journal of Supercomputing, 68(1), 274-301.

Solution $1_{(2/4)}$: Matching Algorithm-based Ontology Subset generation.

Bottom-up Ontology Parsing and Hierarchy Consolidation Algorithm



Related Publication

- Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong-Ho Kang (2015). Performance-based Ontology Matching, A data-parallel approach for an effectiveness-independent performance-gain in ontology matching. Applied Intelligence DOI 10.1007/s10489-015-0648-z
- Muhammad Bilal Amin, Rabia Batool, Wajahat Ali Khan, Sungyoung Lee, Eui-Nam Huh. (2014). SPHeRe: A Performance Initiative Towards Ontology Matching by Implementing Parallelism over Cloud Platform, Journal of Supercomputing, 68(1), 274–301.

Solution 1_(3/4): Matching Algorithm-based Ontology Subset generation.

Algorithm 1 Method owlLoad

```
Require: O_x \neq NULL and O_t \neq NULL
  Hash_s \leftarrow Utility.calculateHash(O_s)
  Hash_t \leftarrow Utility.calculateHash(O_t)
  ontologyCache ← OntologyCache.getInstance()
  parser \leftarrow Parser.createInstance()
  if Hash<sub>s</sub>, Hash<sub>t</sub> lin ontologyCache then
     parser.parse(O_s, O_t)
     parser.serialize(O_s, O_t)
  else
     if Hash, lin ontologyCache and Hash, in ontologyCache then
        parser.parse(O_t)
        parser.serialize(O_t)
     else if Hashs !in ontologyCache and Hasht in ontologyCache then
       parser.parse(O_s)
       parser.serialize(O_s)
     end if
  end if
  deserialize(Hash<sub>3</sub>, Hash<sub>1</sub>)
  return
```

Algorithm 2 Method nameParser

Require: $O_x \neq NULL, x \in \{s, t\}$ thing \leftarrow Thing.createInstance(url) while O_x has classes do concept \leftarrow OClass.createInstance(currentClassName) thing.addConcept(&concept) end while return thing

Algorithm 3 Method labelParser

Require: $O_x \neq NULL, x \in \{s, t\}$ thing \leftarrow Thing.createInstance(url) while O_x has classes do concept \leftarrow OClass.createInstance(currentClassName) while currentClass has labels do label \leftarrow Annotation.createLabel(labelName) concept.addAnnotation(&label) end while thing.addConcept(&concept) end while return thing

Related Publication

 Muhammad Bilal Amin, Rabia Batool, Wajahat Ali Khan, Sungyoung Lee, Eui-Nam Huh. (2014). SPHeRe: A Performance Initiative Towards Ontology Matching by Implementing Parallelism over Cloud Platform, Journal of Supercomputing, 68(1), 274–301.

Solution 1_(4/4): Matching Algorithm-based Ontology Subset generation.

Algorithm 4 Method propertyParser

Require: $O_x \neq NULL, x \in \{s, t\}$ thing \leftarrow Thing.createInstance(url) while O_x has classes do concept \leftarrow OClass.createInstance(currentClassName) while currentClass has properties do property \leftarrow OProperty.createInstance(propertyName) concept.addProperty(&property) end while thing.addConcept(&concept) end while return thing

Algorithm 5 Method hierarchyParser **Require:** $O_x \neq NULL, x \in \{s, t\}$ thing ← Thing.createInstance(url) while Ox has classes do concept ← OClass.createInstance(currentClassName) while currentClass has parents do if !thing.exists(parent) then parent ← OClass.createInstance(parentName) thing.addConcept(&parent) else parent ← thing.getConcept(parentName) end if concept.addConcept(&parent) end while thing.addConcept(&concept) end while return thing

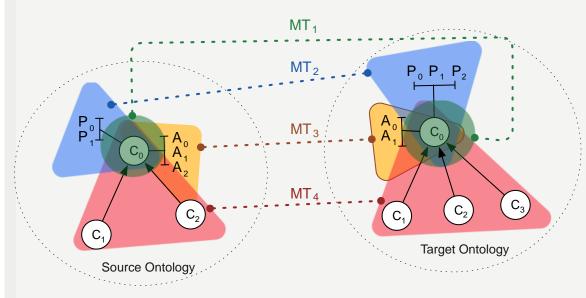
Related Publication

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Solution $2_{(1/4)}$: Parallel and Distributed Ontology Matching.

Matching Task (MT) Definition

MT is the unit of matching process; defined as, a single independent execution of a matching algorithm over a resource from source (O_S) and target ontologies (O_T)



Related Publications

- Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong-Ho Kang (2015). Performance-based Ontology Matching, A data-parallel approach for an effectivenessindependent performance-gain in ontology matching. Applied Intelligence DOI 10.1007/ s10489-015-0648-z
- Muhammad Bilal Amin, Rabia Batool, Wajahat Ali Khan, Sungyoung Lee, Eui-Nam Huh. (2014). SPHeRe: A Performance Initiative Towards Ontology Matching by Implementing Parallelism over Cloud Platform, Journal of Supercomputing, 68(1), 274–301. doi:10.1007/s11227-013-1037-1

 $egin{aligned} MT &= f(m,n,MatchingAlgorithm_i) \ MT_i igcap MT_{i+1} igcap MT_{i+2}....igcap MT_n = \phi \ MT_{Total} \geq m imes n \; \; orall \; m \; \; \epsilon \; \; O_s \; \; \& \; \; n \; \; \epsilon \; \; O_t \ MT_{Core} \leftarrow rac{MT_{Total}}{Cores_{Total}} \end{aligned}$

Differences from Existing Approaches

- Current Systems and approaches do not implement any parallel and distributed ontology matching methodologies
- Adding more computational resources directly impacts the overall performance of the matching process

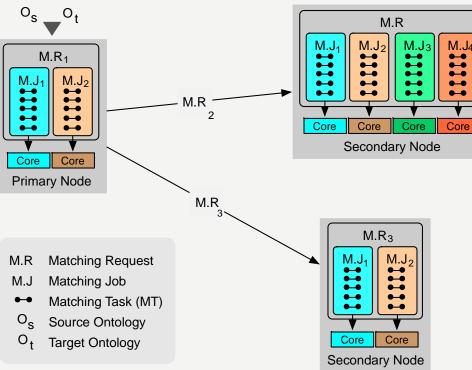
Salient Features and Benefits

1.

- Highly efficient for medium to large-scale ontology matching problem
- 2. Independent Matching Task, leading to no communication overhead during matching process
- 3. Data parallelism implementation by thread-level parallelism
- 4. Size-based partitioning of matching tasks at finerlevel for optimal computing resource utilization

Solution $2_{(2/4)}$: Parallel and Distributed Ontology Matching.

Distribution Abstractions



Related Publications

- Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong-Ho Kang (2015). Performance-based Ontology Matching, A data-parallel approach for an effectivenessindependent performance-gain in ontology matching. Applied Intelligence DOI 10.1007/ s10489-015-0648-z
- Muhammad Bilal Amin, Rabia Batool, Wajahat Ali Khan, Sungyoung Lee, Eui-Nam Huh. (2014). SPHeRe: A Performance Initiative Towards Ontology Matching by Implementing Parallelism over Cloud Platform, Journal of Supercomputing, 68(1), 274–301. doi:10.1007/s11227-013-1037-1

$$egin{aligned} MR \leftarrow \sum_{i=1}^n MR_i &: n &= TotalNodes \ MR_i \leftarrow \sum_{i=1}^c MJ_i &: c = TotalCoresPerNode \ MJ_i \leftarrow \left\{igcup_{i=1}^t MT_i
ight\} &: t = TotalTasksPerCore \end{aligned}$$

Differences from Existing Approaches

- Current Systems and approaches do not implement any parallel and distributed ontology matching methodologies
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Salient Features and Benefits

- 1. Highly efficient for medium to large-scale ontology matching problem
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- 3. Data parallelism implementation by thread-level parallelism
- 4. Size-based partitioning of matching tasks at finerlevel for optimal computing resource utilization

Solution $2_{(3/4)}$: Parallel and Distributed Ontology Matching.

Algorithm 1 Generate socket table

```
Require: node \ge 2.
  temp = 1
  uuidMsg \leftarrow generateUUID()
  cores ← Runtime.getNumberofCores()
  rank \leftarrow getRankforThisNode()
  while temp < ShiftLeft(1, nodes) do
     if temp \ge nodes then
         stop
     end if
     sender = rank
     receiver \leftarrow XOR(rank, temp)
     socket \leftarrow getSocket(receiver)
     if sender > receiver then
         sendMessage(socket, uuidMsg, cores)
         socketTable.add(socket,receiveMessage(socket))
     else
         socketTable.add(socket,receiveMessage(socket))
         sendMessage(socket, uuidMsg)
     end if
     temp = temp + 1
  end while
```

Algorithm 2 Distributor algorithm

Require: nodes > 0if nodes=1 then MulticoreDistributor(O_s, O_T) else Multi-nodeDistributor(O_s, O_T) end if

Related Publications

 Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong-Ho Kang (2015). Performance-based Ontology Matching, A data-parallel approach for an effectiveness-independent performance-gain in ontology matching. Applied Intelligence DOI 10.1007/s10489-015-0648-z

Solution $2_{(4/4)}$: Parallel and Distributed Ontology Matching.

Algorithm 3 Multicore distributor algorithm

```
Require: nodes > 0
  cores ←Runtime.getNumberOfCores()
  if nodes=1 then
     start=0
     bigOnt \leftarrow (size_S \ge size_T)?O_S : O_T
     smallOnt \leftarrow (size_S < size_T)?O_S : O_T
     Partition_{slab} = [bigOnt.size/cores]
     SPAWN MATCHER THREADS:
     for doi = 1 to cores do
        end = start + Partition_{slab}
        if end \leq bigOnt.size then
            end = bigOnt.size
        end if
        MatchingJob.create(MatchingTasks[start,
        end), big, small, matcher)
        thread.run(matchingJob)
        start = end
     end for
  else
     RECEIVE MATCHING REQUEST:
     controlMessage.receive(matchingRequest)
     Partition_{slab} = (end - start)/cores
     GOTO SPAWN MATCHER THREADS
  end if
```

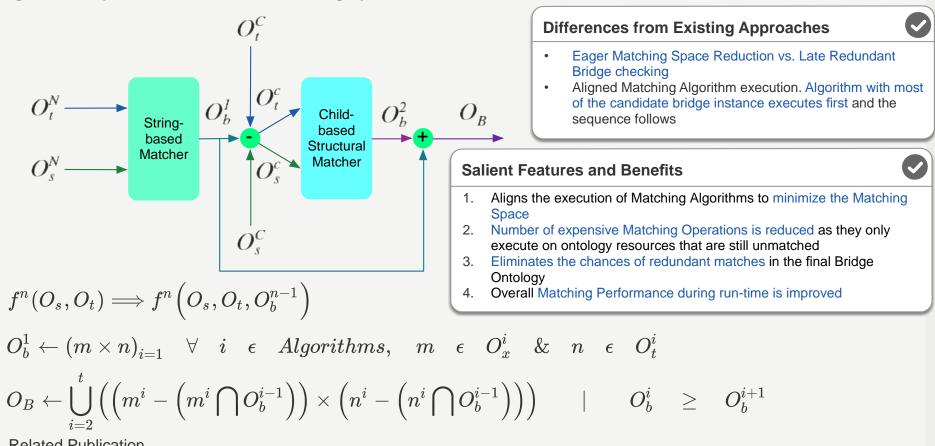
```
Algorithm 4 Multi-node distributor algorithm
Require: nodes > 1
  nodes ←initDaemon.getNoOfNodes()
  participatingCores = \sum node.\#cores
  start=0
  end=0
  bigOnt \leftarrow (size_S \ge size_T)?O_S : O_T
  smallOnt \leftarrow (size_S < size_T)?O_S : O_T
  Distribution<sub>slab</sub> = [bigOnt.size/
  participatingCores]
  for node \leftarrow nodes do
      end = start + Distribution_{slab} \times node.#cores
      if end \leq bigOnt.size then
         end = bigOnt.size
      end if
      MatchingRequest.create([start, end), big, small,
      matcher)
      if node.isLocal then
         local.MulticoreDistributor(matchingRequest)
      else
         controlMessage.send(matchingRequest)
      end if
      start = end
  end for
```

Related Publications

 Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong-Ho Kang (2015). Performance-based Ontology Matching, A data-parallel approach for an effectiveness-independent performance-gain in ontology matching. Applied Intelligence DOI 10.1007/s10489-015-0648-z

Solution 3 : Eager Matching Space Reduction.

Algorithm Sequence to Minimize the Matching Space



Related Publication

Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong-Ho Kang (2015). Performance-based Ontology Matching, A data-parallel approach for an effectiveness-independent performance-gain in ontology matching. Applied Intelligence DOI 10.1007/s10489-015-0648-z

Solution $4_{(1/2)}$: Ontology Matching Runtime as a Service and a Platform.

Differences from Existing Approaches

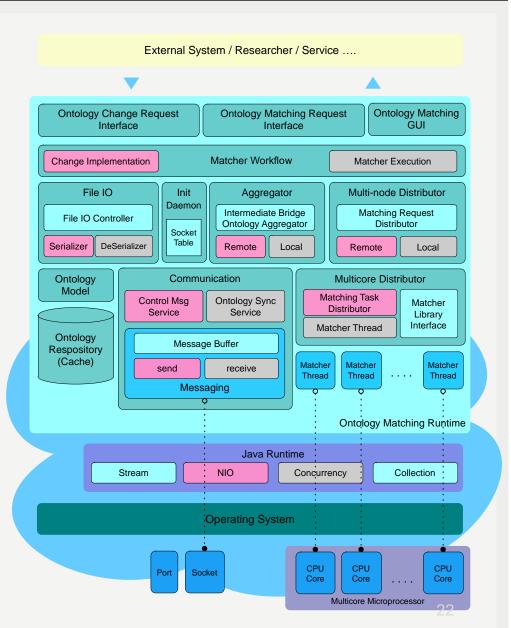
- Decoupled platform and runtime built for performance aspects of ontology matching
- Support for parallel and distributed matching
- Can work as a monolithic implementation and dedicated ontology matching platform
- Built with Cloud aspects (Virtual Machines) in consideration

Salient Features and Benefits

- 1. Decoupled Performance Platform from Ontology Matching Algorithms
- 2. Parallel serializers and deserializers for ontology subset loading and persistence
- 3. Support for local parallel matching by multicore distributors
- 4. Support for distributed parallel matching by multi-node distributors
- 5. High Performance Socket-based communication for Candidate Ontology subset replications and repository synchronization
- 6. Thread-level parallelism for parallel matching
- 7. Interface for Ontology Matching Request via Ontology Matching as a Service (SaaS)
- 8. Share-ability by Service, Platform, and Results

Related Publications

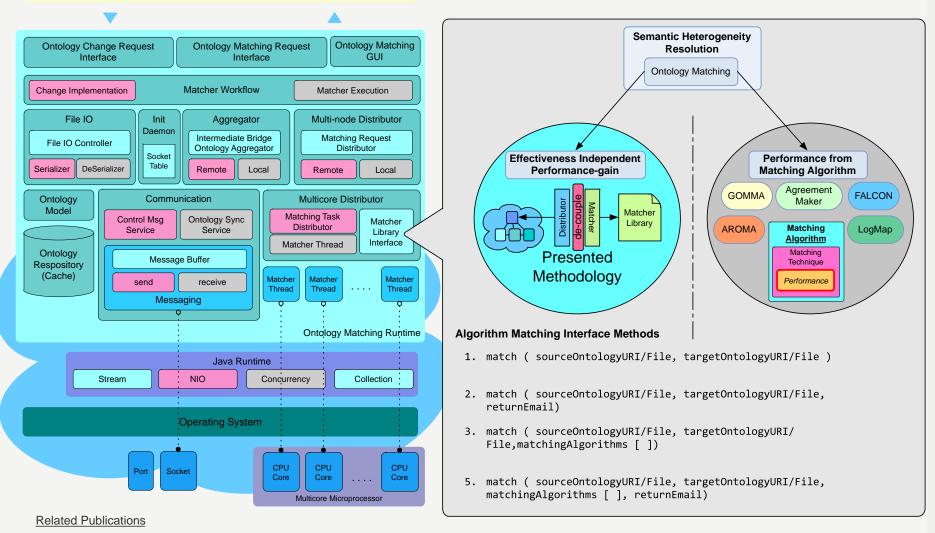
- Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong-Ho Kang (2015). Performance-based Ontology Matching, A data-parallel approach for an effectiveness-independent performance-gain in ontology matching. Applied Intelligence DOI 10.1007/s10489-015-0648-z
- Muhammad Bilal Amin, Rabia Batool, Wajahat Ali Khan, Sungyoung Lee, Eui-Nam Huh. (2014). SPHeRe: A Performance Initiative Towards Ontology Matching by Implementing Parallelism over Cloud Platform, Journal of Supercomputing, 68(1), 274–301. doi:10.1007/s11227-013-1037-1
- Muhammad Bilal Amin, Aamir Shafi, Shujaat Hussain, Wajahat Ali Khan, Sungyoung Lee, High Performance Java Sockets for Scientific Health Clouds, 14th International Conference on e-Health Networking, Applications and Services (Healthcom 2012), Beijing, China
- Muhammad Bilal Amin, Wajahat Ali Khan, Asad Masood Khattak, Maqbool Hussain, Sungyoung Lee, System for Parallel Heterogeniety Resolution (SPHeRe) 2013 OAEI results, ISWC Ontology Matching Workshop, Sydney 2012.



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Solution $4_{(2/2)}$: Ontology Matching Runtime as a Service and a Platform.

External System / Researcher / Service

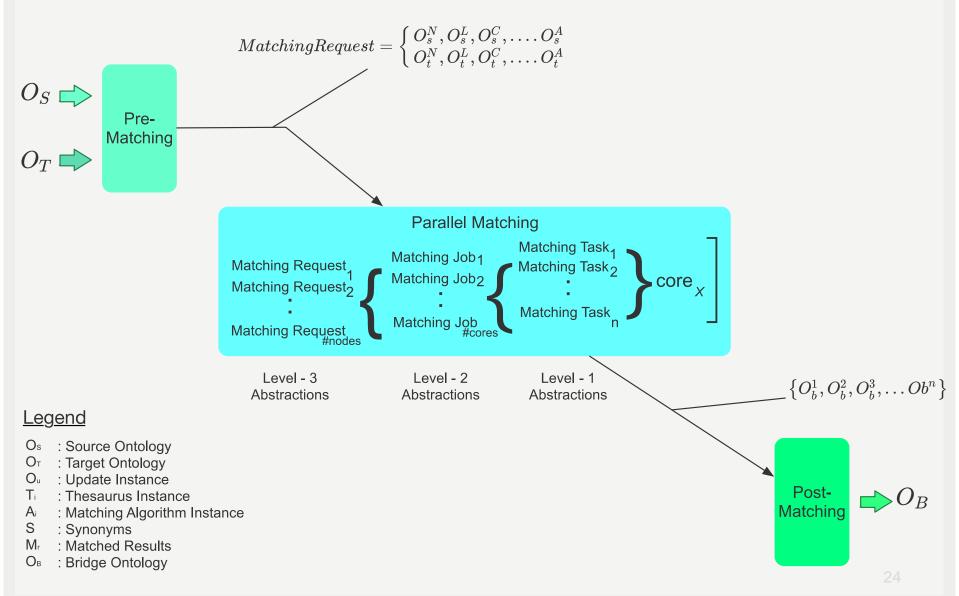


• Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong-Ho Kang (2015). Performance-based Ontology Matching, A data-parallel approach for an effectiveness-independent performance-gain in ontology matching. Applied Intelligence DOI 10.1007/s10489-015-0648-z

Muhammad Bilal Amin, Mahmood Ahmad, Wajahat Ali Khan, Sungyoung Lee, Biomedical Ontology Matching as a Service, ICOST 2014, Advances in Cognitive Technologies, Denver Colorado USA; 06/2014

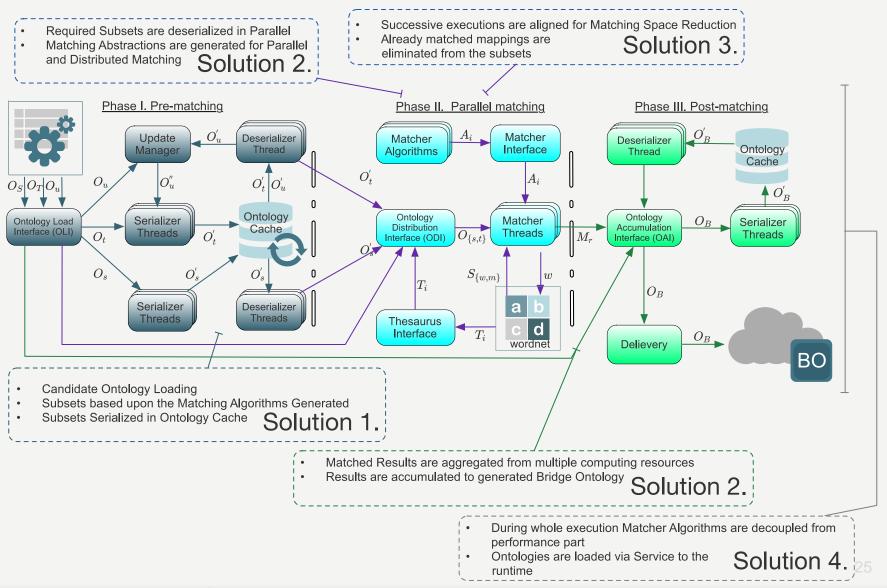
Over-all Execution flow.

High Level Representation



Over-all Execution flow.

Detail Level Representation



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Evaluation Results.(1/19)

Loading Time Comparison

Dataset Source

- OAEI 2012-2013 Standard Evaluation Dataset of Real-world Ontologies
- Candidate Ontologies: FMA = 78,989 concepts NCI = 66,724 concepts SNOMED = 49,622 concepts

Testbed

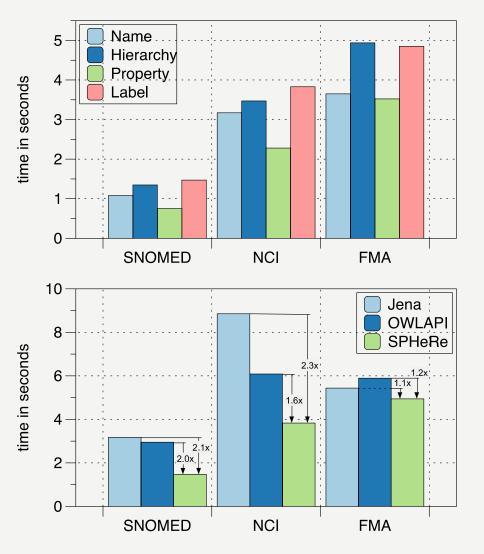
Cloud: Tri-node private cloud equipped with Intel(R) Core(TM) i7 CPU, 16 GB memory with Xen Hypervisor, Java 1.6

Description

- This evaluation is in Regards to Solution 1
- ~2.5x fast Ontology Loading from Serialized Subsets as compared to Jena and OWL Api

Published In

 Muhammad Bilal Amin, Rabia Batool, Wajahat Ali Khan, Sungyoung Lee, Eui-Nam Huh, SPHeRe, A Performance Initiative Towards Ontology Matching by Implementing Parallelism over Cloud Platform, Jr. of Supercomputing (SCI, IF:0.95) (2014) 68:274-301



Evaluation Results.(2/19)

Memory Stress Comparison

Dataset Source

- OAEI 2012-2013 Standard Evaluation Dataset of Real-world Ontologies
- Candidate Ontologies: FMA = 78,989 concepts NCI = 66,724 concepts SNOMED = 49,622 concepts

Testbed

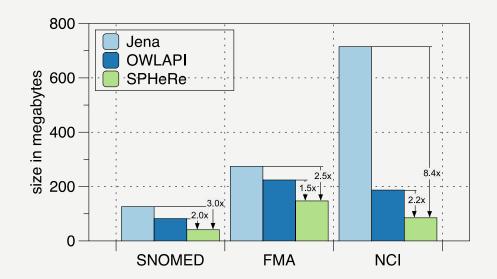
Cloud: Tri-node private cloud equipped with Intel(R) Core(TM) i7 CPU, 16 GB memory with Xen Hypervisor, Java 1.6

Description

- This evaluation is in Regards to Solution 1
- Memory stress varies from Ontology's complexity, reduced memory foot print from 1.5x to 8.4x as compared to Jena and OWLApi

Published In

 Muhammad Bilal Amin, Rabia Batool, Wajahat Ali Khan, Sungyoung Lee, Eui-Nam Huh, SPHeRe, A Performance Initiative Towards Ontology Matching by Implementing Parallelism over Cloud Platform, Jr. of Supercomputing (SCI, IF:0.95) (2014) 68:274-301



Evaluation Results.(3/19)

Reduction Rate

Dataset Source

- OAEI 2012-2013 Standard Evaluation Dataset of Real-world Ontologies
- Candidate Ontologies: MA = 2,000 concepts
 FMA = 78,989 concepts
 NCI = 66,724 concepts
 SNOMED = 49,622 concepts

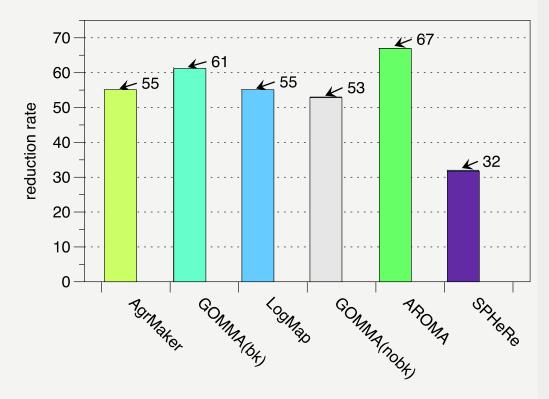
Testbed

Cloud:

Tri-node private cloud equipped with Intel(R) Core(TM) i7 CPU, 16 GB memory with Xen Hypervisor, Java 1.6

Description

- This evaluation is in Regards to Solution 2
- Measures the scalability aspect of the system
- Measures the optimal resource utilization by a system
- OAEI standard reduction formula is used
- ~40% better reduction score than GOMMA



Published In

 Muhammad Bilal Amin, Rabia Batool, Wajahat Ali Khan, Sungyoung Lee, Eui-Nam Huh, SPHeRe, A Performance Initiative Towards Ontology Matching by Implementing Parallelism over Cloud Platform, Jr. of Supercomputing (SCI, IF:0.95) (2014) 68:274-301

Evaluation Results.(4/19)

Performance Comparison with GOMMA

Dataset Source

 Candidate Ontologies: MA = 2,737 concepts (OAEI 2012) NCI = 3,298 concepts (OAEI 2012) MF = 9,395 concepts (GO, 2009) BP = 17,104 concepts (GO, 2009)

Testbed

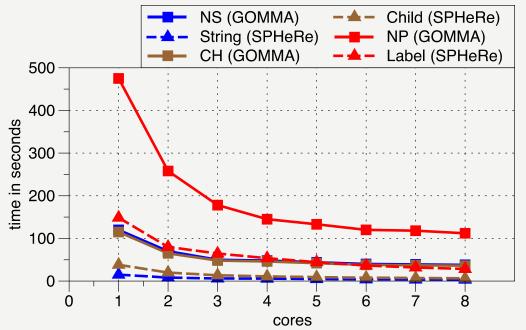
Cloud: Tri-node private cloud equipped with Intel(R) Core(TM) i7 CPU, 16 GB memory with Xen Hypervisor, Java 1.6

Description

- This evaluation is in Regards to Comparison with most performance efficient ontology matching system GOMMA
- ~4 times better performance than GOMMA

Published In

 Muhammad Bilal Amin, Rabia Batool, Wajahat Ali Khan, Sungyoung Lee, Eui-Nam Huh, SPHeRe, A Performance Initiative Towards Ontology Matching by Implementing Parallelism over Cloud Platform, Jr. of Supercomputing (SCI, IF:0.95) (2014) 68:274-301



Evaluation Results. (5/19)

OAEI Anatomy Track

Dataset Source

- OAEI 2013-2014 Standard Evaluation Dataset of **Real-world Ontologies**
- Matching Library: String-Label-ChildBased
- Magnitude: Medium-scale (MT > 27 Million)
- Candidate Ontologies: ٠ Adult Mouse Anatomy = 2,744 concepts NCI Thesaurus = 3,304 concepts

Testbed

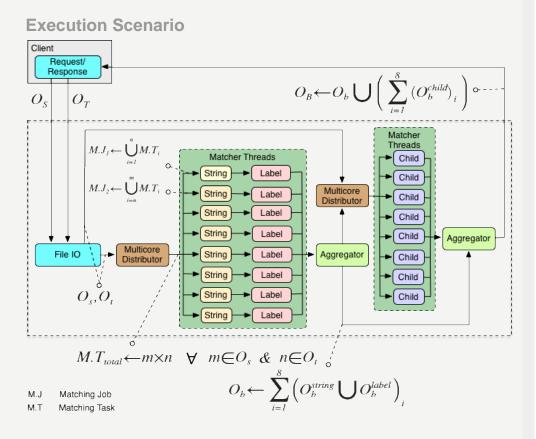
- Multicore Desktop: 3.4 GHz Intel(R) Core i7(R) Hyper-Threaded (Intel(R) HT Technology) CPU (2 threads/ core) with 16 GB memory, Java 1.8 and Windows 7 64 bit OS
- Cloud:

Microsoft Azure standard A4 VM instances with 8 cores, 14 GB of memory, Java 1.8, and Windows 2012 R2 Guest OS running over an AMD Opteron(TM) 2.1 GHz CPU

Description

- This evaluation is in Regards to Overall Performance particularly Solution 3, 4
- Designed by OAEI experts for trivial and non-trivial mappings
- 4x performance-gain over desktop
- 5.5x performance-gain over cloud node
- Accuracy measures stay preserved through-out the process

Published In Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong Ho Kang, Performance-based ontology matching, A data parallel approach for an effectiveness-independent performance-gain in ontology matching, Applied Intelligence (SCI, IF:1.85) (2015)



Evaluation Results.(6/19)

OAEI Anatomy Track

Dataset Source

- OAEI 2013-2014 Standard Evaluation Dataset of Real-world Ontologies
- Matching Library: String-Label-ChildBased
- Magnitude: Medium-scale (MT > 27 Million)
- Candidate Ontologies: Adult Mouse Anatomy = 2,744 concepts NCI Thesaurus = 3,304 concepts

Testbed

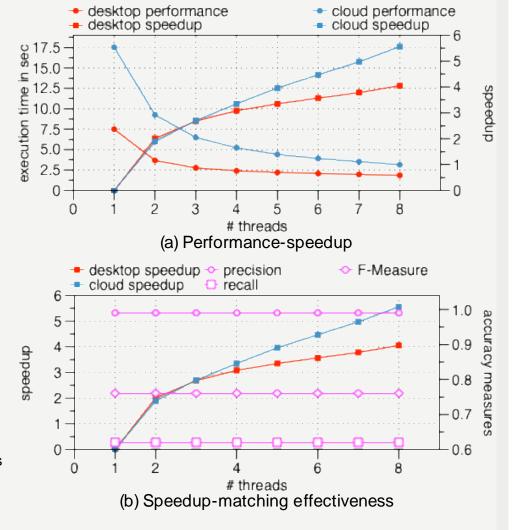
- Multicore Desktop
 3.4 GHz Intel(R) Core i7(R) Hyper-Threaded
 (Intel(R) HT Technology) CPU (2 threads/ core) with 16 GB memory, Java 1.8 and
 Windows 7 64 bit OS
- Cloud:

Microsoft Azure standard A4 VM instances with 8 cores, 14 GB of memory, Java 1.8, and Windows 2012 R2 Guest OS running over an AMD Opteron(TM) 2.1 GHz CPU

Description

- This evaluation is in Regards to Overall Performance
 particularly Solution 3, 4
- Designed by OAEI experts for trivial and non-trivial mappings
- 4x performance-gain over desktop
- 5.5x performance-gain over cloud node
- Accuracy measures stay preserved through-out the process

Published In Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong Ho Kang, Performance-based ontology matching, A data parallel approach for an effectiveness-independent performance-gain in ontology matching, Applied Intelligence (SCI, IF:1.85) (2015)



Evaluation Results.(7/19)

OAEI Library Track

Dataset Source

- OAEI 2013-2014 Standard Evaluation Dataset of Real-world Ontologies
- Matching Library: String-Label-ChildBased
- Magnitude: Medium to Large scale (MT > 165 Million)
- Candidate Ontologies: STW = 8,376 concepts TheSoz = 6,575 concepts

Testbed

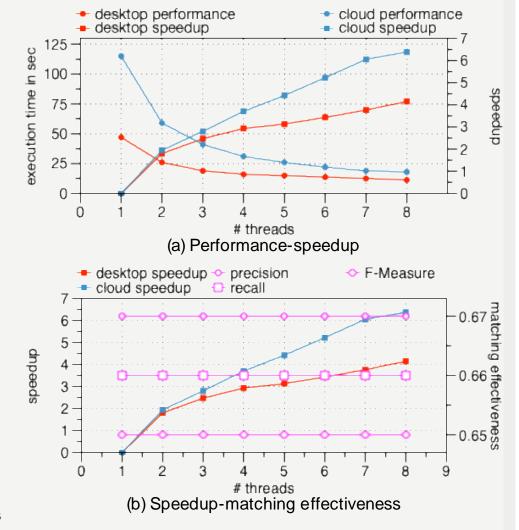
- Multicore Desktop: 3.4 GHz Intel(R) Core i7(R) Hyper-Threaded (Intel(R) HT Technology) CPU (2 threads/ core) with 16 GB memory, Java 1.8 and Windows 7 64 bit OS
- Cloud:

Microsoft Azure standard A4 VM instances with 8 cores, 14 GB of memory, Java 1.8, and Windows 2012 R2 Guest OS running over an AMD Opteron(TM) 2.1 GHz CPU

Description

- This evaluation is in Regards to Overall Performance
 particularly Solution 3, 4
- Used for Library Indexation and retrieval
- 4.15x performance-gain over desktop
- 6.38x performance-gain over cloud node
- Accuracy measures stay preserved through-out the process

Published In Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong Ho Kang, Performance-based ontology matching, A data parallel approach for an effectiveness-independent performance-gain in ontology matching, Applied Intelligence (SCI, IF:1.85) (2015)



Evaluation Results.(8/19)

OAEI Large-scale Biomedical Track: task 1

Dataset Source

- OAEI 2013-2014 Standard Evaluation Dataset of Real-world Ontologies
- Matching Library: String-Annotation-ChildBased
- Magnitude: Medium to Large scale (MT > 71 Million)
- Candidate Ontologies:
 FMA = 3,696 concepts
 NCI = 6,488 concepts

Testbed

Multicore Desktop: 3.4 GHz Intel(R) Core i7(R) Hyper-Threaded (Intel(R) HT Technology) CPU (2 threads/ core) with 16 GB memory, Java 1.8 and Windows 7 64 bit OS

Cloud:

Microsoft Azure standard A4 VM instances with 8 cores, 14 GB of memory, Java 1.8, and Windows 2012 R2 Guest OS running over an AMD Opteron(TM) 2.1 GHz CPU

Description

- This evaluation is in Regards to Overall Performance
 particularly Solution 3, 4
- 4.27x performance-gain over desktop
- 6.53x performance-gain over cloud node
- Accuracy measures stay preserved through-out the process

Matche $M. J_1 \leftarrow \bigcup_{i=1}^{n} M. T_i$ Threads Matcher Threads Child String - Annotation Child Multicore String - Annotation ► Child Distributor $M. J_2 \leftarrow \bigcup M. T_i$ String Annotation Child String - Annotation Child Aggregator Multicore String Annotation File IO Aggregator ► Child Distributor String - Annotation Child O_s O_t String - Annotation Child String Annotation $M. T_{total} \leftarrow m imes n \quad orall { ilde{v}} m \in O_s \quad \& \quad n \in O_t$ $O_b \leftarrow \sum_{i=1}^8 (O_b^{string} \bigcup O_b^{annotation})_i$ M J Matching Job M.T Matching Task

 $O_B \leftarrow O_b igcup \Big(\sum_{i=1}^{s} (O_b^{child})_i$

Published In Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong Ho Kang, Performance-based ontology matching, A data parallel approach for an effectiveness-independent performance-gain in ontology matching, Applied Intelligence (SCI, IF:1.85) (2015)

Execution Scenario

Client

 O_S

Request/

Response

 O_T

Evaluation Results.(9/19)

OAEI Large-scale Biomedical Track: task 1

Dataset Source

- OAEI 2013-2014 Standard Evaluation Dataset of Real-world Ontologies
- Matching Library: String-Annotation-ChildBased
- Magnitude: Medium to Large scale (MT > 71 Million)
- Candidate Ontologies:
 FMA = 3,696 concepts
 NCI = 6,488 concepts

Testbed

• Multicore Desktop:

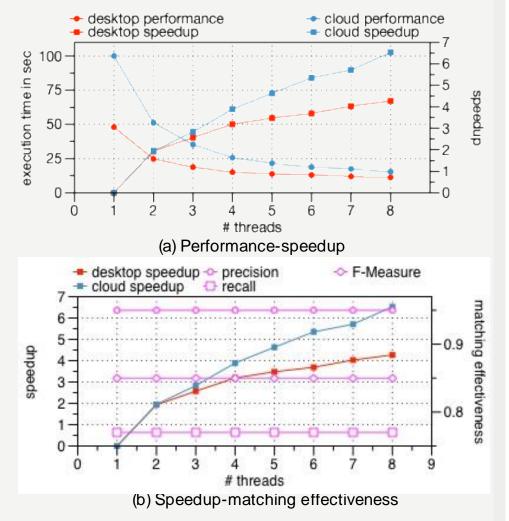
3.4 GHz Intel(R) Core i7(R) Hyper-Threaded (Intel(R) HT Technology) CPU (2 threads/ core) with 16 GB memory, Java 1.8 and Windows 7 64 bit OS

Cloud:

Microsoft Azure standard A4 VM instances with 8 cores, 14 GB of memory, Java 1.8, and Windows 2012 R2 Guest OS running over an AMD Opteron(TM) 2.1 GHz CPU

Description

- This evaluation is in Regards to Overall Performance
 particularly Solution 3, 4
- 4.27x performance-gain over desktop
- 6.53x performance-gain over cloud node
- Accuracy measures stay preserved through-out the process



Published In Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong Ho Kang, Performance-based ontology matching, A data parallel approach for an effectiveness-independent performance-gain in ontology matching, Applied Intelligence (SCI, IF:1.85) (2015)

Evaluation Results.(10/19)

OAEI Large-scale Biomedical Track: task 2

Dataset Source

- OAEI 2013-2014 Standard Evaluation Dataset of Real-world Ontologies
- Matching Library: String-Annotation-ChildBased
- Magnitude: Very Large scale (MT > 15 Billion)
- Candidate Ontologies:
 FMA = 78,989 concepts
 NCI = 66,724 concepts

Testbed

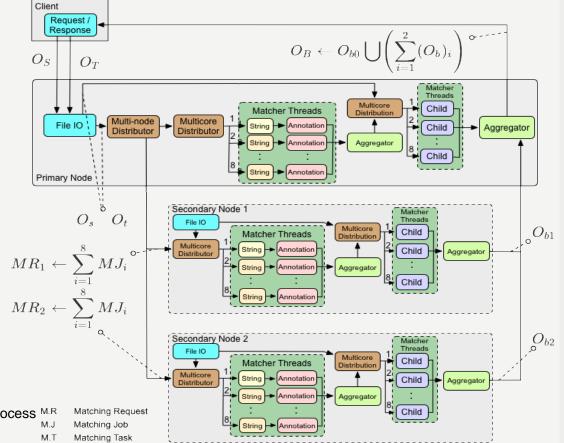
- Multicore Desktop: 3.4 GHz Intel(R) Core i7(R) Hyper-Threaded (Intel(R) HT Technology) CPU (2 threads/ core) with 16 GB memory, Java 1.8 and Windows 7 64 bit OS
- Cloud:

Microsoft Azure standard A4 VM instances with 8 cores, 14 GB of memory, Java 1.8, and Windows 2012 R2 Guest OS running over an AMD Opteron(TM) 2.1 GHz CPU

Description

- This evaluation is in Regards to Overall Performance particularly Solution 3, 4
- 14.7x performance-gain over desktop
- 21.8x performance-gain over cloud node
- Accuracy measures stay preserved through-out the process M.R.





Published In Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong Ho Kang, Performance-based ontology matching, A data parallel approach for an effectiveness-independent performance-gain in ontology matching, Applied Intelligence (SCI, IF:1.85) (2015)

Evaluation Results.(11/19)

OAEI Large-scale Biomedical Track: task 2

Dataset Source

- OAEI 2013-2014 Standard Evaluation Dataset of **Real-world Ontologies**
- Matching Library: String-Annotation-ChildBased
- Magnitude: Very Large scale (MT > 15 Billion)
- Candidate Ontologies: FMA = 78,989 concepts NCI = 66,724 concepts

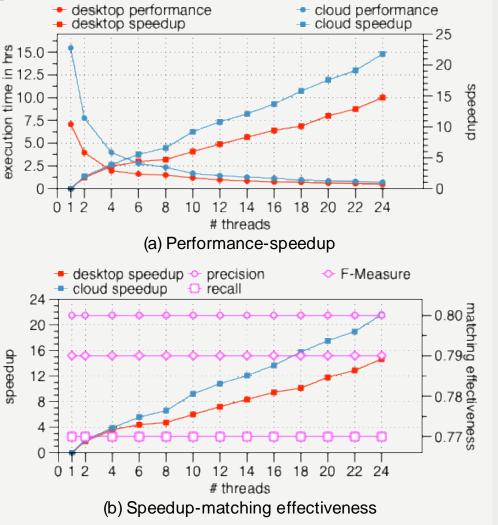
Testbed

- Multicore Desktop: 3.4 GHz Intel(R) Core i7(R) Hyper-Threaded (Intel(R) HT Technology) CPU (2 threads/ core) with 16 GB memory, Java 1.8 and Windows 7 64 bit OS
- Cloud:

Microsoft Azure standard A4 VM instances with 8 cores, 14 GB of memory, Java 1.8, and Windows 2012 R2 Guest OS running over an AMD Opteron(TM) 2.1 GHz CPU

Description

- This evaluation is in Regards to Overall Performance particularly Solution 3, 4
- 14.7x performance-gain over desktop
- 21.8x performance-gain over cloud node
- Accuracy measures stay preserved through-out the process



Published In Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong Ho Kang, Performance-based ontology matching, A data parallel approach for an effectiveness-independent performance-gain in ontology matching, Applied Intelligence (SCI, IF:1.85) (2015)

Evaluation Results.(12/19)

OAEI Large-scale Biomedical Track: task 3

Dataset Source

- OAEI 2013-2014 Standard Evaluation Dataset of Real-world Ontologies
- Matching Library: String-Annotation-ChildBased
- Magnitude: Large scale (MT > 400 Million)
- Candidate Ontologies:
 FMA = 10,157 concepts
 NCI = 13,412 concepts

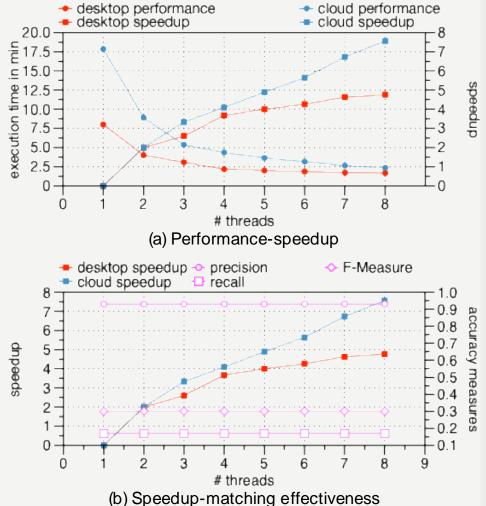
Testbed

- Multicore Desktop: 3.4 GHz Intel(R) Core i7(R) Hyper-Threaded (Intel(R) HT Technology) CPU (2 threads/ core) with 16 GB memory, Java 1.8 and Windows 7 64 bit OS
- Cloud:

Microsoft Azure standard A4 VM instances with 8 cores, 14 GB of memory, Java 1.8, and Windows 2012 R2 Guest OS running over an AMD Opteron(TM) 2.1 GHz CPU

Description

- This evaluation is in Regards to Overall Performance particularly Solution 3, 4
- 4.76x performance-gain over desktop
- 7.56x performance-gain over cloud node
- Accuracy measures stay preserved through-out the process



Evaluation Results.(13/19)

OAEI Large-scale Biomedical Track: task 4

Dataset Source

- OAEI 2013-2014 Standard Evaluation Dataset of Real-world Ontologies
- Matching Library: String-Annotation-ChildBased
- Magnitude: Very Large scale (MT > 29 Billion)
- Candidate Ontologies: FMA = 78,989 concepts SNOMED = 122,464 concepts

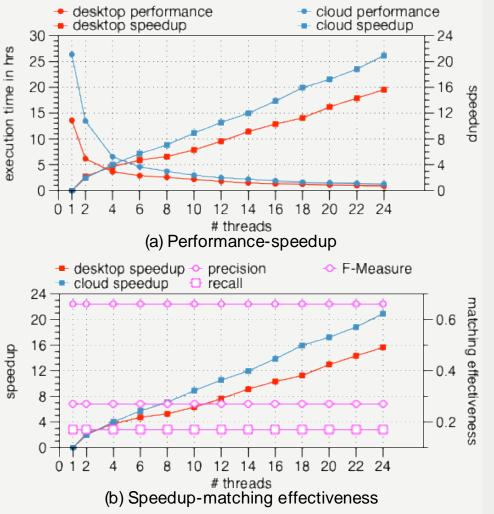
Testbed

- Multicore Desktop: 3.4 GHz Intel(R) Core i7(R) Hyper-Threaded (Intel(R) HT Technology) CPU (2 threads/ core) with 16 GB memory, Java 1.8 and Windows 7 64 bit OS
- Cloud:

Microsoft Azure standard A4 VM instances with 8 cores, 14 GB of memory, Java 1.8, and Windows 2012 R2 Guest OS running over an AMD Opteron(TM) 2.1 GHz CPU

Description

- This evaluation is in Regards to Overall Performance particularly Solution 3, 4
- 15.64x performance-gain over desktop
- 21x performance-gain over cloud node
- Accuracy measures stay preserved through-out the process



Evaluation Results.(14/19)

OAEI Large-scale Biomedical Track: task 5

Dataset Source

- OAEI 2013-2014 Standard Evaluation Dataset of Real-world Ontologies
- Matching Library: String-Annotation-ChildBased
- Magnitude: Large scale (MT > 3 Billion)
- Candidate Ontologies: FMA = 51,128 concepts NCI = 23,958 concepts

Testbed

• Multicore Desktop:

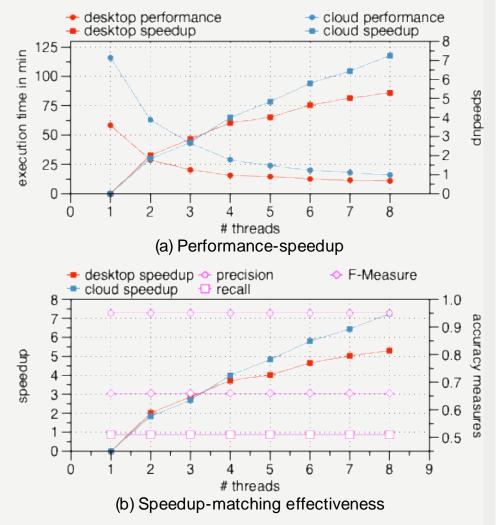
3.4 GHz Intel(R) Core i7(R) Hyper-Threaded (Intel(R) HT Technology) CPU (2 threads/ core) with 16 GB memory, Java 1.8 and Windows 7 64 bit OS

Cloud:

Microsoft Azure standard A4 VM instances with 8 cores, 14 GB of memory, Java 1.8, and Windows 2012 R2 Guest OS running over an AMD Opteron(TM) 2.1 GHz CPU

Description

- This evaluation is in Regards to Overall Performance particularly Solution 3, 4
- 5.31x performance-gain over desktop
- 7.25x performance-gain over cloud node
- Accuracy measures stay preserved through-out the process



Evaluation Results.(15/19)

OAEI Large-scale Biomedical Track: task 6

Dataset Source

- OAEI 2013-2014 Standard Evaluation Dataset of Real-world Ontologies
- Matching Library: String-Annotation-ChildBased
- Magnitude: Very Large scale (MT > 24 Billion)
- Candidate Ontologies: NCI = 66,724 concepts SNOMED = 122,464 concepts

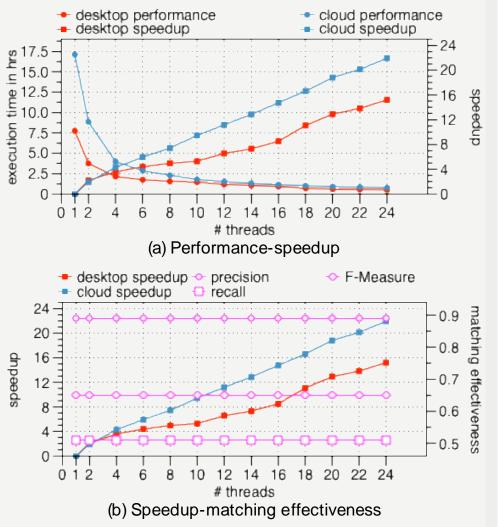
Testbed

- Multicore Desktop: 3.4 GHz Intel(R) Core i7(R) Hyper-Threaded (Intel(R) HT Technology) CPU (2 threads/ core) with 16 GB memory, Java 1.8 and Windows 7 64 bit OS
- Cloud:

Microsoft Azure standard A4 VM instances with 8 cores, 14 GB of memory, Java 1.8, and Windows 2012 R2 Guest OS running over an AMD Opteron(TM) 2.1 GHz CPU

Description

- This evaluation is in Regards to Overall Performance
 particularly Solution 3, 4
- 15.19x performance-gain over desktop
- 22x performance-gain over cloud node
- Accuracy measures stay preserved through-out the process



Evaluation Results.(16/19)

OAEI Conference Track

Dataset Source

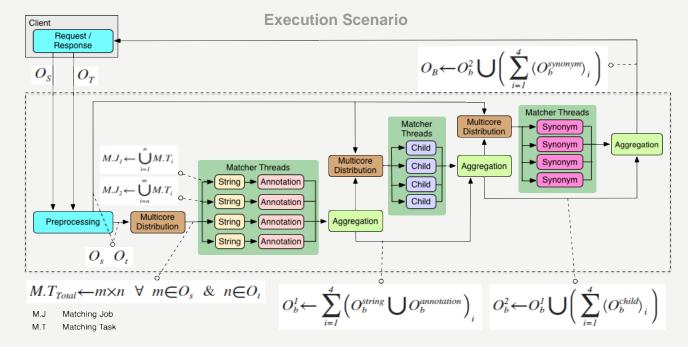
Testbed

- OAEI 2013-2014 Standard Evaluation Dataset of Real-world Ontologies
- Matching Library: String-Annotation-ChildBased-Synonym
- Magnitude: Small scale

Cloud: Microsoft Azure standard A2 VM instances with 2 cores, 1.5 GB of memory, Java 1.8, and Windows 2012 R2 Guest OS running over an AMD Opteron(TM) 2.1 GHz CPU

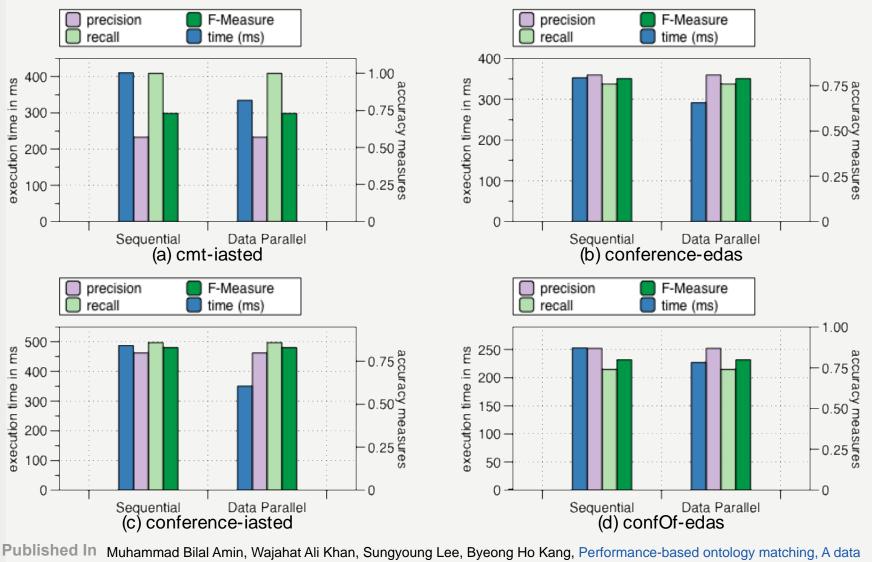
Description

- This evaluation is in Regards to Overall Performance particularly Solution 3, 4
- 1.2x performance-gain over cloud node
- Accuracy measures stay preserved
 through-out the process



Evaluation Results.(17/19)

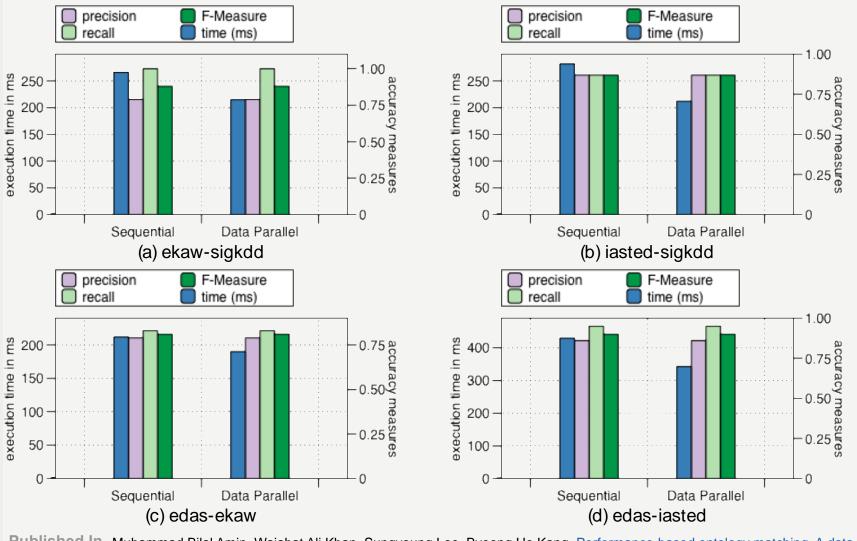
OAEI Conference Track



Published In Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong Ho Kang, Performance-based ontology matching, A data parallel approach for an effectiveness-independent performance-gain in ontology matching, Applied Intelligence (SCI, IF:1.85) 42 (2015)

Evaluation Results.(18/19)

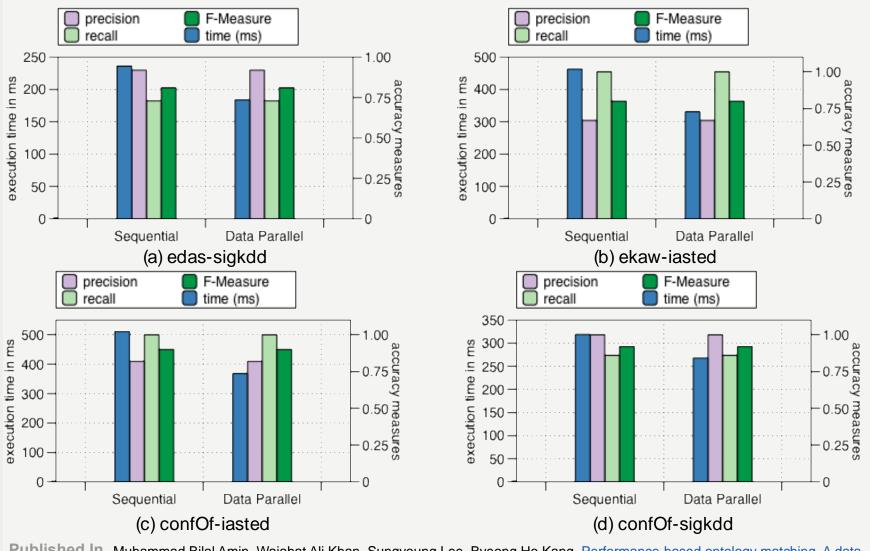
OAEI Conference Track



Published In Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong Ho Kang, Performance-based ontology matching, A data parallel approach for an effectiveness-independent performance-gain in ontology matching, Applied Intelligence (SCI, IF:1.85) (2015)

Evaluation Results.(19/19)

OAEI Conference Track



Published In Muhammad Bilal Amin, Wajahat Ali Khan, Sungyoung Lee, Byeong Ho Kang, Performance-based ontology matching, A data parallel approach for an effectiveness-independent performance-gain in ontology matching, Applied Intelligence (SCI, IF:1.85)₄₄ (2015)

Result Summary.

	Matching problem	Domain	Platform	Speed up	Precision
mall	cmt-iasted	Conference	Single-node Cloud VM	1.22	0.57
	conference-edas		Single-node Cloud VM	1.25	0.81
	conference-iaste	xd	Single-node Cloud VM	1.39	0.80
	confof-edas		Single-node Cloud VM	1.11	0.87
	confof-iasted		Single-node Cloud VM	1.38	0.82
	confof-sigkdd		Single-node Cloud VM	1.19	1.00
	edas-sigkdd		Single-node Cloud VM	1.28	0.92
	ekaw-iasted		Single-node Cloud VM	1.39	0.67
	ekaw-sigkdd		Single-node Cloud VM	1.23	0.79
	iasted-sigkdd		Single-node Cloud VM	1.33	0.87
	edas-ekaw		Single-node Cloud VM	1.11	0.79
	edas-iasted		Single-node Cloud VM	1.25	0.86
Medium	24	Anatomy	Single-node Desktop	4.05	0.99
		desktop	Single-node Cloud VM	5.56	0.99
	22 STW-TheSoz	cloud (Azure VM)	Single-node Desktop	4.15	0.67
	31 w-11c302		Single-node Cloud VM	6.38	0.67
	20				
	20	Biomedical	Single-node Desktop	4.27	0.95
			Single-node Cloud VM	6.53	0.95
Large	18 FMA _w -SNOME	D _s	Single-node Desktop	4.76	0.93
	-		Single-node Cloud VM	7.56	0.93
			Sinala noda Daskton	5.31	0.95
		D _S	Single-node Desktop Single-node Cloud VM	7.25	0.95
			Single-node Cloud VM		0.95
Very			Multi-node Desktop	14.75	0.80
Large	be -		Multi-node Cloud VM	21.80	0.80
	0 12 MA SNOME	D ₁	Multi-node Desktop	15.64	0.66
	gg _		Multi-node Cloud VM	20.91	0.66
	dn 14 _{MAw} -NCL eds 12 _{MAw} -SNOME a 12 _{MAw} -SNOME				
	S WCI _* -SNOMEI	D _l	Multi-node Desktop	15.19	0.89
			Multi-node Cloud VM	21.93	0.89
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		small (dual core)	medium (8 cores)	large (8	cores)

Contribution and Uniqueness.

Ontology Loading and Memory Stress

- An Ontology model based on scalable data structures, provides thread-safety and supports parallelism. (2.5 times better performance)
- Ontology subset creation, substantially reduces the memory load within the 2Gb of Heap (8 times smaller than Jena and OWLApi) as System only loads the required ontology resources
- Parallel and distributed Ontology Matching
 - Provides a 3 layer abstraction over ontology matching process, matching from grainer to finer level with the help of thread level parallelism (40% better Reduction Score)
 - Exploits the multi-core desktops and cloud platforms for its benefit in performance gain (From 4 to 22 times performance-gain depending upon the size of the ontologies and execution environment)
- Aligned Execution for Zero Redundant matching operations (Eager Matching Space Reduction)
- A non-monolithically runtime, platform is sharable by services for clients and by platform for semantic web experts
 - 9 Matching Libraries ported for execution without any change in the ontology matching algorithms
- Accuracy Preservance through-out the performance-gain (Effectiveness-Independent Resolution), No loss of accuracy with the performance-gain in the matching process

Achievements.

Accepted Proposals

- Microsoft Research Asia 2013-2014, Beijing, China
 - Semantic Heterogeneity Resolution by Implementing Parallelism over Multicore Cloud Platform, Muhammad Bilal Amin and Sungyoung Lee
- Azure4Research Award 2014, Microsoft Research, Redmond, USA
 - Enabling Data Parallelism for large-scale Biomedical Ontology Matching over Multicore Cloud Instances, Muhammad Bilal Amin and Sungyoung Lee ^[6]





- Ontology Alignment Evaluation Initiative (OAEI 2013-2014)
 - Proposed Methodology as SPHeRe's Runtime for Ontology Matching
 - Evaluation of all 6 task over 9 real-world ontology matching problems of vario complexities
 - Only 23 from 54 participating systems completed all the tasks in-time
 - Ranked among top 12 Ontology Matching Systems of 2013-2014 ^[7]



Conclusion and Future Work

- This thesis explicitly discusses the performance issues and bottlenecks of the ontology matching problem
- Present methodology provides end-to-end resolution by catering performance from ontology loading, memory management, matching and delivery
- Results have shown a substantial gain in performance with Accuracy preservance by adopting the presented proposal
 - 2.5x faster Ontology Loading
 - 8x smaller Memory Footprint with No Heap Issues
 - 40% better reduction score due to abstraction based parallelism
 - 4 21x overall performance-gain depending upon the size of the matching problem and provided environment
- Future Work & Research
 - Presents and opportunity for the semantic-web and cloud community to use proposed implementation as a platform for heterogeneity resolution and matching algorithm evaluation
 - Cloud-based High Performance Ontology Matching and Algorithm evaluation portal

Publications.

- Patents (6)
 - Domestic: 5
 - International: 1
- Journals (7)
 - SCI:
 - First Author (2) •
 - Co-author (1) •
 - SCI(E):
 - Co-authors (3)
 - Non-SCI:
 - Co-authors (1)
- Conferences (21)
 - International:
 - First Author (4)
 - Co-author (12) •
 - Domestic :
 - First Author (5)

34 Publications 1 Major Revision 1 Under review

Telemedicine CCGrid Healthcom

SuperComputing **PervasiveHealth** ACM ISWC IEEE HealthTechnology

Sensors

AppliedIntelligence e-Health MedicalSystems ICUIMC

InformationScience

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Thank you

Appendix

Ontology Loading Algorithms.(1/2)

Algorithm 1 Method owlLoad

```
Require: O_s \neq NULL and O_t \neq NULL
  Hash_s \leftarrow Utility.calculateHash(O_s)
  Hash_t \leftarrow Utility.calculateHash(O_t)
  ontologyCache ← OntologyCache.getInstance()
  parser \leftarrow Parser.createInstance()
  if Hash, Hash, !in ontologyCache then
     parser.parse(O_s, O_t)
     parser.serialize(O_s, O_t)
  else
     if Hash, lin ontologyCache and Hash, in ontologyCache then
       parser.parse(O_t)
       parser.serialize(O_t)
     else if Hash, lin ontologyCache and Hash, in ontologyCache then
       parser.parse(O_s)
       parser.serialize(O_x)
     end if
  end if
  deserialize(Hash<sub>s</sub>, Hash<sub>t</sub>)
  return
```

Algorithm 2 Method nameParser

Require: $O_x \neq NULL, x \in \{s, t\}$ thing \leftarrow Thing.createInstance(url) while O_x has classes do concept \leftarrow OClass.createInstance(currentClassName) thing.addConcept(&concept) end while return thing

Algorithm 3 Method labelParser

```
Require: O_x \neq NULL, x \in \{s, t\}

thing \leftarrow Thing.createInstance(url)

while O_x has classes do

concept \leftarrow OClass.createInstance(currentClassName)

while currentClass has labels do

label \leftarrow Annotation.createLabel(labelName)

concept.addAnnotation(&label)

end while

thing.addConcept(&concept)

end while

return thing
```

Ontology Loading Algorithms.(2/2)

Algorithm 4 Method propertyParser

Require: $O_x \neq NULL, x \in \{s, t\}$ thing \leftarrow Thing.createInstance(url) while O_x has classes do concept \leftarrow OClass.createInstance(currentClassName) while currentClass has properties do property \leftarrow OProperty.createInstance(propertyName) concept.addProperty(&property) end while thing.addConcept(&concept) end while return thing

Algorithm 5 Method hierarchyParser **Require:** $O_x \neq NULL, x \in \{s, t\}$ while O_x has classes do concept ← OClass.createInstance(currentClassName) while currentClass has parents do if !thing.exists(parent) then parent ← OClass.createInstance(parentName) thing.addConcept(&parent) else parent ← thing.getConcept(parentName) end if concept.addConcept(&parent) end while thing.addConcept(&concept) end while return thing

Barrier Read Algorithm

Algorithm 1 Method owlLoad

```
Require: O_s \neq NULL and O_t \neq NULL
  Hash_s \leftarrow Utility.calculateHash(O_s)
  Hash_t \leftarrow Utility.calculateHash(O_t)
  ontologyCache \leftarrow OntologyCache.getInstance()
  parser ← Parser.createInstance()
  if Hashs, Hasht !in ontologyCache then
     parser.parse(O_s, O_t)
     parser.serialize(O_s, O_t)
  else
     if Hasht lin ontologyCache and Hashs in ontologyCache then
       parser.parse(O_t)
       parser.serialize(O_t)
     else if Hashs !in ontologyCache and Hasht in ontologyCache then
       parser.parse(O_s)
       parser.serialize(O_s)
     end if
  end if
  deserialize(Hashs, Hasht)
  return
```

Distribution Algorithms.

Algorithm 2 Distributor algorithm Require: nodes > 0if nodes=1 then MulticoreDistributor(O_s, O_T) else Multi-nodeDistributor(O_s, O_T) end if Algorithm 3 Multicore distributor algorithm Require: nodes > 0 cores ←Runtime.getNumberOfCores() if nodes=1 then start=0 $bigOnt \leftarrow (size_S \ge size_T)?O_S : O_T$ smallOnt \leftarrow (size_S < size_T)?O_S : O_T Partition_{slab} = [bigOnt.size/cores] SPAWN MATCHER THREADS: for doi = 1 to cores do $end = start + Partition_{slab}$ if end < bigOnt.size then end = bigOnt.sizeend if MatchingJob.create(MatchingTasks[start, end), big, small, matcher) thread.run(matchingJob) start = endend for else RECEIVE MATCHING REQUEST: controlMessage.receive(matchingRequest) $Partition_{slab} = (end - start)/cores$ GOTO SPAWN MATCHER THREADS end if

Algorithm 4 Multi-node distributor algorithm

Require: nodes > 1 nodes ←initDaemon.getNoOfNodes() $participatingCores = \sum node. #cores$ start=0 end=0 $bigOnt \leftarrow (size_S \ge size_T)?O_S : O_T$ $smallOnt \leftarrow (size_S < size_T)?O_S : O_T$ Distributionslab = [bigOnt.size/ participatingCores] for node \leftarrow nodes do $end = start + Distribution_{slab} \times node.#cores$ if end < bigOnt.size then end = bigOnt.sizeend if MatchingRequest.create([start, end), big, small, matcher) if node.isLocal then local.MulticoreDistributor(matchingRequest) else controlMessage.send(matchingRequest) end if start = endend for

Class Diagrams and Conceptual Models.(1/2)

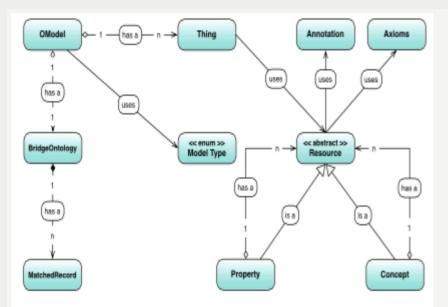


Fig. 2 Ontology Model class diagram

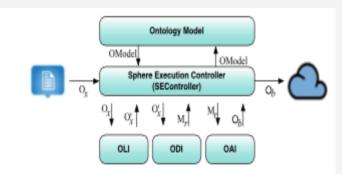


Fig. 3 SPHeRe's execution controller

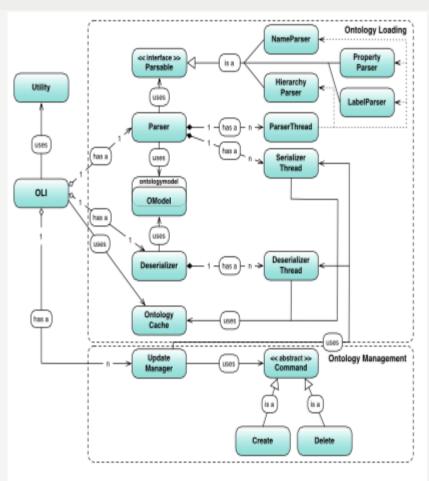


Fig. 4 Class diagram for loading and management component

Class Diagrams and Conceptual Models.(2/2)

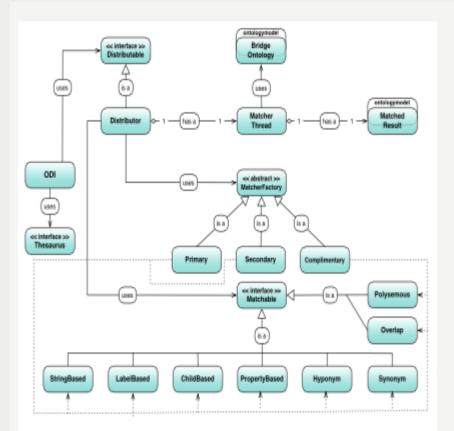


Fig. 5 Class diagram for distribution and matching component

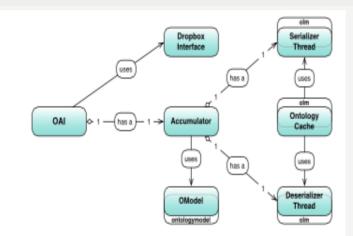


Fig. 6 Class diagram for accumulation and delivery component

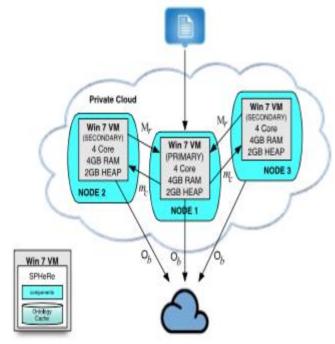
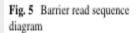
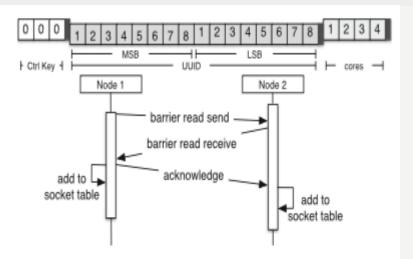
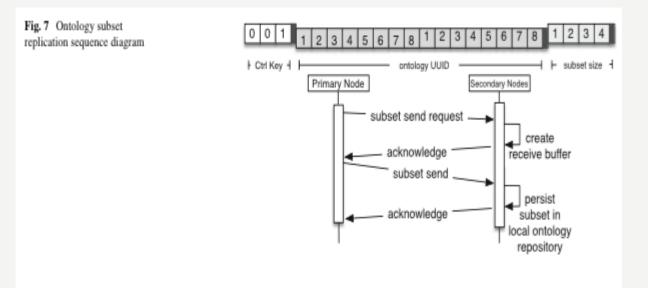


Fig. 7 SPHeRe's deployment setup

Communication and Sequence Diagrams.(1/2)







Communication and Sequence Diagrams.(2/2)

Fig. 8 Ontology change request sequence diagram

