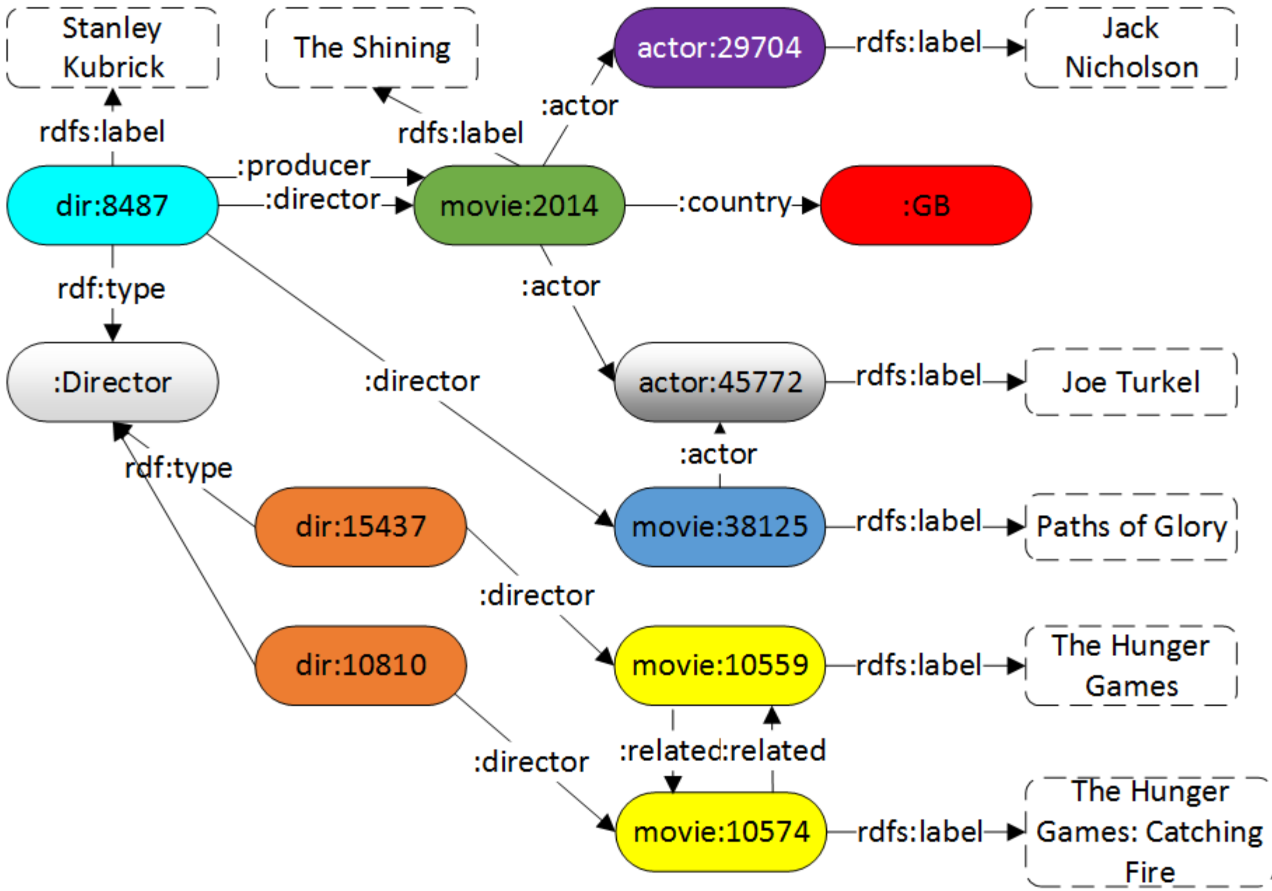
MIE1512 Data Analytics

Graph Analytics

Big Graphs

Natural to model relationships as **graphs**



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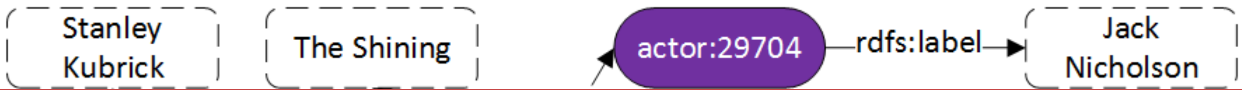
Natural to model relationships as **graphs**

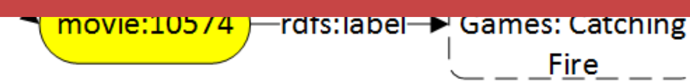


It is a challenge to **query and analyze large graphs**

due to **variety** and **volume**

DBpedia describes ~***315 million*** people, places, etc.

Twitter has ~***2 billion*** follower edges between people.



Motivation to Summarize Large Graphs

- Well Known Problem
  - Compute the ***bisimilar contraction*** (a summary) of a labelled graph.
- Practical Applications
  - Data Management: ***exploration*** and ***query optimization*** for semi-structured/XML/RDF data. Motivation to **summarize large graphs** for exploration and query optimization.
- Construction Implementations Exploiting Parallelism
  - Message Passing Interface, Map-Reduce
  - ***Scalable Graph Systems with a Vertex-centric Model***

Background: Bisimulation Contractions

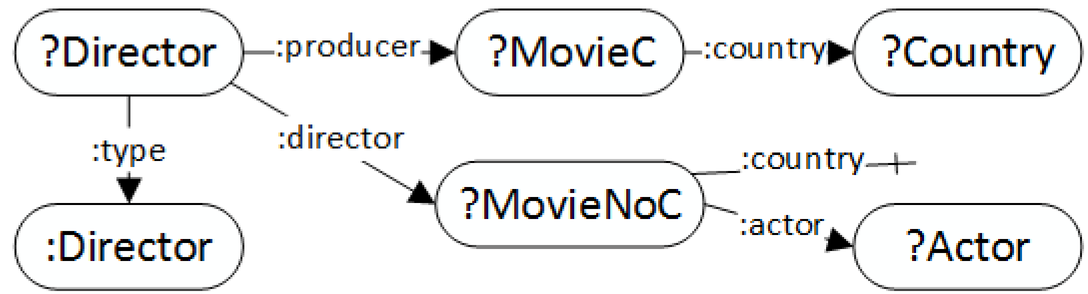
- Two nodes v, v' are ***FWBW bisimilar*** (written v ≈ v'):
  - (FW) if (v, w) is an edge with label l, then there is an outgoing edge (v', w') with label l, and w ≈ w'; and
  - (BW) if (w, v) is an edge with label l, then there is an incoming edge (w', v') with label l, and w ≈ w'.

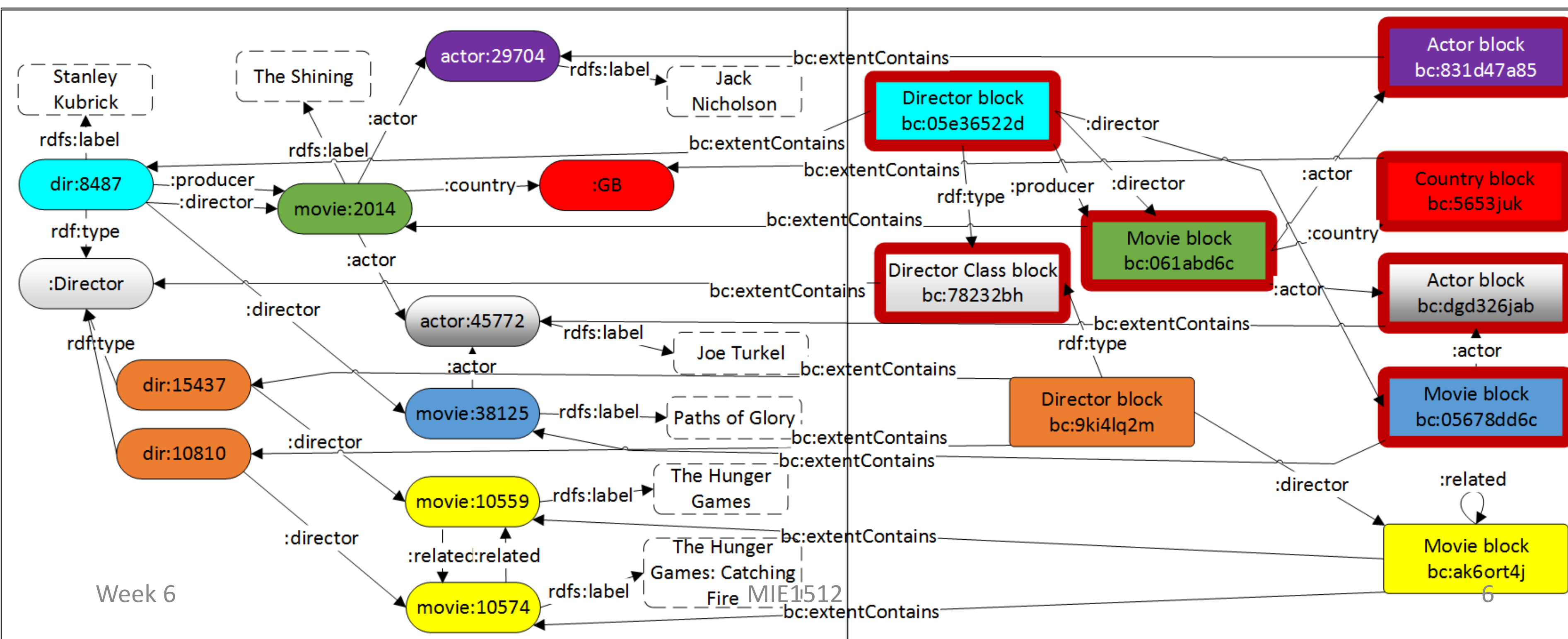
- A summary has ***blocks*** and ***block edges***
  - Each block has an ***extent*** that groups ***all*** bisimilar nodes; this leads to a summary containing the fewest possible blocks and is commonly referred to as a *contraction*.
  - A ***singleton*** block contains exactly 1 node in its extent, i.e., the node is not bisimilar to any other node.

Query Optimization Using Summaries

A ***navigational query*** returns only the query's endpoints.

EXAMPLE: *Find **actors** who appear in **movies without country** information; additionally, the **director** of those movies should also be the **producer** of a movie with **country** information.*





Query Optimization Using Summaries

A … s.

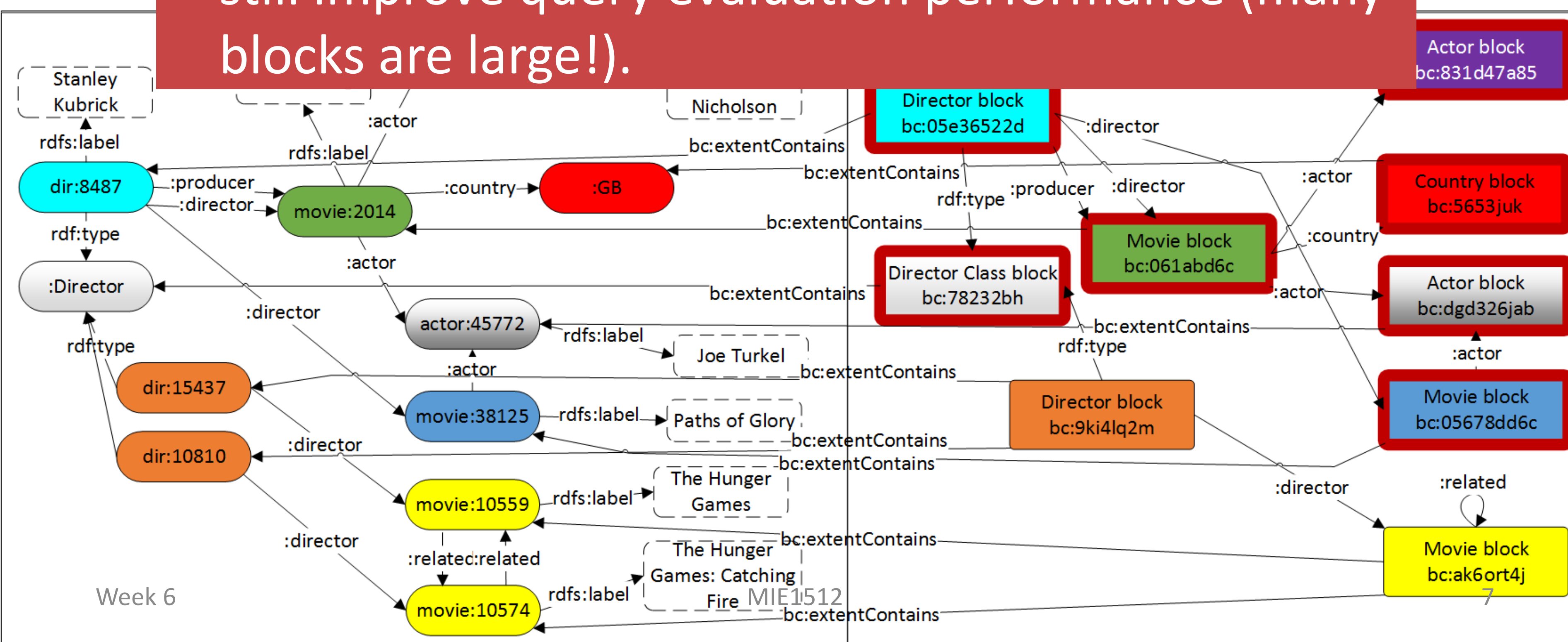
EXAMPL…
movies v…
additiona…
movies s…
a movie

Like in the example below, in many real-world datasets, the ***majority*** of blocks are **singletons**.

Even if a summary has mostly singletons, it can still improve query evaluation performance (many blocks are large!).

…Country

…Actor



Summary Construction State of the Art

- Naïve algorithm by [Kanellakis,Smolka'90]
- MPI implementation by [Blom,Orzan'02] processes ***unstable*** blocks
  - A block is unstable if a node in that block has an edge to a block that was split
- Map-Reduce implementations
  - Address block size (and reducer load) skew [Lange,Fletcher,Bra,Hidders,Wu'13]
  - (HP,HL) Reduce MR tasks per iteration from 3 to 2 [Schatzle,Neu,Lausen,PrzyjacielZablocki'13]

Summary Construction State of the Art

- Naïve algorithm by [Kanellakis,Smolka'90]
- MPI implementation by [Blom,Orzan'02] processes ***unstable*** blocks

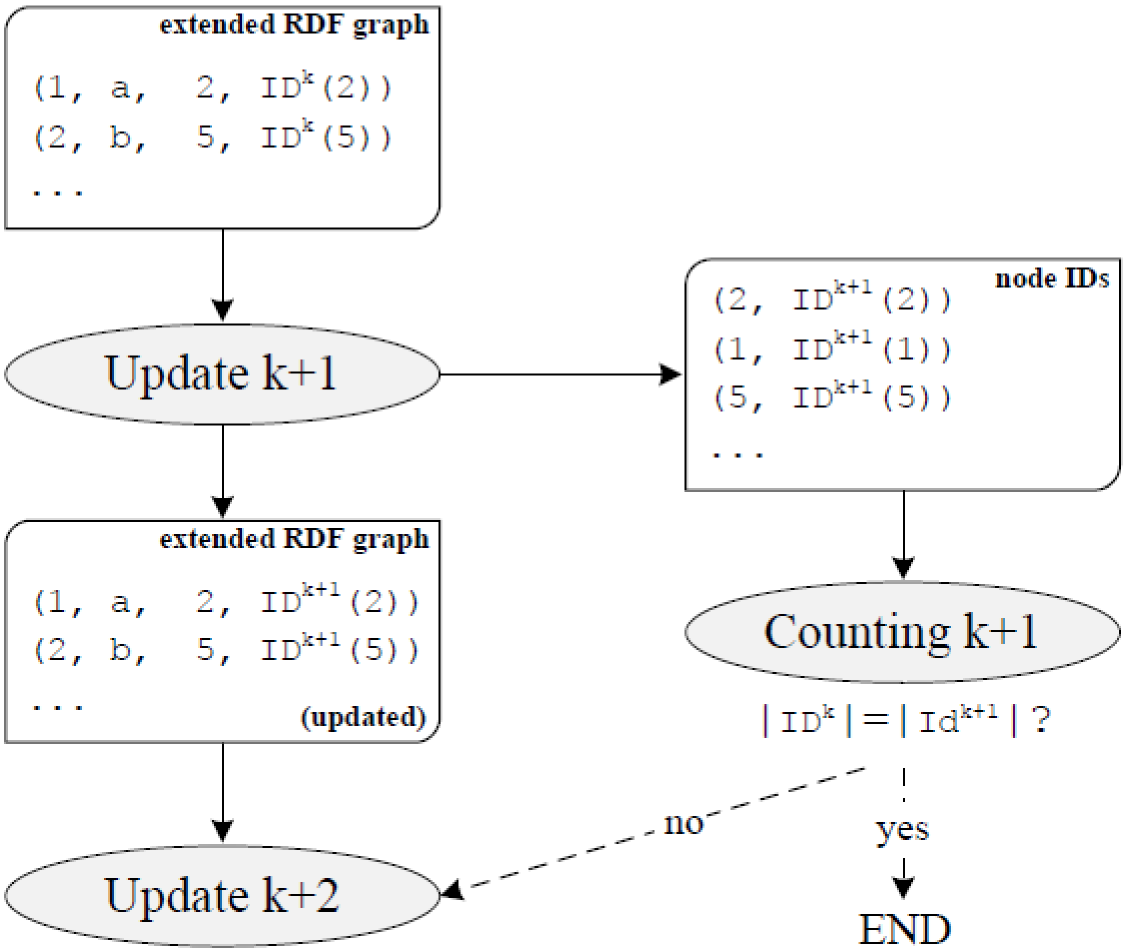
All exhibit similar per-iteration times.

Empirical observation: 10-30 iterations are needed.

- Map-Reduce implementations
  - Address block size (and reducer load) skew [Lange,Fletcher,Bra,Hidders,Wu'13]
  - (HP,HL) Reduce MR tasks per iteration from 3 to 2 [Schatzle,Neu,Lausen,PrzyjacielZablocki'13]

Bisimilarity in MR

From [Schatzle,Neu,Lausen,PrzyjacielZablocki’13]



Map

Algorithm 4: update job - **map**(key, value)

input : *key*: byte offset in input file, can be ignored
value: a quad $(s, p, o, ID^k(o))$

$(s, p, o, ID^k(o)) \leftarrow \text{parseQuad}(value)$

emit$((s,0),\ (s, p, o, ID^k(o)))$

emit$((o,1),\ (s, p, o, ID^k(o)))$

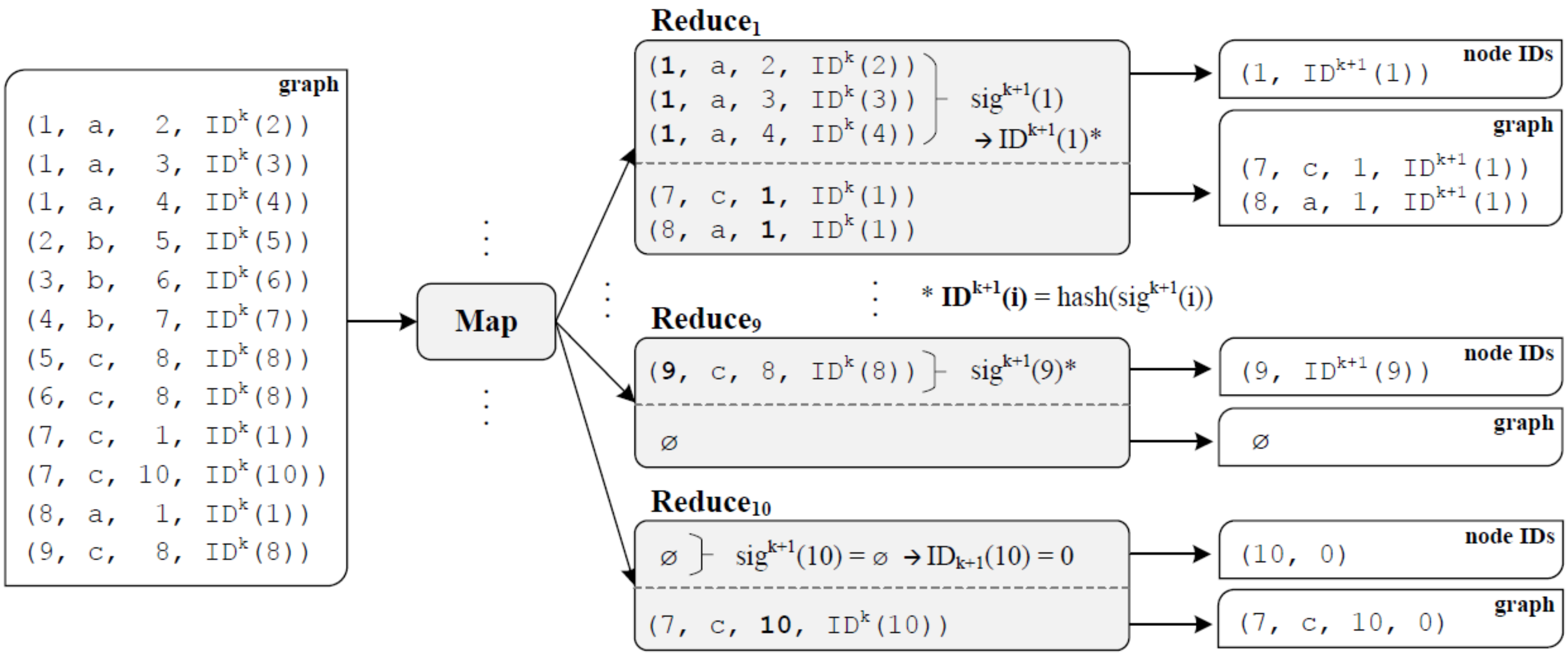
Reduce

Algorithm 5: update job - **reduce**(key, values)

input : *key*: composite key (node s, sortOrder)
values: a list of quads $[(s, p, o, ID^k(o))]$

$sig^{k+1}(s) \leftarrow \{\ \}$
while $value\ in\ values \wedge key.sortOrder = 0$ **do**
    $(s, p, o, ID^k(o)) \leftarrow \text{parseQuad}(value)$
    $sig^{k+1}(s) \leftarrow sig^{k+1}(s) \cup \{(p, ID^k(o))\}$
end
// new signature of s complete
$ID^{k+1}(s) \leftarrow hash(sig^{k+1}(s))$
while $value\ in\ values \wedge key.sortOrder = 1$ **do**
    $(x, p, s, ID^k(s)) \leftarrow \text{parseQuad}(value)$
    emit("graph", $(x, p, s, ID^{k+1}(s))$)
end
// generate separate node ID list for counter job
emit("node IDs", s, $ID^{k+1}(s)$)

MR Iteration Workflow



Efficient Summary Construction

Joint work with Shahan Khatchadourian, Valeria Fiona, Giuseppe Pirro

- Vertex-centric construction of bisimulation summaries using the ***GraphChi*** [Kyrola,Blelloch,Guestrin'12] parallel graph processing framework
  - Similar model to other vertex-centric scalable graph analytics tools (Pregel, Giraph, Hama, GraphLab, PowerGraph, GraphX)
- A novel and very effective ***singleton optimization*** that drastically reduces per-iteration times after only a few iterations
- Experimental validation
  - Significantly outperforms Hadoop state of the art
  - Validation of summary construction times comparable to dataset load and summary write
  - Fast construction of different summaries

GraphChi Processing Model

- Support for ***Bulk Synchronous Parallel*** model [Valiant'90]
  - Nodes execute an Update method in parallel that compute a new block identifier using previous iteration values as input.

$$\boxed{\textbf{parallel foreach } v \in V_G \textbf{ do } \text{V-Update}(v) \textbf{ end}}$$

  - GraphChi is effective at processing large graphs because it loads outgoing edges of nodes into main-memory then streams their incoming edges from disk.

Used by singleton optimization to disable singletons

- Support for ***scheduling*** $\boxed{\textbf{disable vertex } v}$
  - Common in graph algorithms, e.g., BFS.
  - GraphChi skips loading disabled nodes from disk.

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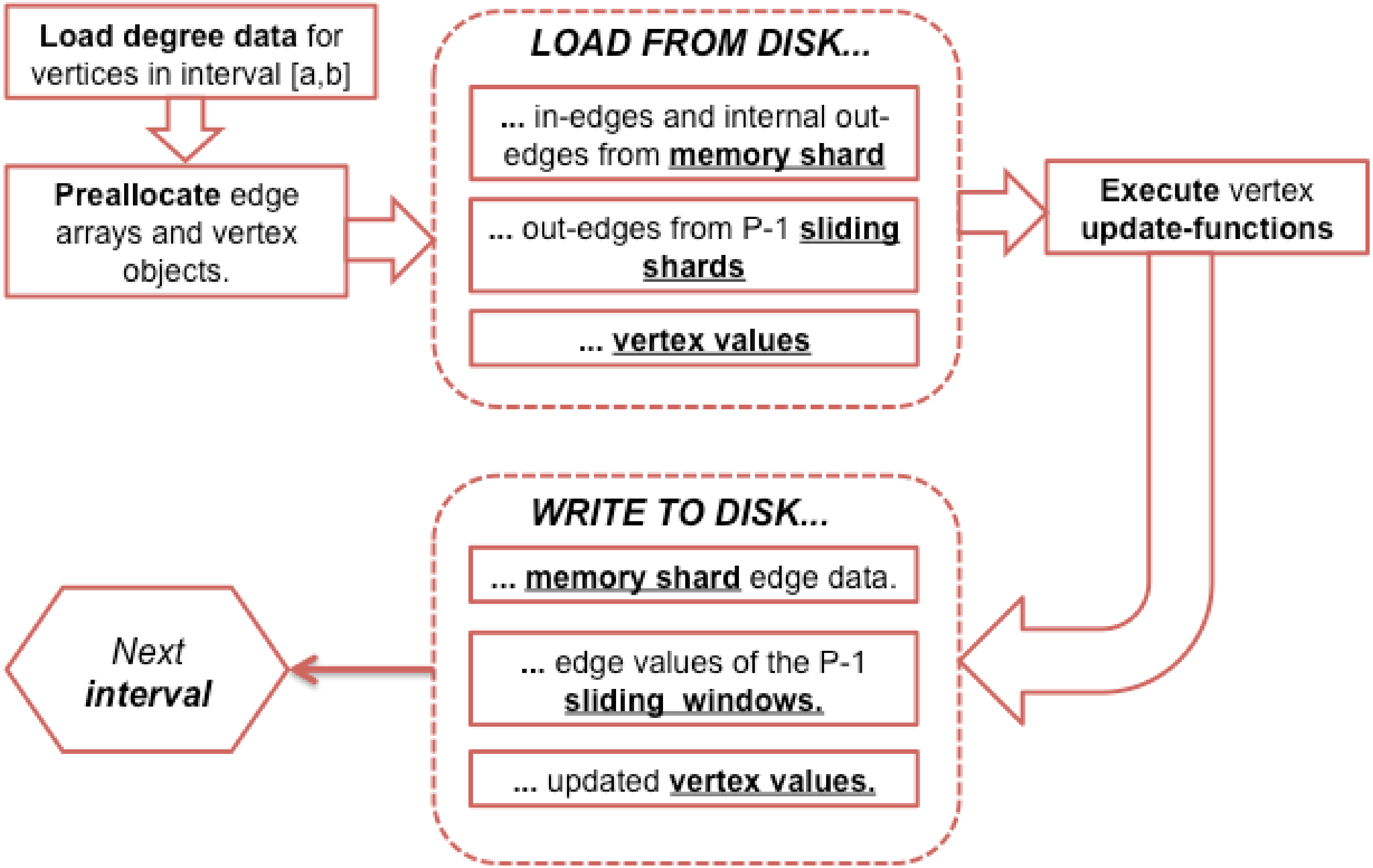
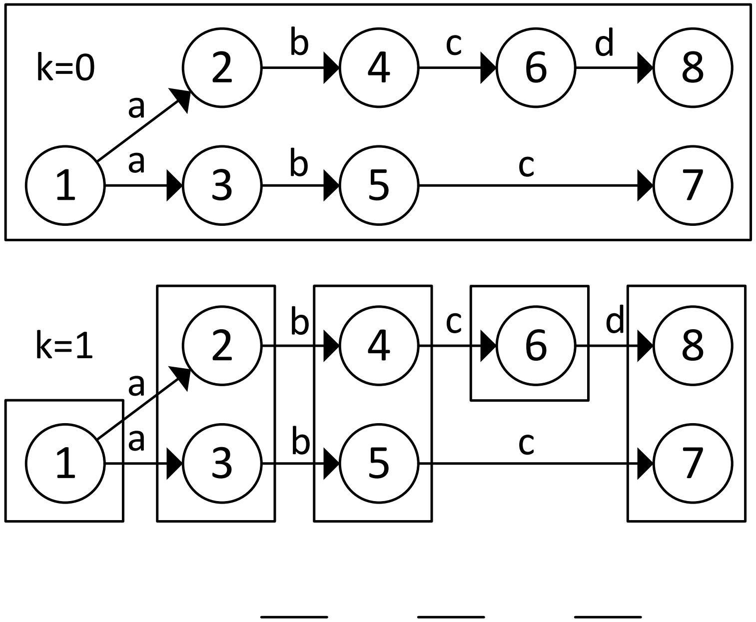
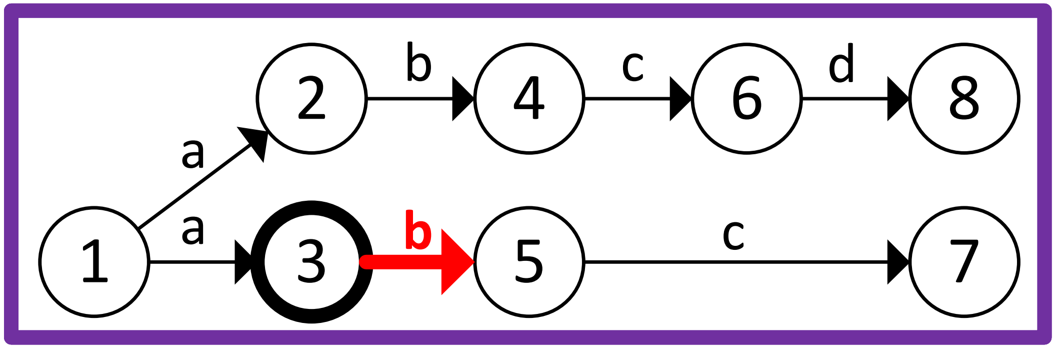
GraphChi Platform on Multicore+Disk



Node V-Update function



Iteration 1



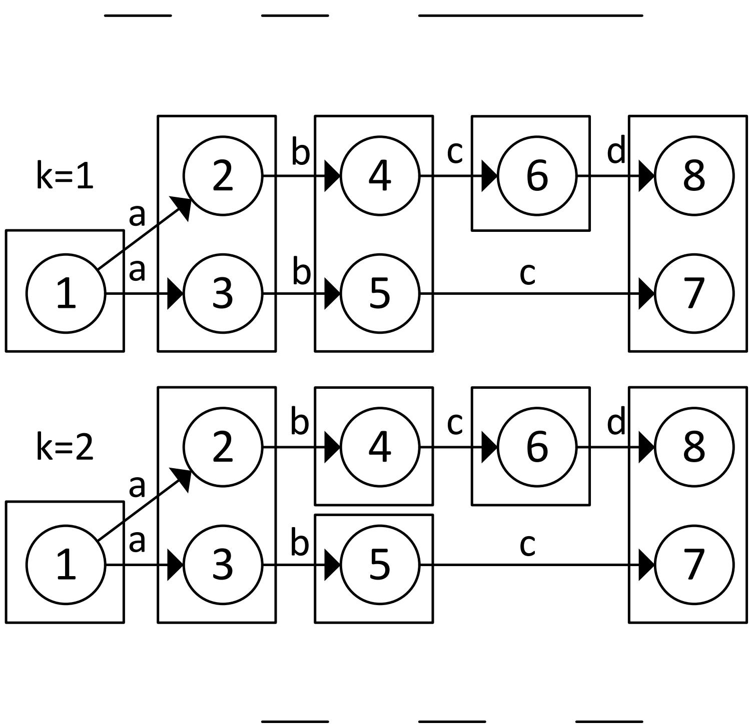
block$_1$(1)=hash(sort({(**a**,**block$_0$(2)**)}))

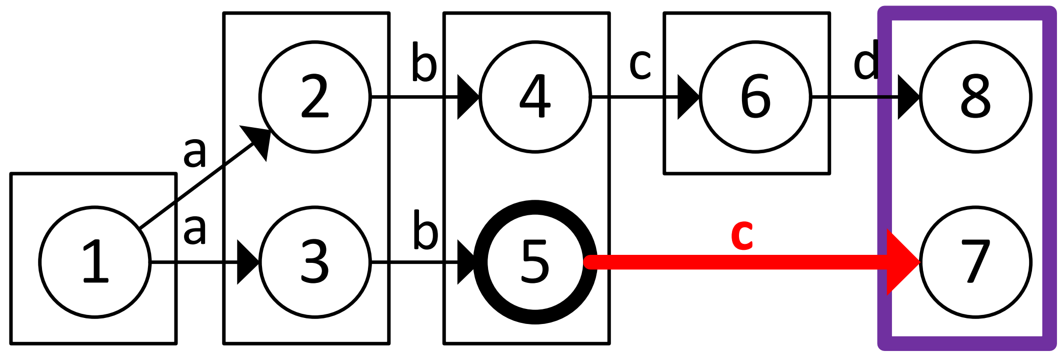
block$_1$(2)=hash(sort({(**b**,**block$_0$(4)**)}))

block$_1$(3)=hash(sort({(**b**,**block$_0$(5)**)}))

Node V-Update function

Iteration 2





$\mathbf{block_2(2)} = \text{hash}(\text{sort}(\{(b, block_1(4))\}))$

$\mathbf{block_2(3)} = \text{hash}(\text{sort}(\{(b, block_1(5))\}))$

$\mathbf{block_2(4)} = \text{hash}(\text{sort}(\{(c, block_1(6))\}))$

$\mathbf{block_2(5)} = \text{hash}(\text{sort}(\{(c, block_1(7))\}))$

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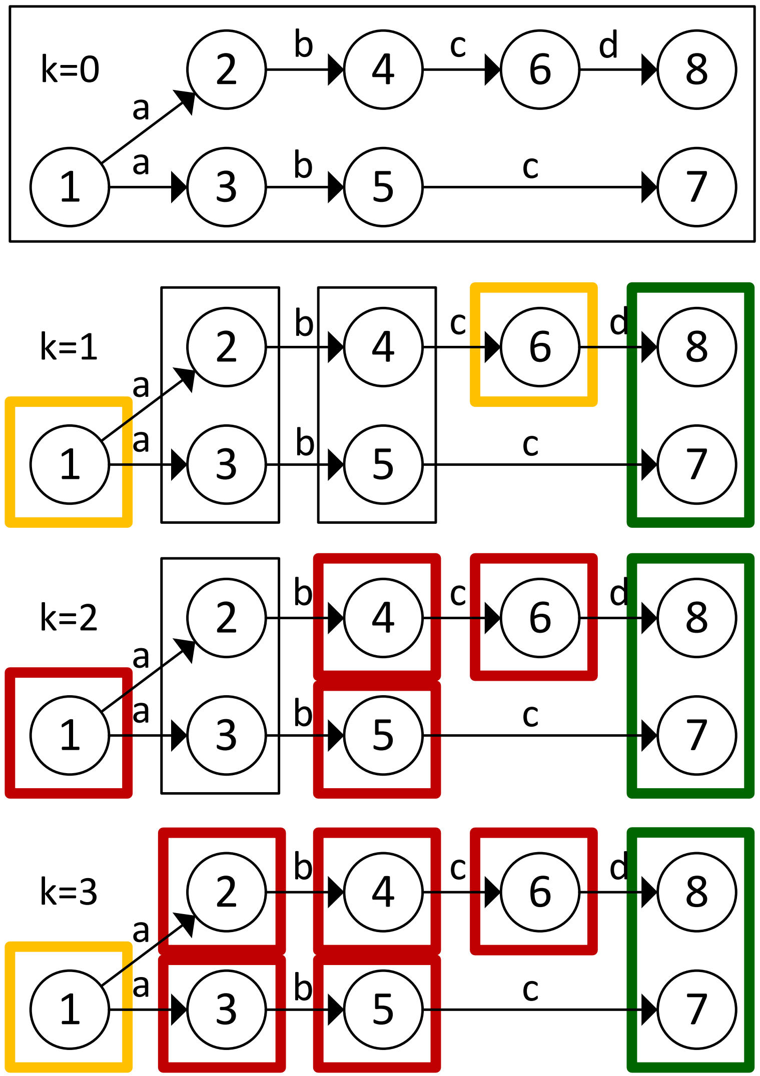
Stability ≠ Singleton



Stability and Singleton do not reduce to the other.

- **Non-singleton blocks that are Stable**
- **Singleton blocks that are Unstable**

Key empirical observation:
Most blocks are singleton and stable
and singleton is cheaper to check.

Bisimilar Contraction Singleton (B) variation

L1. **foreach** $v \in V_G$ **do** $block_0(v) =$ '0' **end** // initialize
L2. $count_{old} \leftarrow 1, count_{new} \leftarrow 0, k \leftarrow 0$
L3. **while** $count_{old} \neq count_{new}$ **do**
L4.   **parallel foreach** $v \in V_G$ **do** V-Update(v) **end**
L5. $count_{old} \leftarrow count_{new}$
L6. $count_{new} \leftarrow |\{block_{k+1}(v) \mid v \in V_G\}|$
L7. $k \leftarrow k + 1$
L8. **end**
L9. $V_S \leftarrow \{block_k(v) \mid v \in V_G\}$,
$E_S \leftarrow \{(block_k(v), block_k(v')) \mid (v, v') \in E_G\}$

Method: V-Update(v)

V1. $fwsig(v) = \{(+m(v, v'), block_k(v')) \mid (v, v') \in E_G, m(v, v') \in M\}$
V2. $bwsig(v) = \{(-m(v', v), block_k(v')) \mid (v', v) \in E_G, m(v', v) \in M\}$
V3. $block_{k+1}(v) = hash(sort(block_k(v) \cup fwsig(v) \cup bwsig(v)))$

Bisimilar Contraction Singleton (S) variation

L1. **foreach** $v \in V_G$ **do** $block_0(v) =$ '0' **end** // initialize
L2. $count_{old} \leftarrow 1, count_{new} \leftarrow 0, k \leftarrow 0$
L3. **while** $count_{old} \neq count_{new}$ **do**
L4′. **parallel foreach** $v \in V_G$ **do** V-Update-Singleton(v)
L5. $\quad count_{old} \leftarrow count_{new}$
L6. $\quad count_{new} \leftarrow |\{block_{k+1}(v) \mid v \in V_G\}|$
L7. $\quad k \leftarrow k + 1$
L8. **end**
L9. $V_S \leftarrow \{block_k(v) \mid v \in V_G\}$,
$E_S \leftarrow \{(block_k(v), block_k(v')) \mid (v, v') \in E_G\}$

Method: V-Update-Singleton(v)

S1. **if** $|\{v' \mid v' \in block_k(v)\}| > 1$ **then do**
S2. $\quad$ V-Update(v)
S3. **else do**
S4. $\quad$ **disable vertex** v
S5. **end**

Experimental Validation Datasets

Dataset	$\|N\|$	$\|E\|$
lmdb	1,327,120	6,147,717
dbp	48,603,466	317,220,816
Twitter	52,579,678	1,963,263,821

- LinkedMDB [Hassanzadeh,Consens'09] (lmdb) describes movies and related entities using 222 edge labels
- DBpedia (dbp) describes real-world entities such as people and places using 1,393 edge labels
- Twitter has unlabeled edges to describe follower relationships amongst its users

FW Summaries - GraphChi vs. Hadoop

For **LinkedMDB**

- (HP) Pseudo-distributed is over ***2x faster*** than (HL) Local mode.
- S is ***8x faster*** than HP.

For **DBPedia**

- S is around ***6x faster*** than HP and ***3x faster*** than B.
- HP is more than ***7x faster*** than HL.
- HL requires ~ 10 hours per iteration (vs. 10-30 mins).

Summary	$\|N\|$	$\|E\|$	B	S	HL	HP
lmdb	85,714	999,934	4.2	4.0	73	32
dbp	13,429,903	229,490,296	941	331	5,832*	1,972

* time for first 10 iterations

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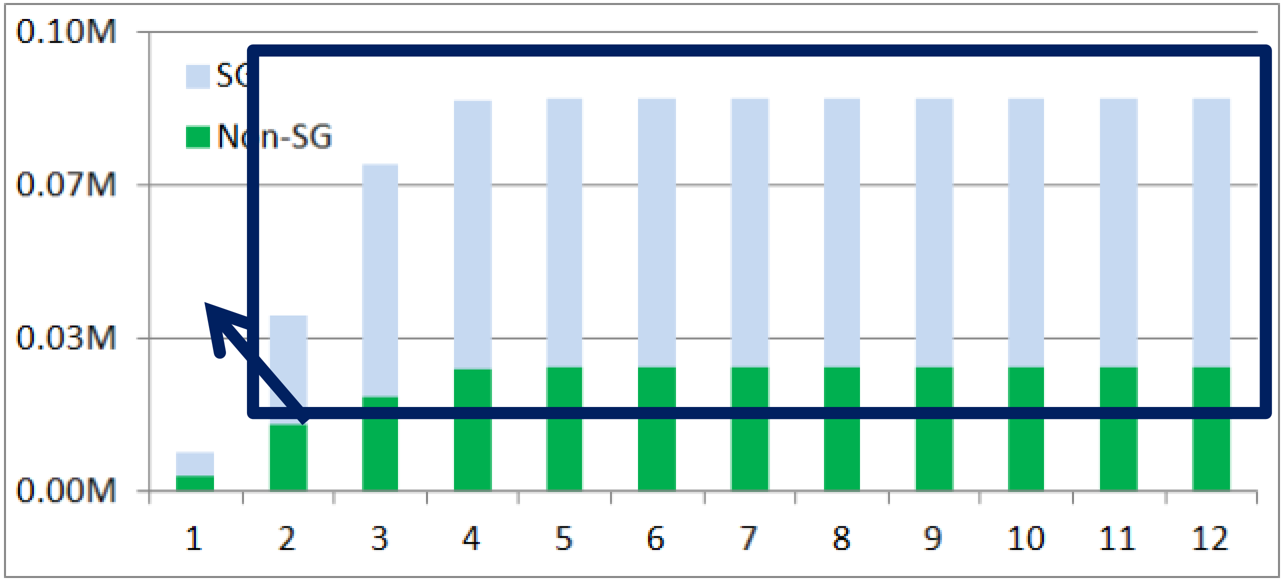
FW Summaries Experimental Results

LinkedMDB

DBpedia



Millions of blocks and singletons per iteration

FWBW Construction vs Load plus Write

- S variation is ~***3x, 4x, and 5x faster*** than the B variation for *LinkedMDB*, *DBpedia*, and *Twitter*, respectively.
- Time taken to *compute* dbp's FWBW summary using the S variation is ***over 50% faster*** than the time to *load* the dataset graph plus *write* the summary.

Summary	$\|N\|$	$\|E\|$	Load	B	S	Write
lmdb	844,877	4,311,098	0.12	8.6	2.8	0.75
dbp	32,274,111	278,182,230	107	775	187	207
Twitter	48,332,025	1,945,307,755		3,118	632	

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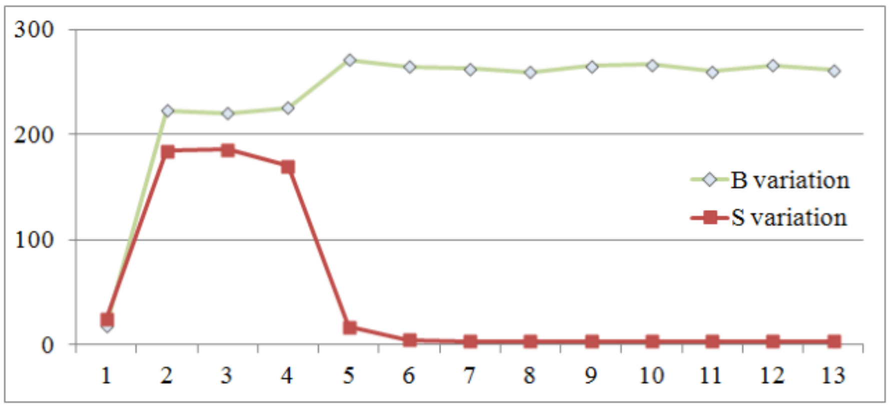
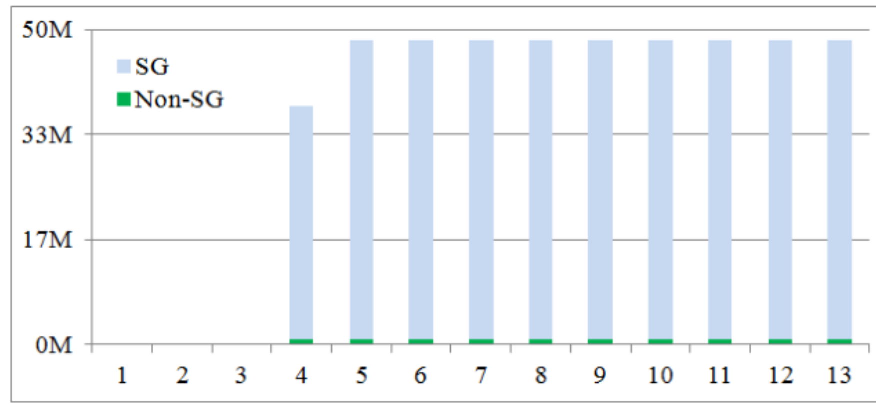
FWBW Summaries Experimental Results



(a) M1 time (in mins) per iteration



(b) Millions of singletons and non-singletons per iteration

Twitter FWBW summary construction

(a) M1 time (in mins) per iteration

(b) Millions of singletons and non-singletons per iteration

Twitter

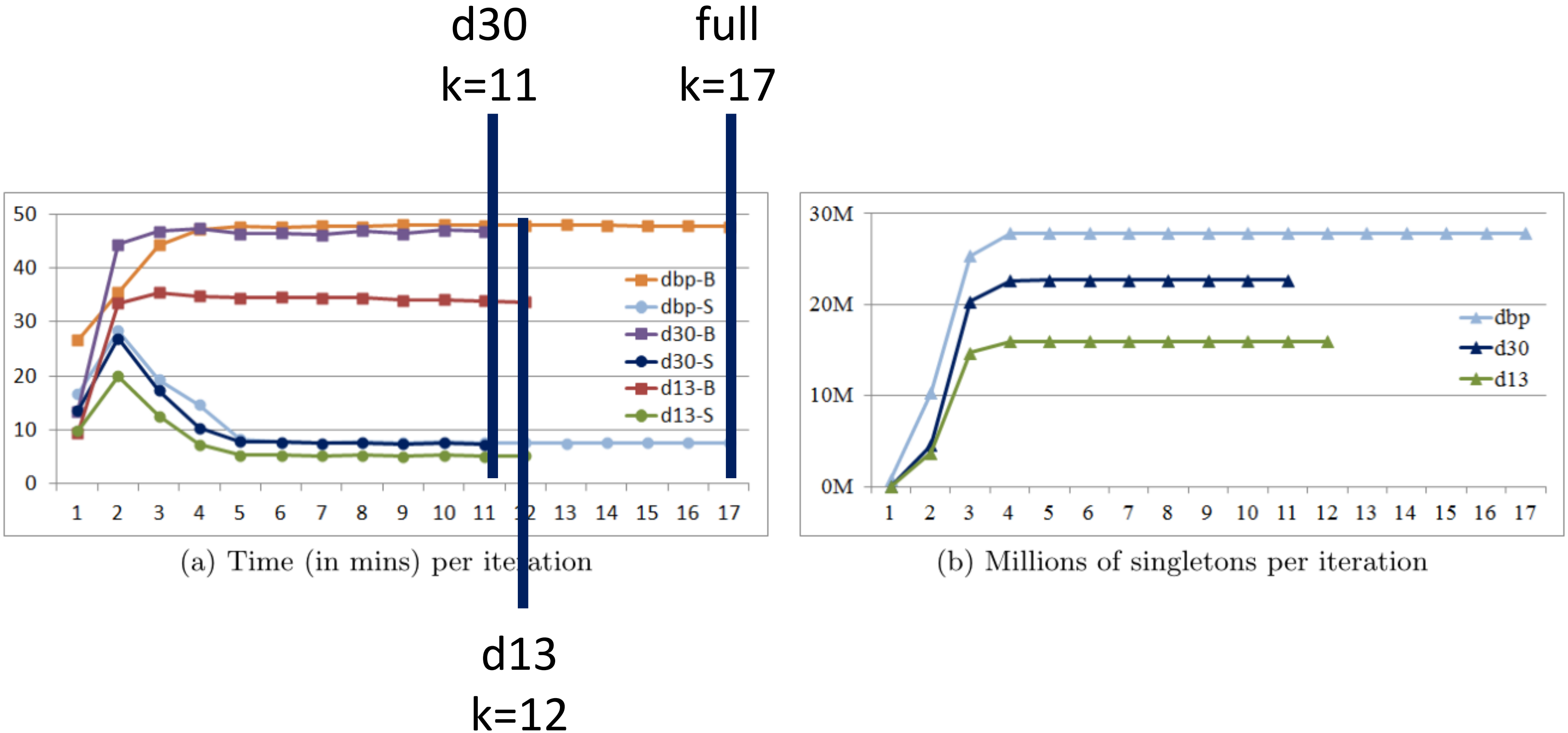
Full and Selective FWBW Summaries

Selective summaries, that summarize a subset of a dataset's predicates, are almost ***2x faster*** to compute than the full summary. The S variation constructs the d13 summary over ***2x faster*** than the instance load plus summary write.

Summary	Load	B	S	Write
dbp	107	775	187	207
d30	160	611	125	125
d13	131	411	95	95

Selective summaries can improve query performance more than a full summary.

Selective Summaries Experimental Results



(a) Time (in mins) per iteration

(b) Millions of singletons per iteration

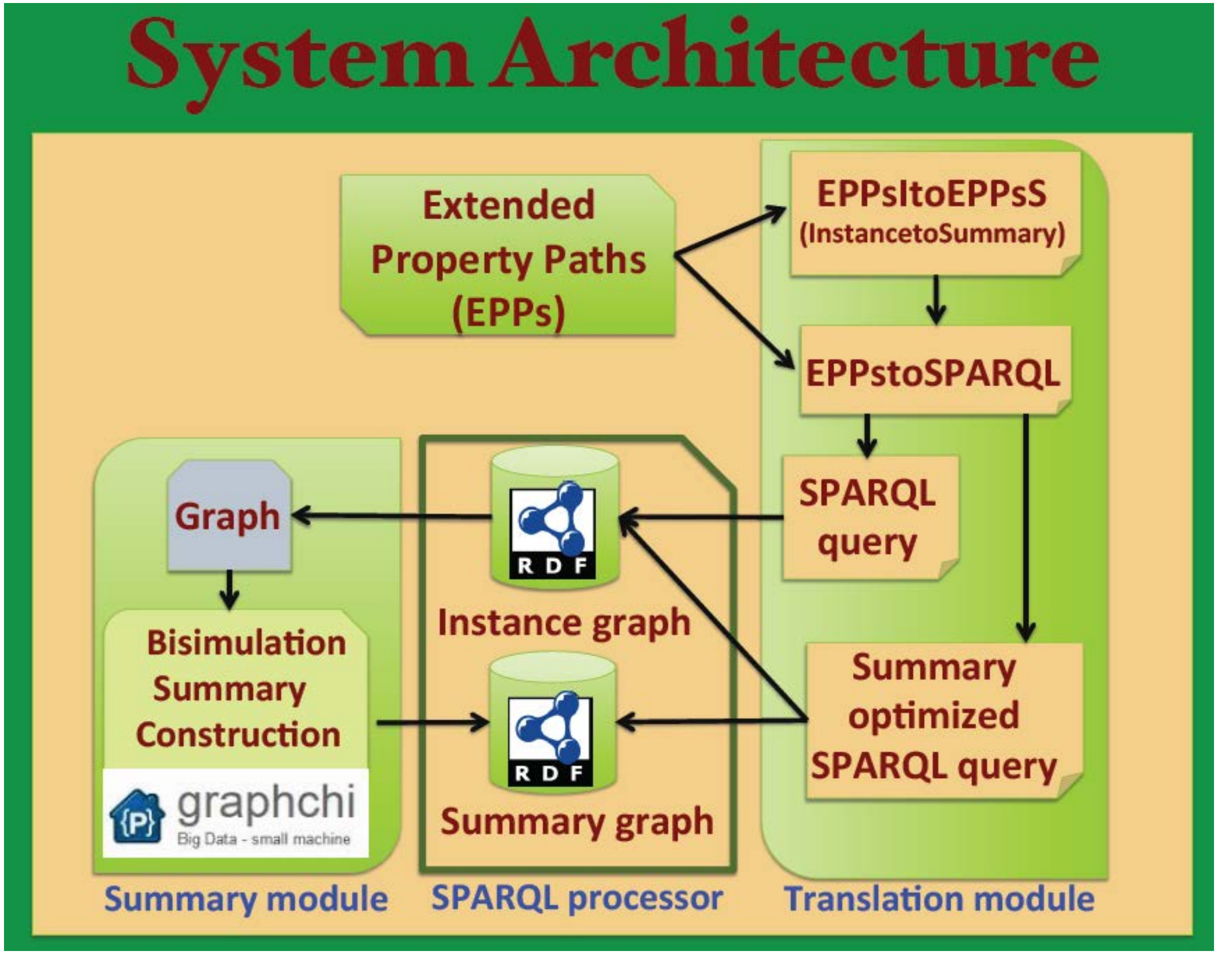
Selective summaries can require different iterations.

Remarks

Large bisimulation summaries can be ***constructed efficiently*** using scalable graph analytics platforms (with big improvements thanks to a novel ***singleton optimization***)

Full and selective summaries can ***improve query performance*** – we developed a system to achieve this on existing (unmodified) SPARQL processors using query translations

An Overview of S+EPPs



[CFKP'15] Consens M. P., Fionda V., Khatchadourian S., Pirrò G. S+EPPs: Construct and Explore Bisimulation Summaries, plus Optimize Navigational Queries; all on Existing SPARQL Systems, PVLDB 2015