Distributed Transactions in Hadoop's HBase and Google's Bigtable

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this talk:

- how to deal with very large amounts of data in a distributed environment (‘cloud’)
- in particular, data consistency for very large sets of data items that get modified concurrently

example: Google search and ranking

- continuously 'crawl' all webpages, store them all on 10,000s of commodity machines (CPU+disk), petabytes of data
- every 3 days (*the old way...), build search index and ranking, involves inverting outlinks to inlinks, Pagerank calculation, etc., via MapReduce distributed processing system, on the same set of machines
- very large database-like storage system is used (Bigtable)
- build a $190billion internet empire on fast and useful search results

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outline

1. cloud computing
2. Google/Hadoop cloud frameworks
3. motivation: large-scale scientific data processing
4. Bigtable and HBase
5. transactions
6. our transactional system for HBase
7. protocol
8. advanced features
9. performance
10. comparison with Google's percolator
11. conclusions

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1. cloud computing

- cloud = set of resources for distributed computing and storage (networked) characterized by
    1. homogeneous environment (often through virtualization)
    2. dedicated (root) access (no batch queues, not shared, no reservations)
    3. scalable on demand (or large enough)

- cloud = 'grid', simplified such that it becomes more easily doable (e.g., it is hard to combine two (different) clouds!)

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cloud computing

- cloud is
  1. homogeneous
  2. dedicated access
  3. scalable on demand
- we are interested in cloud for large-scale, serious computing (not: email and wordprocessing, ...) (but: cloud also useful for business computing, e-commerce, storage, ...)
- there are private (Google internal) and public (Amazon) clouds (it is hard to do hybrid clouds!)

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2. Google/Hadoop cloud frameworks

- cloud (homogeneous, dedicated access, scalable on demand) used for large-scale computing/data processing needs ‘cloud framework’

- Google: first, and most successful (private) cloud (framework) for large-scale computing to date
  - Google File System
  - Bigtable
  - MapReduce

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Google cloud framework

- first, and most successful (private) cloud (framework) for large-scale computing to date
  - Google File System:
    - fault-tolerant, scalable distributed file system
  - Bigtable
    - fault-tolerant, scalable sparse semi-structured data store
  - MapReduce
    - fault-tolerant, scalable parallel processing system

- used for search/ranking, maps, analytics, ...

Hadoop clones Google's system

- Hadoop is an open-source clone of Google's cloud computing framework for large-scale data processing
  - Hadoop File System (HFS) (Google File System)
  - HBase (Bigtable)
  - MapReduce
- Hadoop is used by Yahoo, Facebook, Amazon, ... (and developed/controlled by them)

Hadoop usage

(from wiki.apache.org/hadoop/PoweredBy)

- Yahoo!
  - More than 100,000 CPUs in >36,000 computers running Hadoop
  - Our biggest cluster: 4000 nodes (2*4cpu boxes w 4*1TB disk & 16GB RAM)
    - Used to support research for Ad Systems and Web Search
    - Also used to do scaling tests to support development of Hadoop on larger clusters
  - Our Blog - Learn more about how we use Hadoop.
  - >60% of Hadoop Jobs within Yahoo are Pig jobs.

Hadoop usage

- Twitter
  - We use Hadoop to store and process tweets, log files, and many other types of data generated across Twitter. We use Cloudera's CDH2 distribution of Hadoop, and store all data as compressed LZO files.
  - We use both Scala and Java to access Hadoop's MapReduce APIs
  - We use Pig heavily for both scheduled and ad-hoc jobs, due to its ability to accomplish a lot with few statements.
  - We employ committers on Pig, Avro, Hive, and Cassandra, and contribute much of our internal Hadoop work to opensource (see hadoop-lzo)
  - For more on our use of hadoop, see the following presentations: Hadoop and Pig at Twitter and Protocol Buffers and Hadoop at Twitter
- LinkedIn
  - We have multiple grids divided up based upon purpose. They are composed of the following types of hardware:
    - 100 Nehalem-based nodes, with 2x4 cores, 24GB RAM, 8x1TB storage using ZFS in a JBOD configuration on Solaris.
    - 120 Westmere-based nodes, with 2x4 cores, 24GB RAM, 6x2TB storage using ext4 in a JBOD configuration on CentOS 5.5
  - We use Hadoop and Pig for discovering People You May Know and other fun facts.

Hadoop usage

Facebook

- We use Hadoop to store copies of internal log and dimension data sources and use it as a source for reporting/analytics and machine learning.
- Currently we have 2 major clusters:
  - A 1100-machine cluster with 8800 cores and about 12 PB raw storage.
  - A 300-machine cluster with 2400 cores and about 3 PB raw storage.
  - Each (commodity) node has 8 cores and 12 TB of storage.
  - We are heavy users of both streaming as well as the Java apis. We have built a higher level data warehousing framework using these features called Hive (see the http://hadoop.apache.org/hive/). We have also developed a FUSE implementation over hdfs.

EBay

- 532 nodes cluster (8 * 532 cores, 5.3PB).
- Heavy usage of Java MapReduce, Pig, Hive, HBase
- Using it for Search optimization and Research.

3. motivation: large-scale scientific data processing

- my area of research is scientific computing (scientific simulation methods and applications)
- large-scale computing / data processing
- we have used 'grid' for distributed 'task farming' of bioinformatics problems (BLSC 2007)

Database-driven grid computing with GridBASE

Hans De Sterck[1], Chen Zhang[2], Aleks Papo[1]

RNA
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Natural and artificial RNAs occupy the same restricted region of sequence space

Ryan Kennedy[1], Manuel E. Lladser[2], Zhiyuan Wu[3], Chen Zhang[4], Michael Yarus[5], Hans De Sterck[3] and Rob Knight[6,7]

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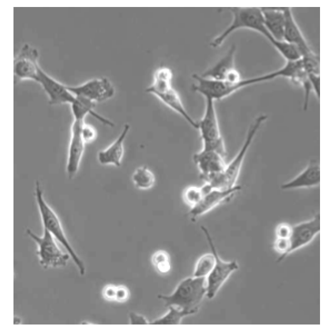
motivation: large-scale scientific data processing

- use Hadoop/cloud for large-scale processing of biomedical images (HPCS 2009)

Case Study of Scientific Data Processing on a Cloud Using Hadoop

Chen Zhang[1], Hans De Sterck[2], Ashraf Aboulnaga[1], Haig Djambazian[3], and Rob Sladek[3]



process 260GB of image data per day

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motivation: large-scale scientific data processing

- workflow system using HBase (Cloudcom 2009)

problem:
HBase does
not have multi-
row transactions

CloudWF: A Computational Workflow System for Clouds Based on Hadoop

Chen Zhang[1] and Hans De Sterck[2]

- batch system using HBase (Cloudcom 2010)

CloudBATCH: A Batch Job Queuing System on Clouds with Hadoop and HBase

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motivation: large-scale scientific data processing

cloud computing (processing) will take off for

- biomedical data (images, experiments)
- bioinformatics
- particle physics
- astronomy
- etc.

4. Bigtable and HBase

- relational DBMS (SQL) are not (currently) suitable for very large distributed data sets:
  - not parallel
  - not scalable
  - relational ‘sophistication’ not necessary for many applications, and these applications require efficiency for other aspects (scalable, fault-tolerant, throughput versus response time, ...)

... Google invents Bigtable

Bigtable: A Distributed Storage System for Structured Data

Fay Chang, Jeffrey Dean, Sanjay Ghemawat, Wilson C. Hsieh, Deborah A. Wallach
Mike Burrows, Tushar Chandra, Andrew Fikes, Robert E. Gruber

{fay,jeff,sanjay,wilsonh,kerr,m3b,tushar,fikes,gruber}@google.com

Google, Inc.

(OSDI 2006)

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Bigtable

A Bigtable is a sparse, distributed, persistent multi-dimensional sorted map. The map is indexed by a row key, column key, and a timestamp; each value in the map is an uninterpreted array of bytes.

	col1	col2	col3	col4	col5	col6
row1	x x	x		x	x	
row2					x x	
row3						x

- sparse tables
- multiple data versions – timestamps
- scalable, fault-tolerant (tens of petabytes of data, tens of thousands of machines) (no SQL)

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HBase

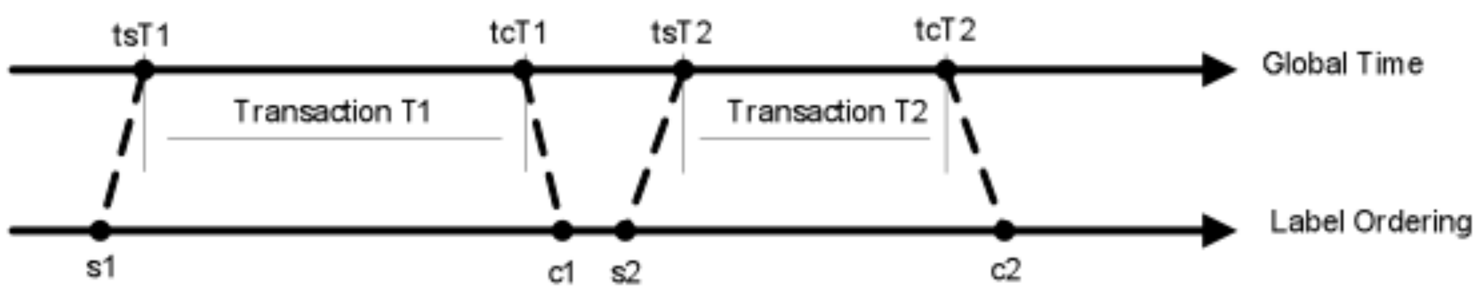
HBase is clone of Google's Bigtable

	col1	col2	col3	col4	col5	col6
row1	x x	x		x	x	
row2					x x	
row3						x

- sparse tables, rows sorted by row keys
- multiple data versions – timestamps
- Random access performance on par with open source relational databases such as MySQL
- single global database-like table view (cloud scale)

5. transactions

- transaction = grouping of read and write operations
- T_i has start time label s_i and commit time label c_i (all read and write operations happen after start time and before commit time)



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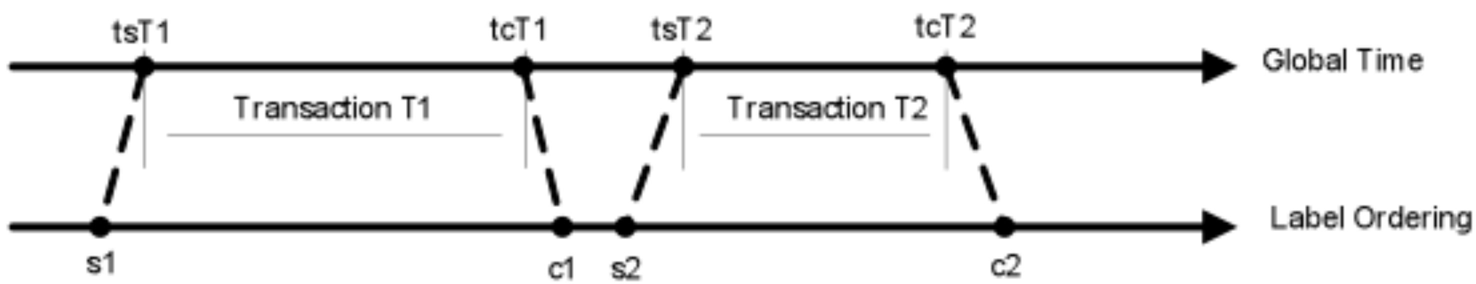
transactions

- we need globally well-ordered time labels s_i and c_i (for our distributed system)
- T_1 and T_2 are concurrent if $[s_1,c_1]$ and $[s_2,c_2]$ overlap
- transaction T_i: either all write operations commit, or none (atomic)



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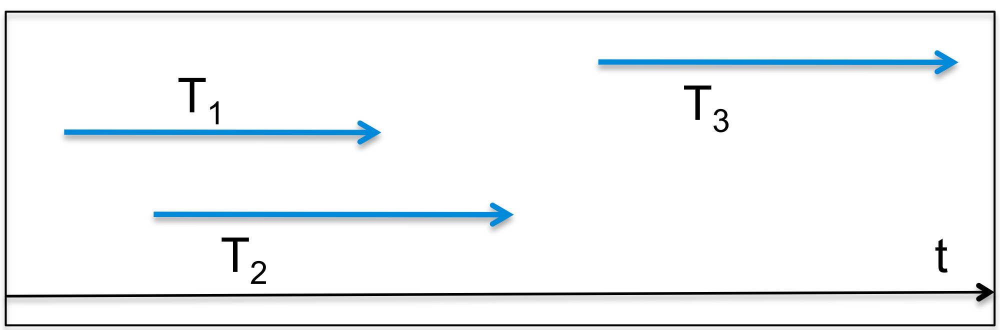
snapshot isolation

define: (strong) snapshot isolation

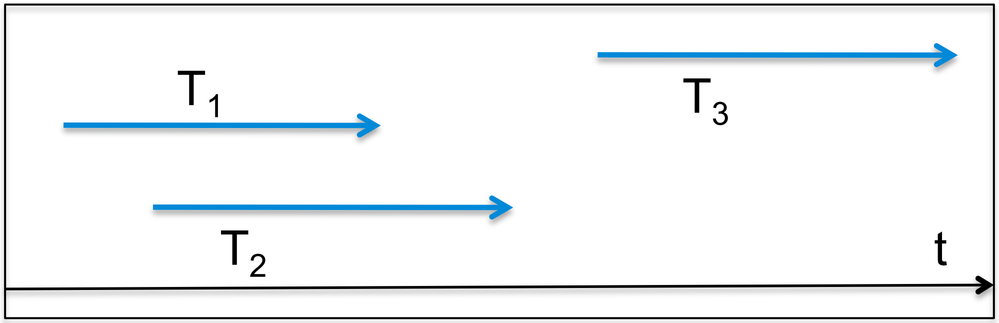
1. T_i reads from the last transaction committed before s_i (that's T_i's snapshot)
2. concurrent transactions have disjoint write sets

(concurrent transactions are allowed for efficiency, but T_1 and T_2 cannot take the same $100 from a bank account)



snapshot isolation

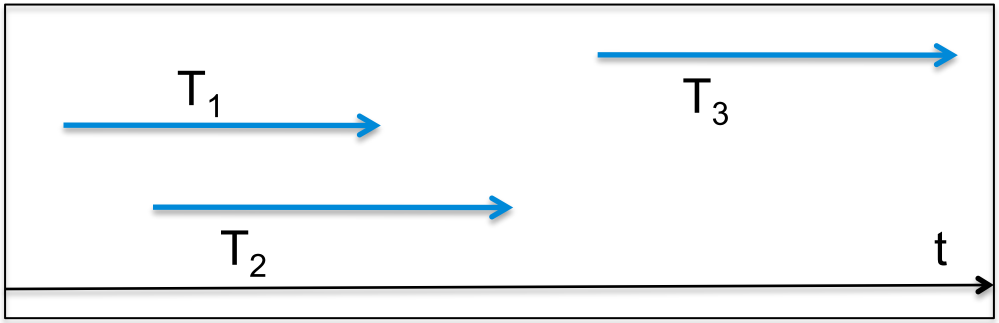
1. T_i reads from the last transaction committed before s_i
2. concurrent transactions have disjoint write sets



- T_2 does not see T_1's writes
- T_3 sees T_1's and T_2's writes
- if T_1 and T_2 have overlapping write sets, at least one aborts

snapshot isolation

- desirables for implementation:
  - first committer wins
  - reads are not blocked
- implemented in mainstream DBMS (Oracle, ...), but scalable distributed transactions do not exist on the scale of clouds



6. our transactional system for HBase

- Grid 2010 conference, Brussels, October 2010

Supporting Multi-row Distributed Transactions with Global Snapshot Isolation Using Bare-bones HBase

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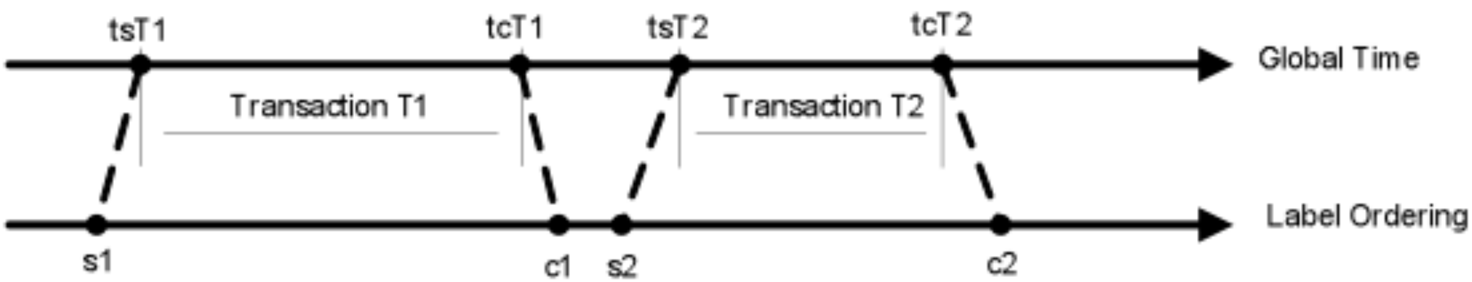
our transactional system for HBase

design principles:

- central mechanism for dispensing globally well-ordered time labels
- use HBase's multiple data versions
- clients decide on whether they can commit (no centralized commit engine)
- two phases in commit
- store transactional meta-information in HBase tables
- use HBase as it is (bare-bones)

7. protocol

- transaction T_i has
  - start label s_i (ordered, not unique)
  - commit label c_i (ordered with the s_i, unique)
  - write label w_i (unique)
  - precommit label p_i (ordered, unique)



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protocol summary

user table

		colx		coly
row1	L_a	$\boxed{m\ q}$		
row2			L_b	$\boxed{n}$

counter table

	w-counter	p-counter	c-counter
row	1211	34	470

precommit queue table (queue up for conflict checking)

write label	precommit label	L_a	L_b
w_1	p_1	w_1	w_1
w_2	p_2	w_2	

committed table

commit label	L_a	L_b	L_c
c_1	w_1	w_1	
c_2	w_2		

commit queue table (queue up for committing)

write label	commit label		
w_1	c_1		
w_2	c_2		

protocol

- user data table I (user, many)

location L_a

location L_b

		colx		coly
row1		m q		
row2				n

- committed table (system, one)

commit label	L_a	L_b	L_c
c_1	w_1	w_1	
c_2	w_2		

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transaction T_i

- at start, reads committed table, $s_i = c_{last}+1$ (no wait)
- obtains w_i from central w counter
- reads L_a by scanning L_a column in committed table, reads from last c_j with $c_j < s_i$
- writes preliminarily to user data table with HBase write timestamp w_i
- after reads/writes, queue up for conflict checking (get p_i from central p counter)
- after conflict checking, queue up for committing (get c_i from central c counter)
- commit by writing c_i and writeset into committed table

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central counters

- dispense unique, well-ordered w_i, p_i, c_i labels
- use HBase's built-in atomic IncrementColumnValue method on a fixed location in an additional system table

  (a separate counter for w_i, p_i and c_i)
- take advantage of single global database-like table view
- c counter table (system, one)

	c-counter	
row	101	

queue up for conflict checking

- precommit queue table (system, one)

write label	precommit label	L_a	L_b
w_1	p_1	w_1	w_1
w_2			

- how to make sure that the T_i get processed in the order of the p_i they get ('first committer wins'): use a distributed queue mechanism
- T_i puts w_i in table, gets p_i from p counter, reads $\{w_j\}$ from table, then puts p_i and writeset in table, waits until all in $\{w_j\}$ get a p_j or disappear, wait for all $p_j<p_i$ (with write conflicts) to disappear, go on for conflict checking

conflict checking

- committed table

commit label	L_a	L_b	L_c
c_1	w_1	w_1	
c_2	w_2		

- T_i checks conflicts in committed table: check for write conflicts with all transactions that have s_i<=c_j, go on to commit if no conflicts, otherwise abort (remove w_i from queue)

queue up for committing

- issue: make sure that committing transactions end up in committed table in the order they get their c_i label (because T_j gets its s_j from committed table, and a gap in c_i in the committed table that gets filled up later may lead to inconsistent snapshots)

commit label	L_a	L_b	L_c
c_2	w_2		

commit label	L_a	L_b	L_c
c_1	w_1	w_1	
c_2	w_2		

queue up for committing

- issue: make sure that committing transactions end up in committed table in the order they get their c_i label:

  use a distributed queue mechanism!
- commit queue table (system, one)

write label	commit label		
w_1	c_1		
w_2			

- T_i puts w_i in table, gets c_i from counter, reads $\{w_j\}$ from table, then puts c_i in table, waits until all in $\{w_j\}$ get a c_j or disappear, goes on to commit: write c_i and writeset in committed table, remove w_i records from the two queues

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protocol summary

user table

		colx		coly
row1	L_a	m q		
row2			L_b	n

counter table

	w-counter	p-counter	c-counter
row	1211	34	470

committed table

commit label	L_a	L_b	L_c
c_1	w_1	w_1	
c_2	w_2		

precommit queue table (queue up for conflict checking)

write label	precommit label	L_a	L_b
w_1	p_1	w_1	w_1
w_2	p_2	w_2	

commit queue table (queue up for committing)

write label	commit label		
w_1	c_1		
w_2	c_2		

(strong) global snapshot isolation!

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8. advanced features

version table (system, one)

	commit label
L_a	c_1
L_b	c_2

committed table (can be long)

commit label	L_a	L_b	L_c
c_1	w_1	w_1	
c_2	w_2		

- row L_a contains commit label of transaction that last updated location L_a
- lazily updated by reading transactions
- T_i that wants to read L_a, first checks version table: if $c_1<s_i$, scan $[c_1+1,s_i-1]$ in committed table; if $s_i<=c_1$, scan $[-inf,s_i-1]$

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advanced features

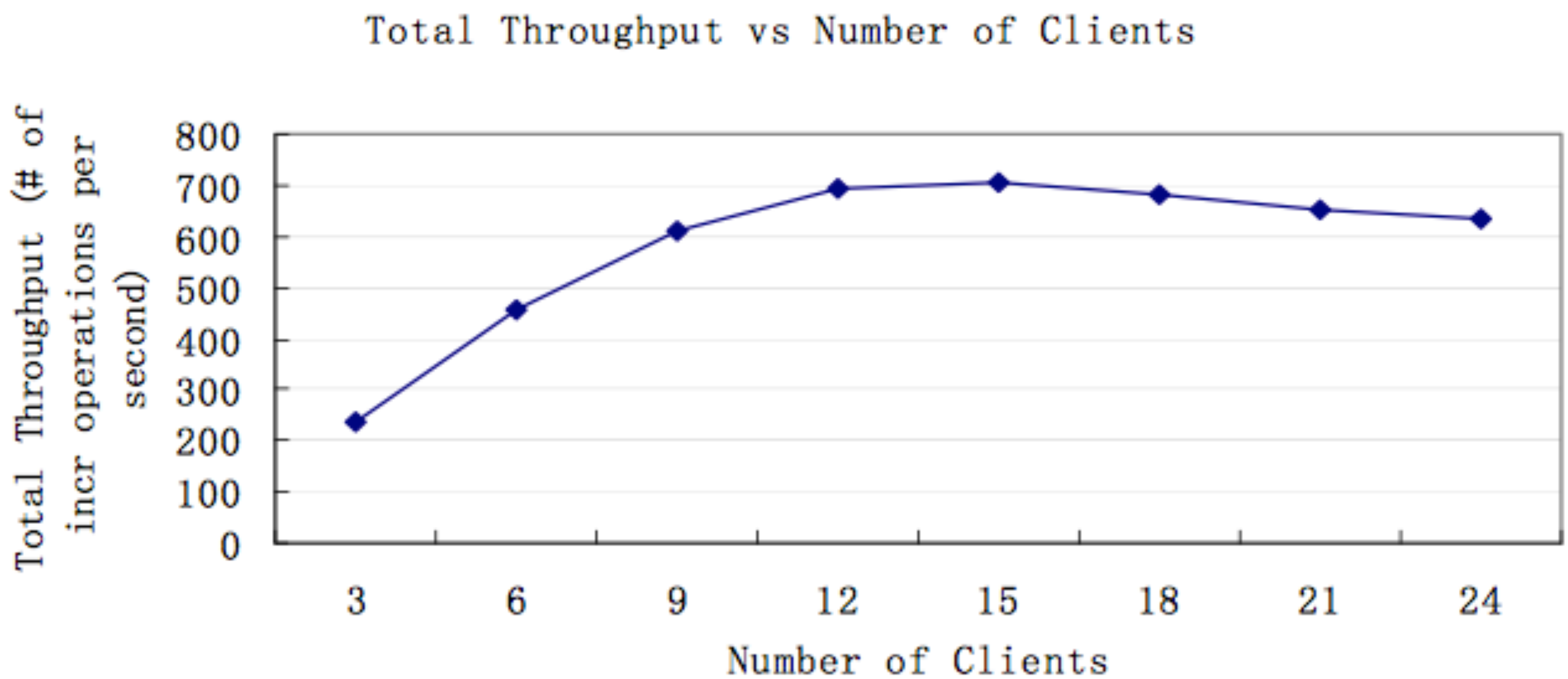
deal with straggling/failing processes

- add a timeout mechanism
- waiting processes can kill and remove straggling/failed processes from queues based on their own clock
- final commit does CheckAndPut on two rows (at once) in committed table

committed table

commit label	L_a	L_b	w_1	w_2
c_1	w_1	w_1		
c_2	w_2			
timeout			N	N

9. performance



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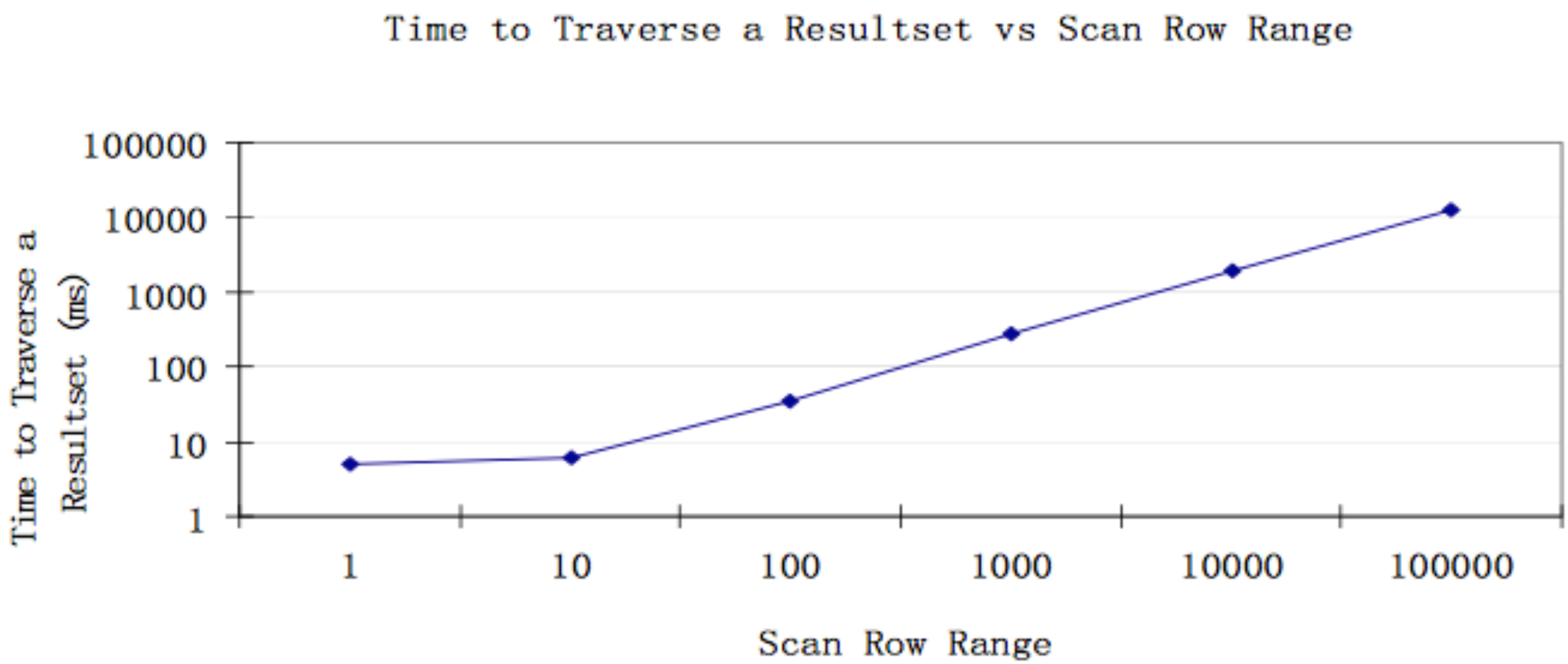
performance



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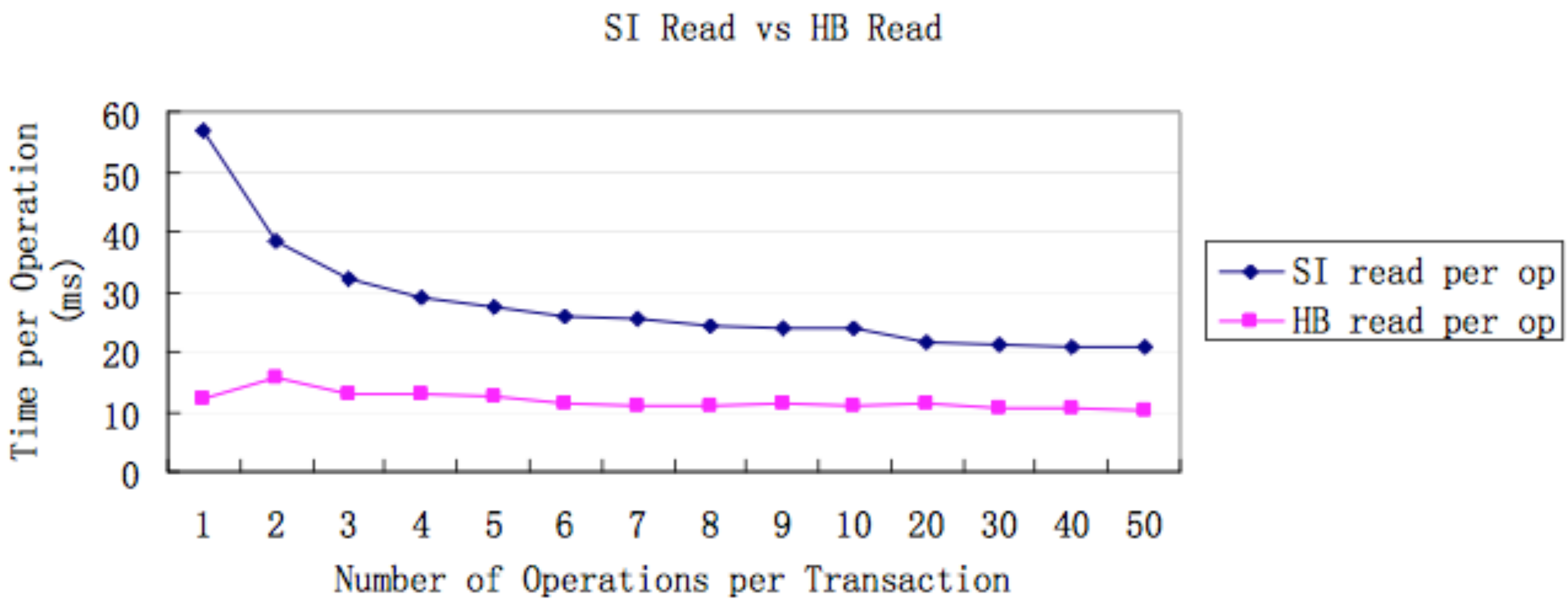
performance



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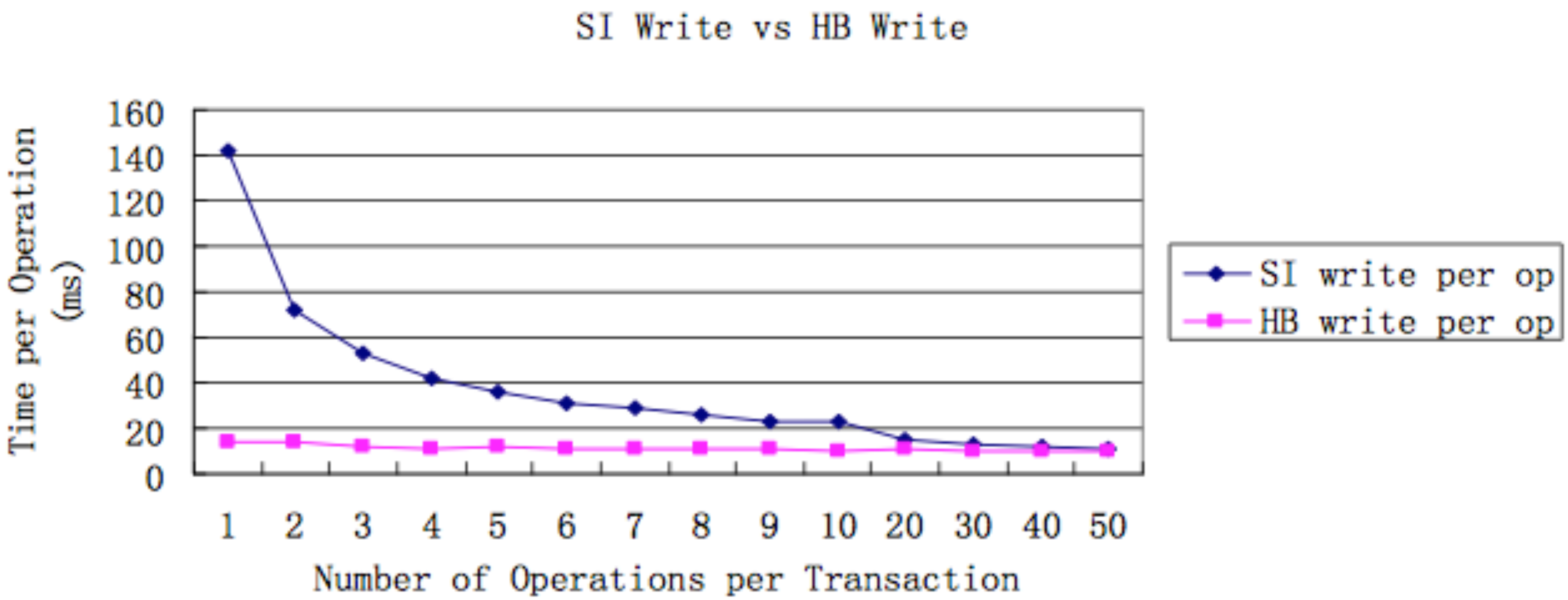
performance



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10. comparison with Google's percolator

- OSDI 2010, October 2010

Large-scale Incremental Processing Using Distributed Transactions and Notifications

Daniel Peng and Frank Dabek
dpeng@google.com, fdabek@google.com
Google, Inc.

- goal: update Google's search/rank index incrementally ('fresher' results, don't wait 3 days)
- replace MapReduce by an incremental update system, but need concurrent changes to data

comparison with Google's percolator

that MapReduce requires. To achieve high throughput, many threads on many machines need to transform the repository concurrently, so Percolator provides ACID-compliant transactions to make it easier for programmers to reason about the state of the repository; we currently implement snapshot isolation semantics [5].

- snapshot isolation for Bigtable!
- percolator manages Google index/ranking since April 2010 (very very large dataset, tens of petabytes): it works and is very useful!

comparison with Google's percolator

similarities with our HBase solution:

- central mechanism for dispensing globally well-ordered time labels
- use built-in multiple data versions
- clients decide on whether they can commit (no centralized commit engine)
- two phases in commit
- store transactional meta-information in tables
- clients remove straggling processes

comparison with Google's percolator

differences with our HBase solution:

- percolator adds snapshot isolation metadata to user tables (more intrusive, but less centralized, no central system tables)
- percolator may block some reads
- percolator does not have strict first-committer-wins (may abort both concurrent T_is)
- different tradeoffs, different performance characteristics (percolator likely more scalable, throughput-friendly, less responsive in some cases)

(note: percolator cannot be implemented directly into HBase because HBase lacks row transactions)

11. conclusions

- we have described the first (global, strong) snapshot isolation mechanism for HBase
- independently and at the same time, Google has developed a snapshot isolation mechanism for Bigtable that uses design principles that are very similar to ours in many ways
- snapshot isolation is now available for distributed sparse data stores
- scalable distributed transactions do now exist on the scale of clouds

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