CC5212-1 Procesamiento Masivo de Datos Otoño 2019

Lecture 9 NoSQL: Overview

> Aidan Hogan aidhog@gmail.com

Hadoop/MapReduce/Pig/Spark: Processing Un/Structured Information



Information Retrieval: Storing Unstructured Information

stop-words information-overload ranking lemmatisation compression pagerank heap's-law Heywords tf-idf zipfs-law robots.txt importance site-map DDoS cosine link-analysis similarity Search posting-lists crawling term-frequency elias-encoding

Storing Structured Information??

P

BIG DATA: Storing Structured Information

Relational Databases





Relational Databases: One Size Fits All?

"One Size Fits All": An Idea Whose Time Has Come and Gone

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Abstract

The last 25 years of commercial DBMS development can be summed up in a single phrase: "One size fits all". This phrase refers to the fact that the traditional DBMS architecture (originally designed and optimized for business data processing) has been used to support many data-centric applications with widely varying characteristics and requirements.

In this paper, we argue that this concept is no longer applicable to the database market, and that the commercial world will fracture into a collection of independent database engines, some of which may be unified by a common front-end parser. We use examples from the stream-processing market and the datawarehouse market to bolster our claims. We also briefly discuss other markets for which the traditional architecture is a poor fit and argue for a critical rethinking of the current factoring of systems services into products. of multiple code lines causes various practical problems, including:

- a cost problem, because maintenance costs increase at least linearly with the number of code lines;
- a compatibility problem, because all applications have to run against every code line;
- a sales problem, because salespeople get confused about which product to try to sell to a customer; and
- a marketing problem, because multiple code lines need to be positioned correctly in the marketplace.

To avoid these problems, all the major DBMS vendors have followed the adage "put all wood behind one arrowhead". In this paper we argue that this strategy has failed already, and will fail more dramatically off into the future.

The rest of the paper is structured as follows. In Section 2, we briefly indicate why the single code-line strategy has failed already by citing some of the key characteristics of the data warehouse market. In Section

SQL

Difficult to optimise

Difficult to distribute



Declarative language

Expressive

ACID

Costly to implement

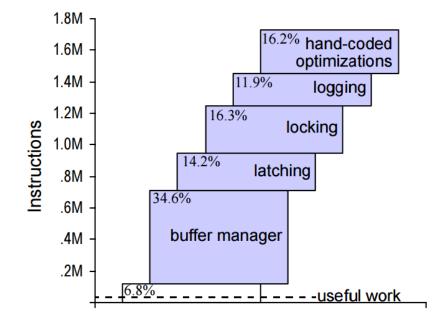
Difficult to distribute



Guarantees correct behaviour

Support transactions

Transactional overhead: the cost of ACID



- 640 transactions per second for system with full transactional support (ACID)
- 12,700 transactions per second for system without logs, transactions or lock scheduling

OLTP Through the Looking Glass, and What We Found There

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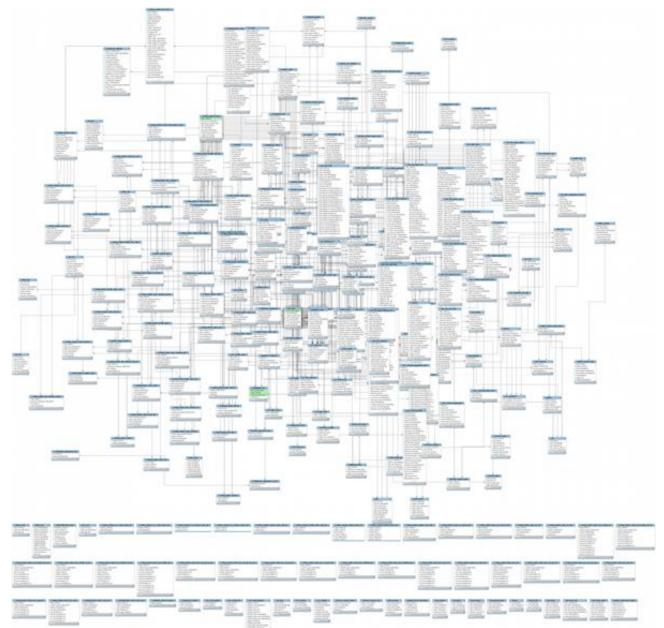
ABSTRACT

Online Transaction Processing (OLTP) databases include a suite of features — disk-resident B-trees and heap files, locking-based concurrency control, support for multi-threading — that were optimized for computer technology of the late 1970's. Advances in modern processors, memories, and networks mean that today's computers are vastly different from those of 30 years ago, such that many OLTP databases will now fit in main memory, and most OLTP transactions can be processed in milliseconds or less. Yet database architecture has changed little

1. INTRODUCTION

Modern general purpose online transaction processing (OLTP) database systems include a standard suite of features: a collection of on-disk data structures for table storage, including heap files and B-trees, support for multiple concurrent queries via lockingbased concurrency control, log-based recovery, and an efficient buffer manager. These features were developed to support transaction processing in the 1970's and 1980's, when an OLTP database was many times larger than the main memory, and when the commuters that ran these databases cost bundreds of thousands to

RDBMS: Complexity

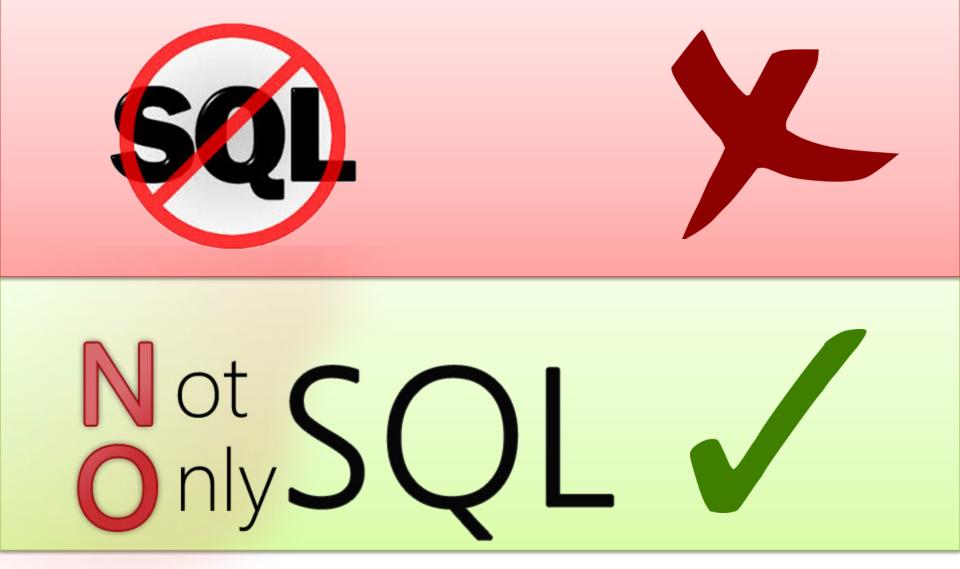


Alternatives to Relational Databases For Big Data?

NoSQL

Anybody know anything about NoSQL?



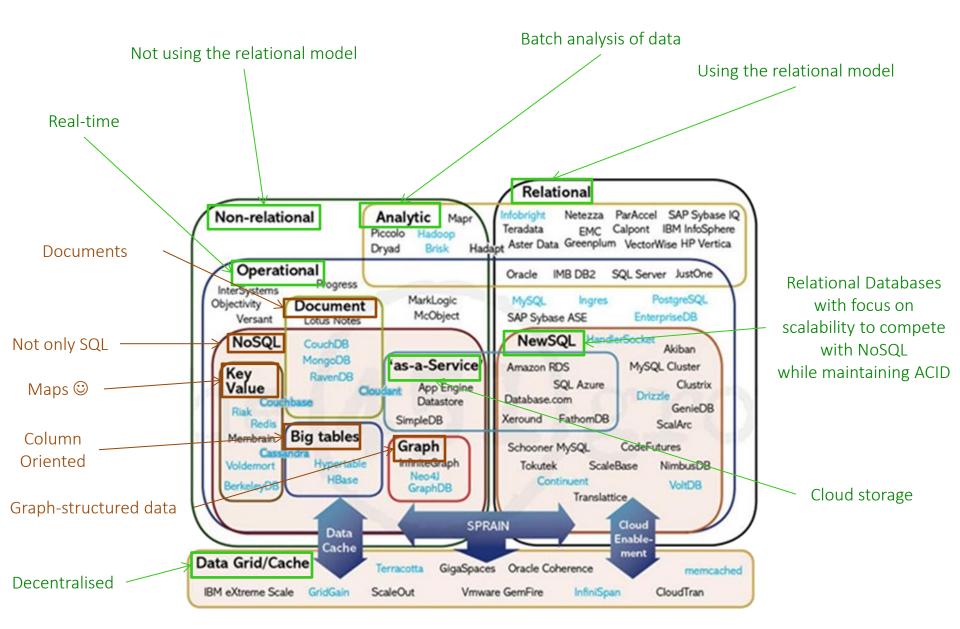


347 systems in ranking, May 2019

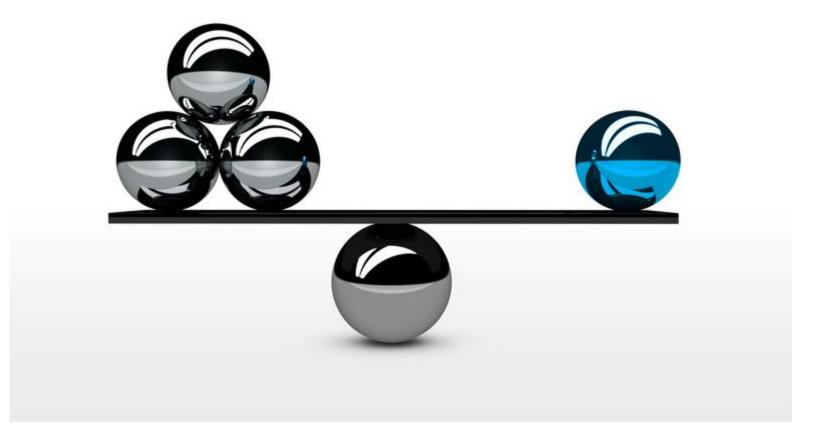
	Rank				Score		
May 2019	Apr 2019	May 2018	DBMS	Database Model	May 2019	Apr 2019	May 2018
1.	1.	1.	Oracle 🖶	Relational, Multi-model 🚺	1285.55	+5.61	-4.87
2.	2.	2.	MySQL 🖶	Relational, Multi-model 🚺	1218.96	+3.82	-4.38
3.	3.	3.	Microsoft SQL Server 🔂	Relational, Multi-model 🚺	1072.19	+12.23	-13.66
4.	4.	4.	PostgreSQL 🔂	Relational, Multi-model 🚺	478.89	+0.17	+77.99
5.	5.	5.	MongoDB 🖶	Document	408.07	+6.10	+65.96
6.	6.	6.	IBM Db2 🖶	Relational, Multi-model 🚺	174.44	-1.61	-11.17
7.	个 8.	个 9.	Elasticsearch 🔂	Search engine, Multi-model 🚺	148.62	+2.62	+18.18
8.	4 7.	4 7.	Redis 🔂	Key-value, Multi-model 🚺	148.40	+2.03	+13.06
9.	9.	4 8.	Microsoft Access	Relational	143.78	-0.87	+10.67
10.	↑ 11.	10.	Cassandra 🖶	Wide column	125.72	+2.11	+7.89
11.	4 10.	11.	SQLite 🚹	Relational	122.90	-1.32	+7.44
12.	12.	个 14.	MariaDB 🔂	Relational, Multi-model 🚺	86.52	+1.29	+21.53
13.	13.	13.	Splunk	Search engine	85.24	+2.15	+20.15
14.	个 15.	个 18.	Hive 🖶	Relational	77.90	+3.19	+20.93
15.	4 14.	4 12.	Teradata 🖶	Relational	76.04	+0.69	+1.63
16.	16.	4 15.	Solr	Search engine	60.80	+0.57	-0.72
17.	17.	17.	HBase	Wide column	59.77	+1.11	-0.18
18.	18.	个 19.	FileMaker	Relational	58.51	+0.09	+3.84
19.	19.	个 21.	Amazon DynamoDB 🔂	Multi-model 🚺	55.93	-0.08	+11.74
20.	个 21.	20.	SAP HANA 🖶	Relational, Multi-model 🚺	55.74	+0.39	+7.37
21.	4 20.	4 16.	SAP Adaptive Server	Relational	55.44	-0.36	-6.07
22.	22.	22.	Neo4j 🖶	Graph	51.03	+1.54	+10.45
23.	23.	个 24.	Couchbase 🔒	Document	34.67	-1.61	+2.26
24.	个 25.	4 23.	Memcached	Key-value	28.90	+0.17	-4.66
25.	4 24.	个 26.	Microsoft Azure SQL Database	Relational, Multi-model 🚺	28.77	-0.02	+3.56

http://db-engines.com/en/ranking

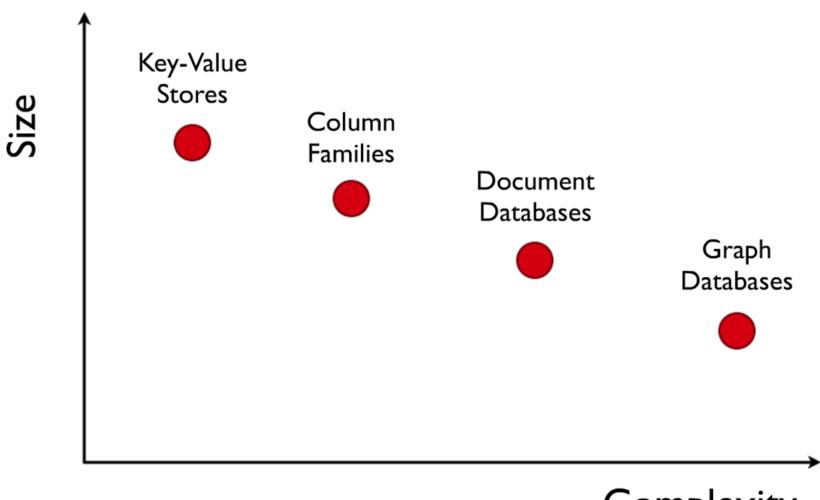
Many types of NoSQL stores



NoSQL: features vs. scale/performance



NoSQL: four main types





NoSQL: common characteristics

- Often distributed
 - Sharding: splitting data over servers "horizontally"
 - Replication
 - Different guarantees: typically not ACID
- Often **simpler** languages than SQL
 - Simpler ad hoc APIs
 - More work for the application
- Different flavours (for different scenarios)
 - Different availability/consistency emphasis
 - Different scalability profiles
 - Different query functionality
 - Different data models

LIMITATIONS OF DISTRIBUTED COMPUTING: CAP THEOREM

But first ... ACID

For traditional (non-distributed) databases ...

1. Atomicity:

- Transactions all or nothing: fail cleanly
- **2.** Consistency:
 - Doesn't break constraints/rules
- **3.** Isolation:
 - Parallel transactions act as if sequential

4. Durability

System remembers changes

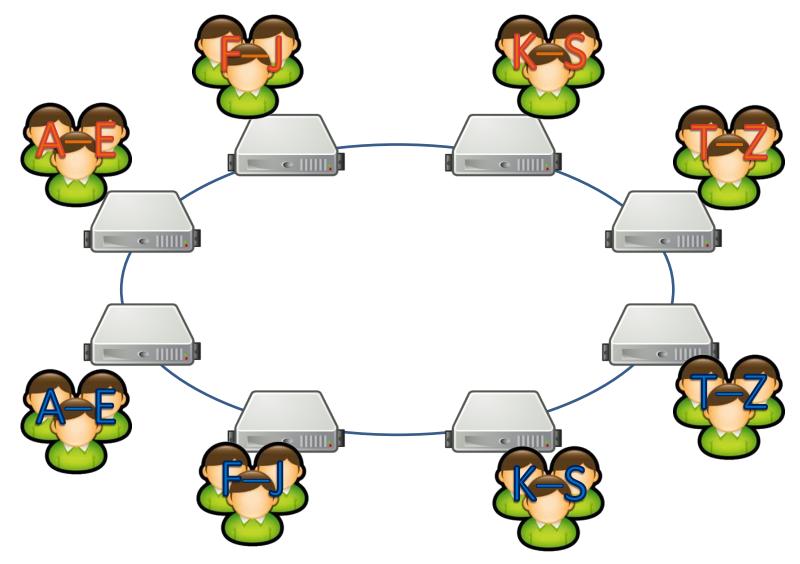
What is CAP?

Three *guarantees* a <u>distributed</u> sys. could make

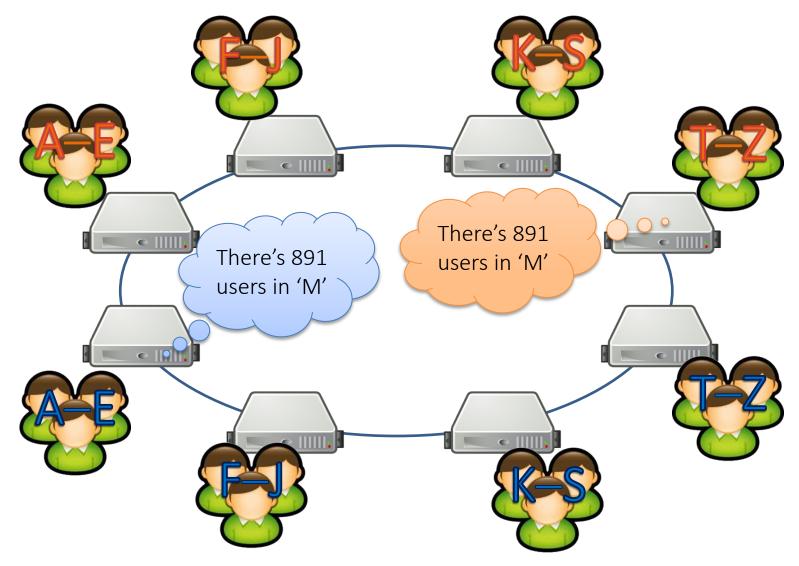
- **1. C**onsistency:
 - All nodes have a consistent view of the system
- **2. A**vailability:
 - Every read/write is acted upon
- **3.** Partition-tolerance:
 - The system works even if messages are lost

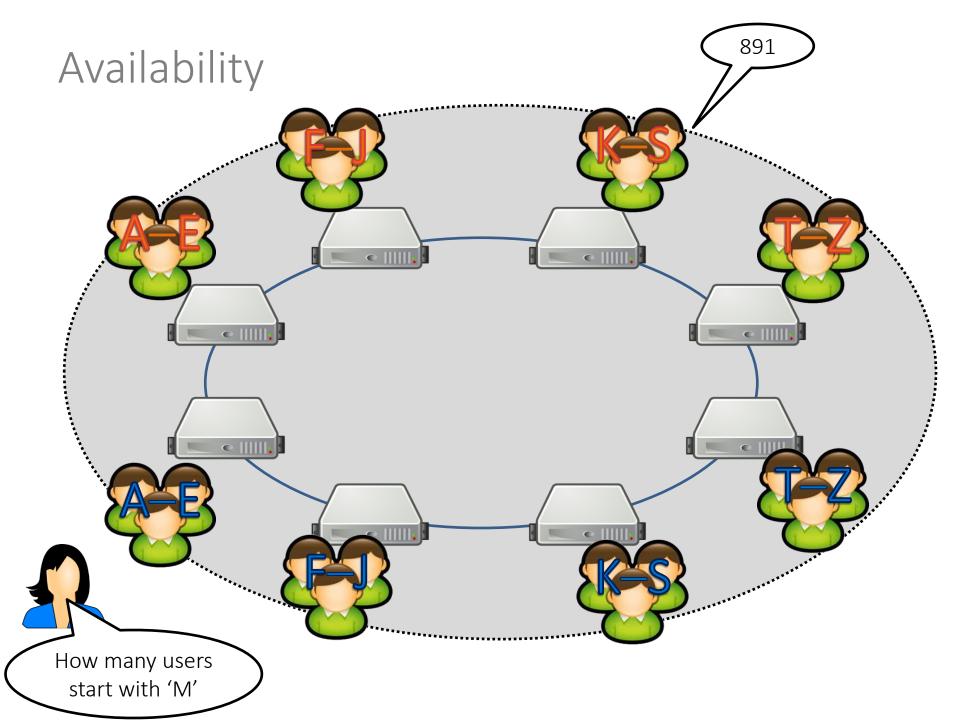


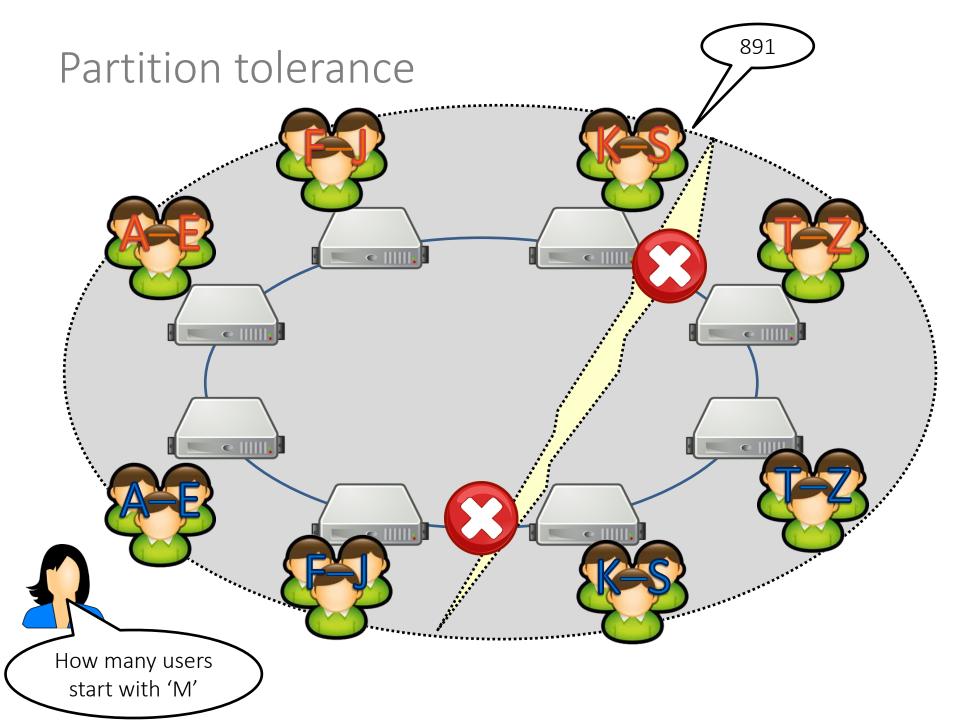
A Distributed System (with Replication)



Consistency







Can a distributed system guarantee consistency (all nodes have the same up-to-date view), availability (every read/write is acted upon) and partition-tolerance (the system works if messages are lost) at the same time?

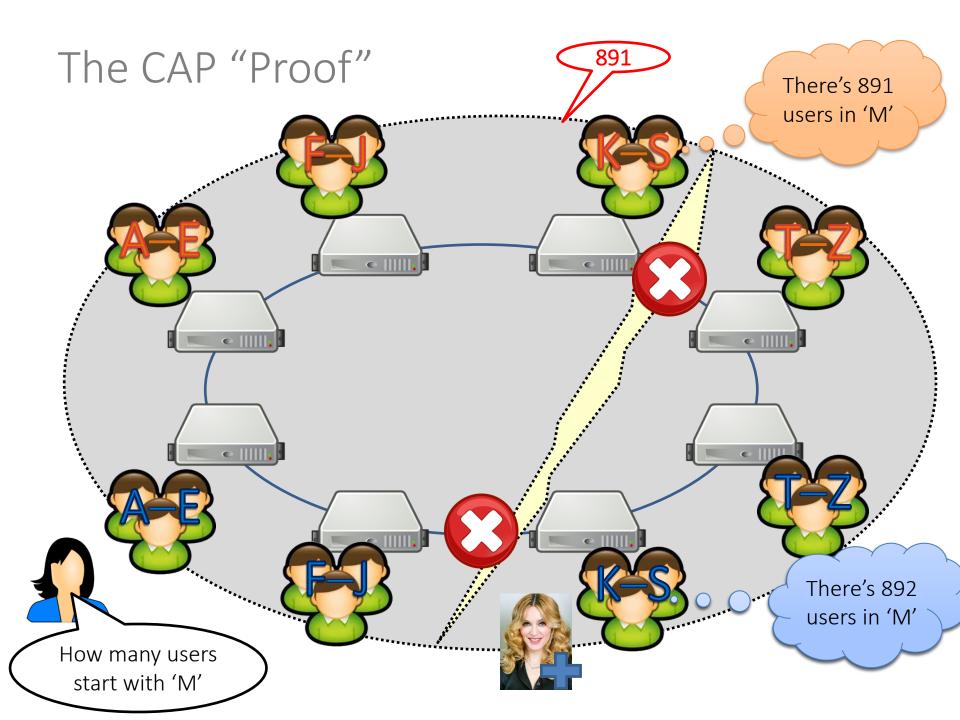
What do you think?



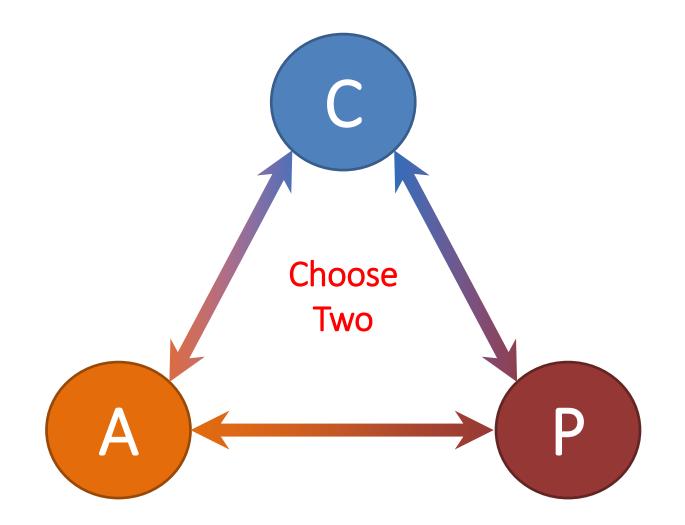
The CAP Answer



A distributed system <u>cannot</u> guarantee consistency (all nodes have the same up-to-date view), availability (every read/write is acted upon) and partition-tolerance (the system works if messages are lost) at the same time!

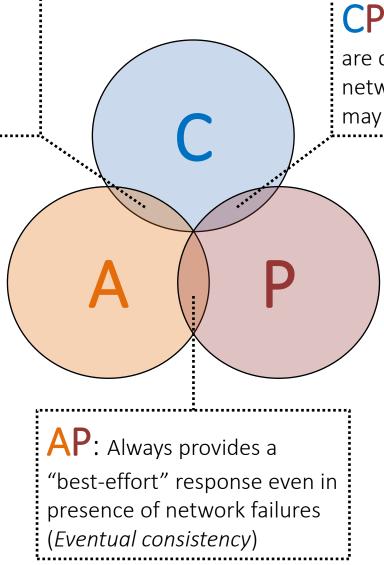


The CAP Triangle



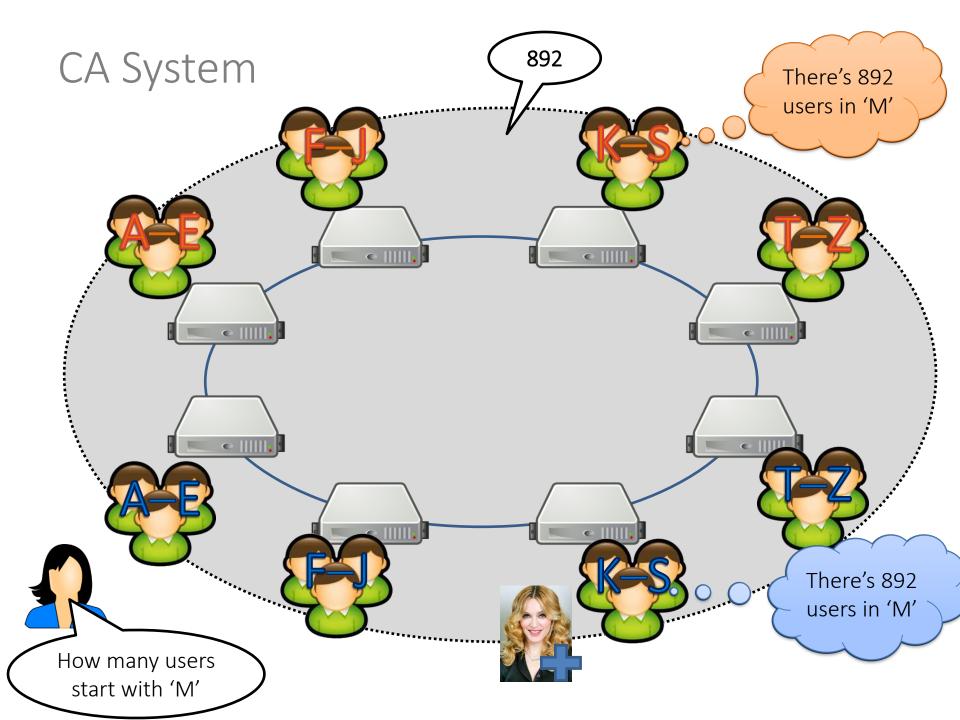
CAP Systems

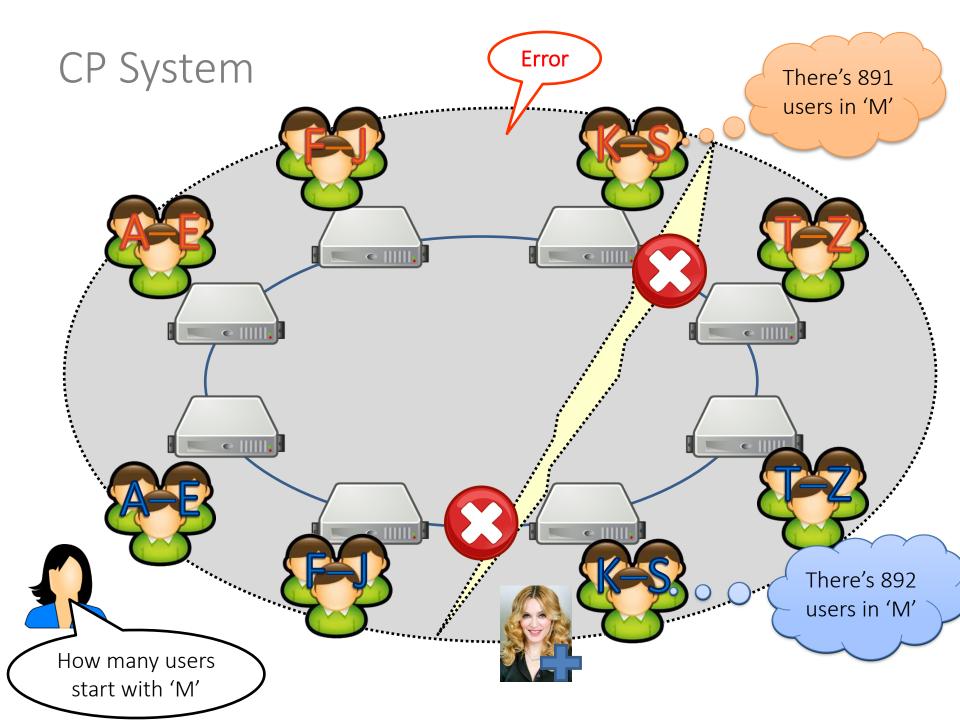
CA: Guarantees to give a correct response but only while network works fine (*Centralised / Traditional*)

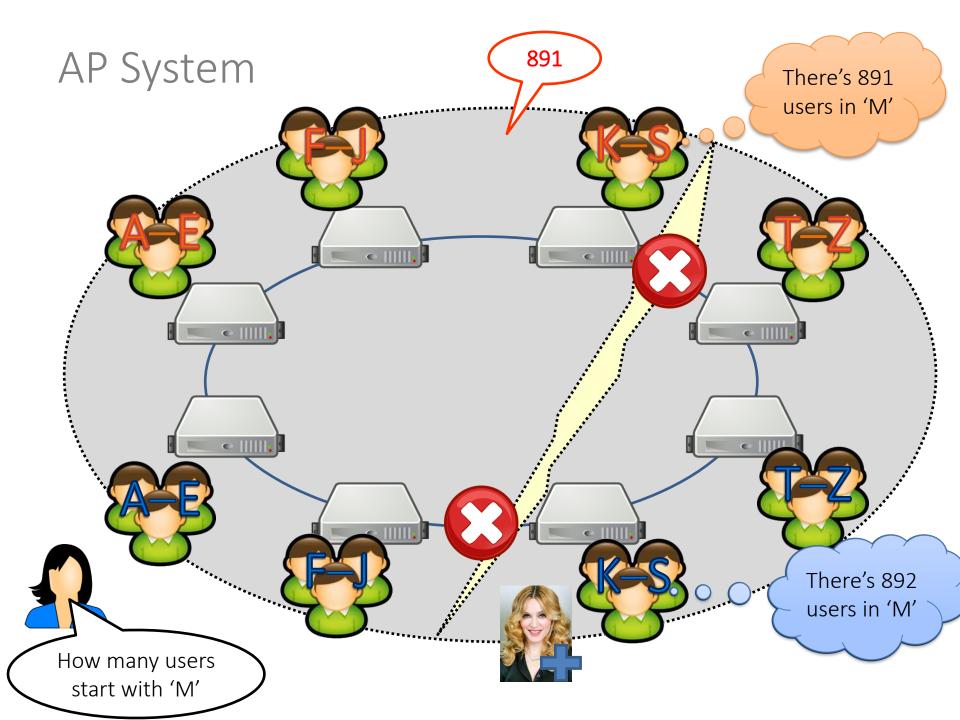


CP: Guarantees responses are correct even if there are network failures, but response may fail (*Weak availability*)

(No intersection)









- Basically Available
 Almost always "up"
- Soft State
 - Replicated, cached data
- Eventual Consistency
 - Stale data tolerated, for a while

In what way does Twitter act as a BASE (AP) system?



High-fanout creates a "partition"



@ladygaga 31 million followers

Users may see retweets of celebrity tweets before the original tweet. Later when the original tweet arrives the timeline will be reordered and made consistent.

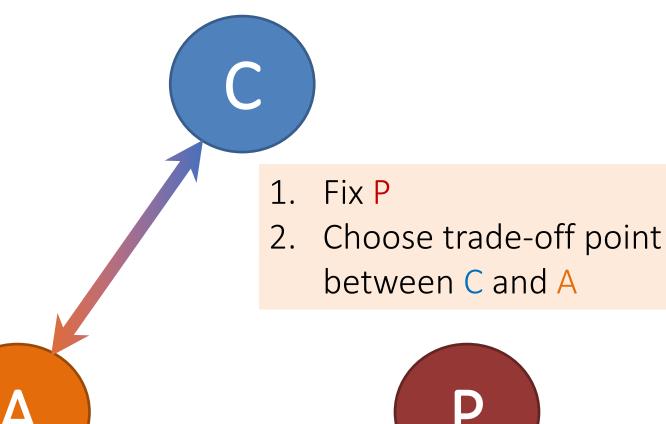


28 million followers



@barackobama
23 million followers

CAP in practical distributed systems



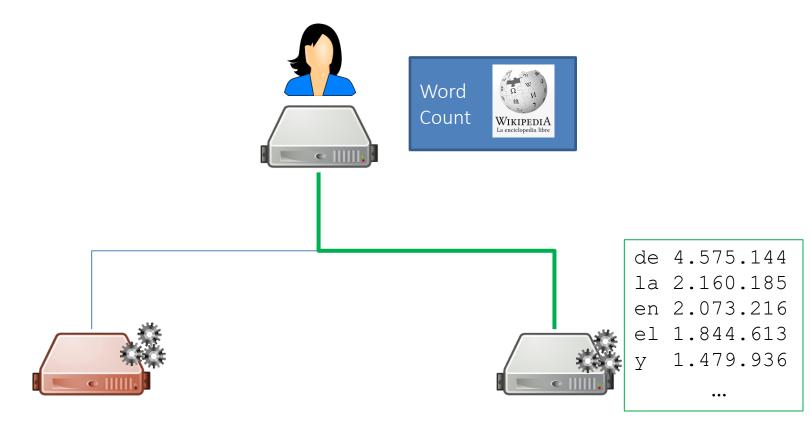
PARTITION TOLERANCE

Faults



Fail–Stop Fault

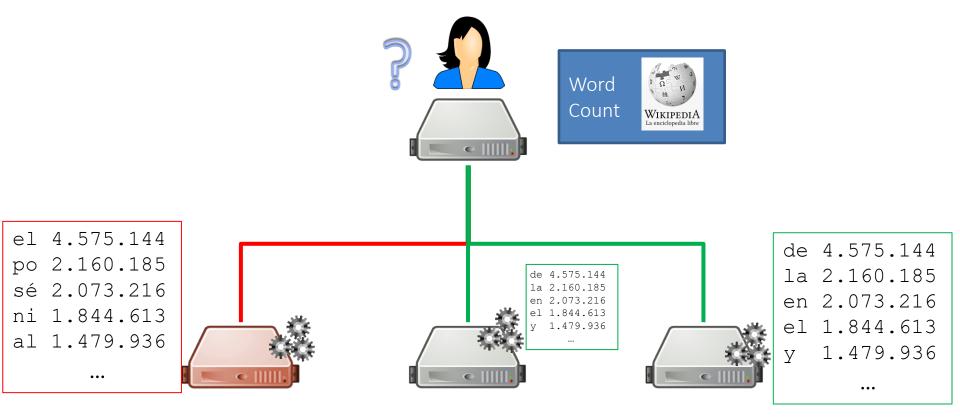
- A machine fails to respond or times-out
 - often hardware or load
 - need at least f + 1 replicated machines
 - f = number of fail-stop failures



Byzantine Fault

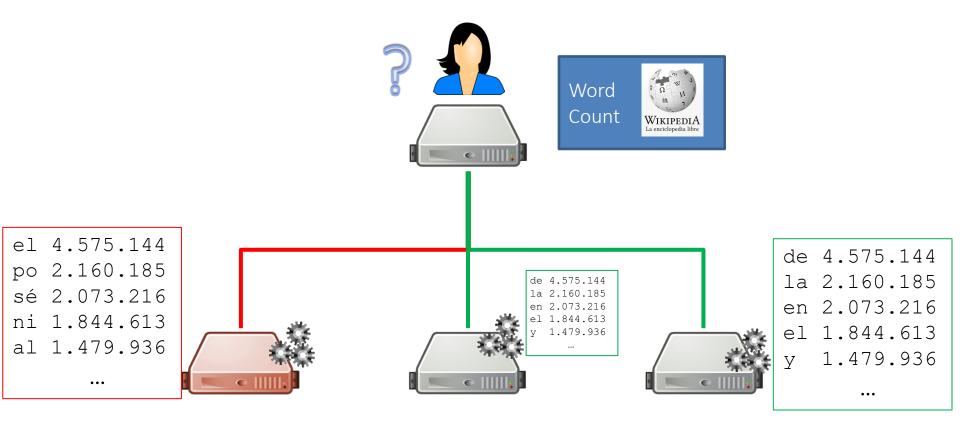
• A machine responds incorrectly/maliciously

How many working machines do we need in the general case to be robust against Byzantine faults?



Byzantine Fault

- A machine responds incorrectly/maliciously
 - Need at least 2f+1 replicated machines
 - f = number of (possibly Byzantine) failures



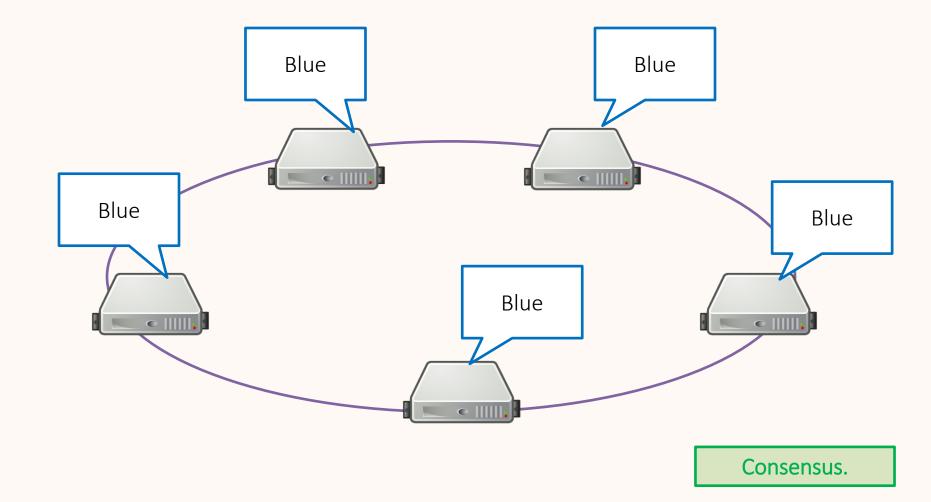
DISTRIBUTED CONSENSUS



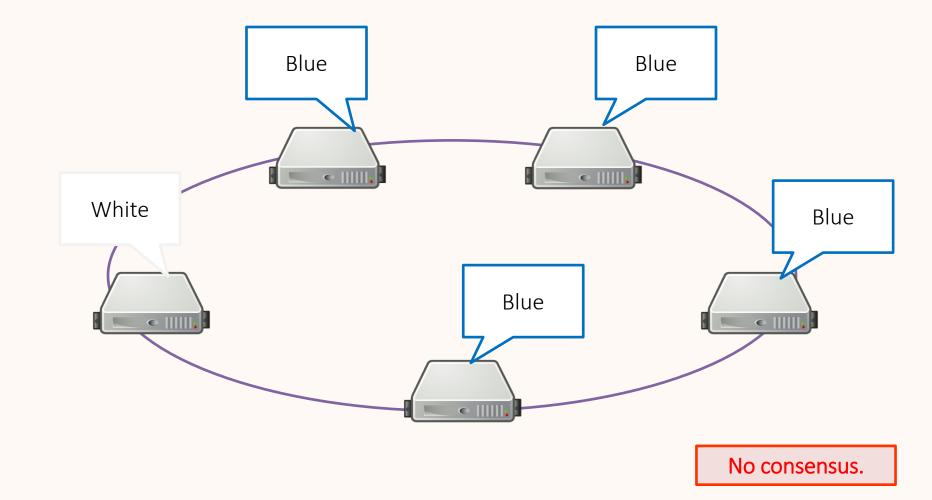
Colour of the dress?

?

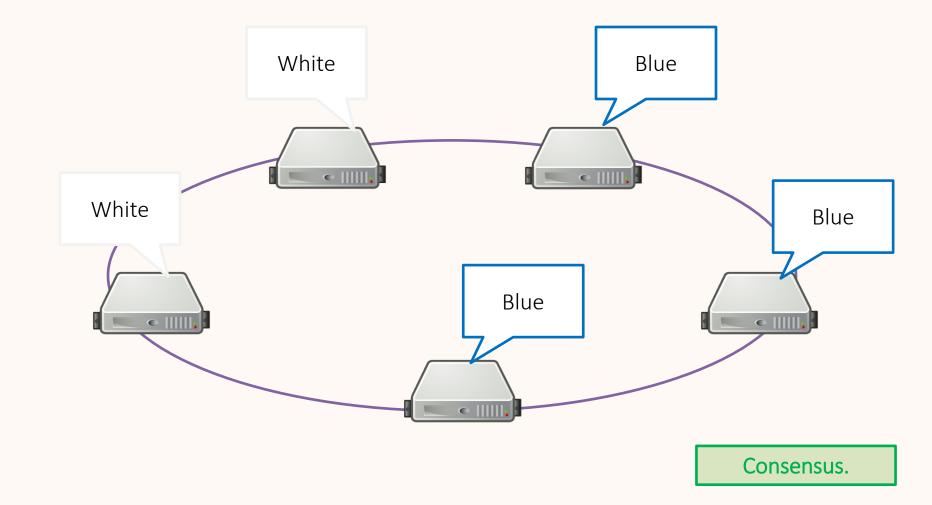
Strong consensus: All nodes need to agree



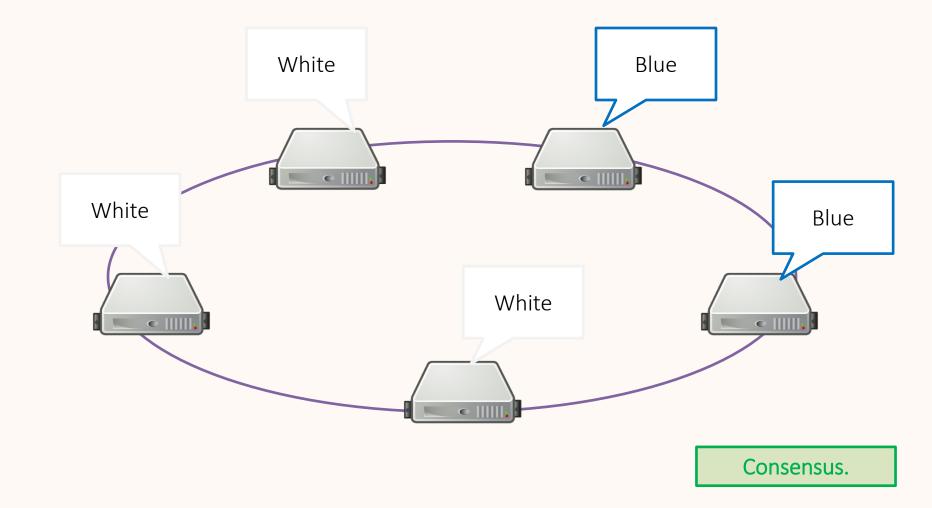
Strong consensus: All nodes need to agree



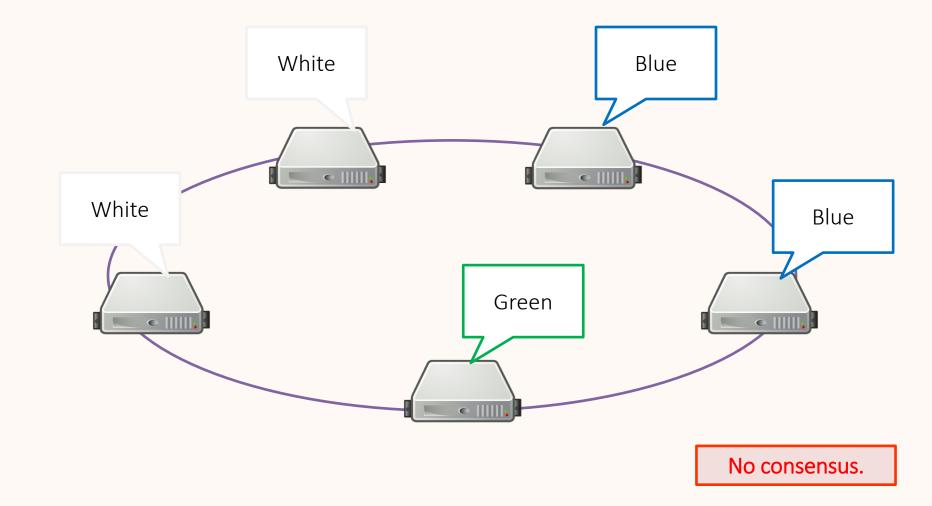
Majority consensus: A majority of nodes need to agree



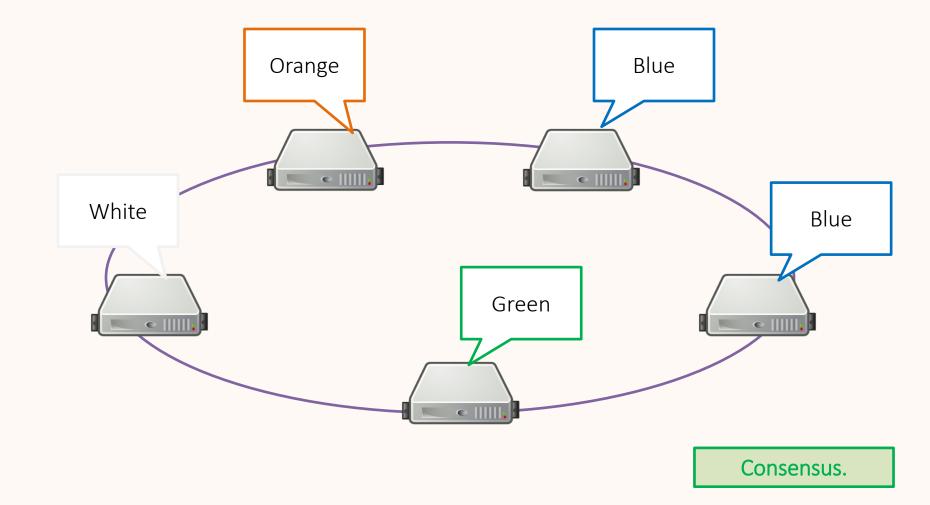
Majority consensus: A majority of nodes need to agree



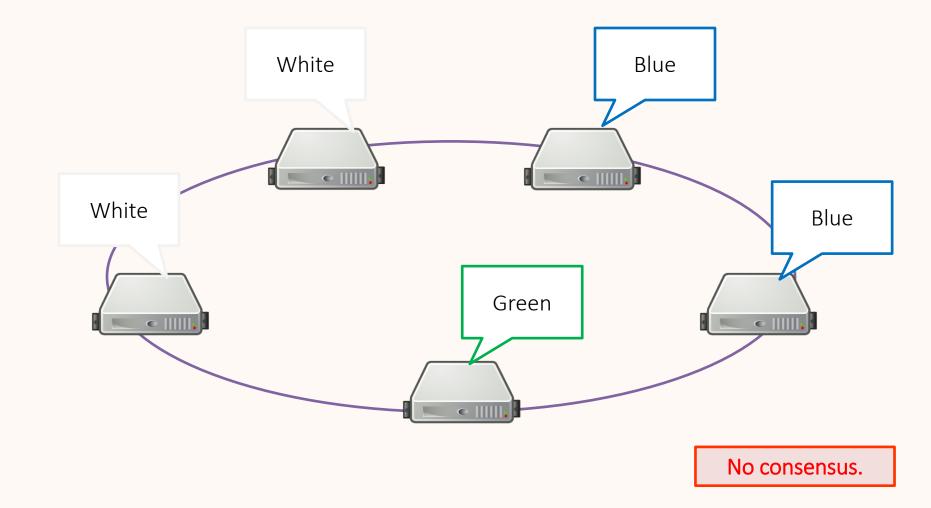
Majority consensus: A majority of nodes need to agree



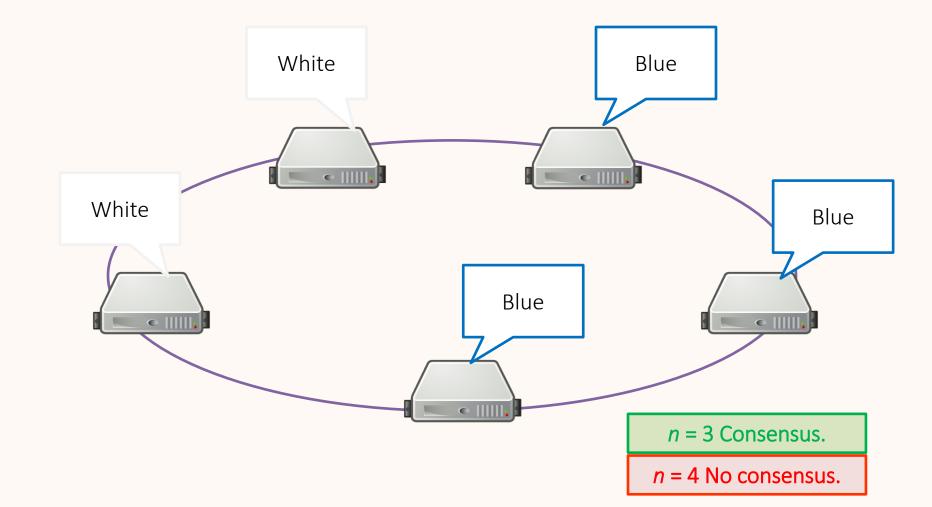
Plurality consensus: A plurality of nodes need to agree



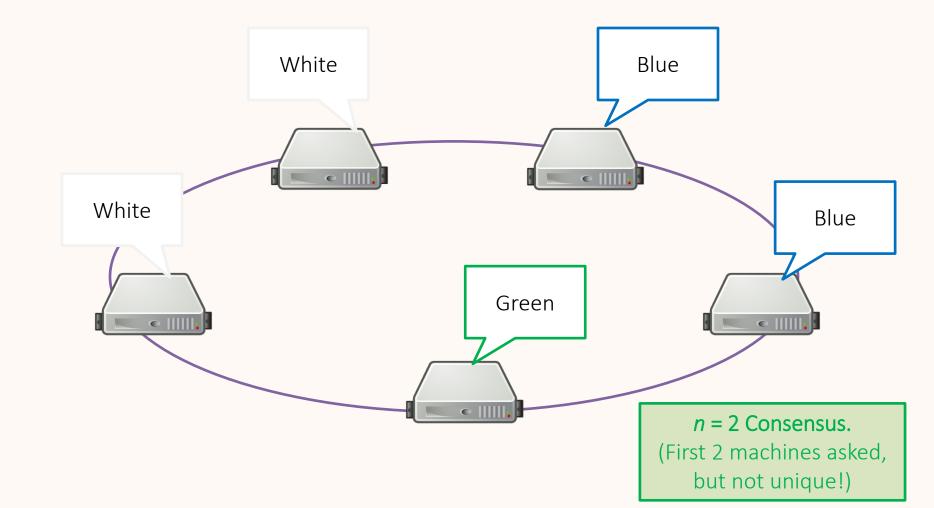
Plurality consensus: A plurality of nodes need to agree



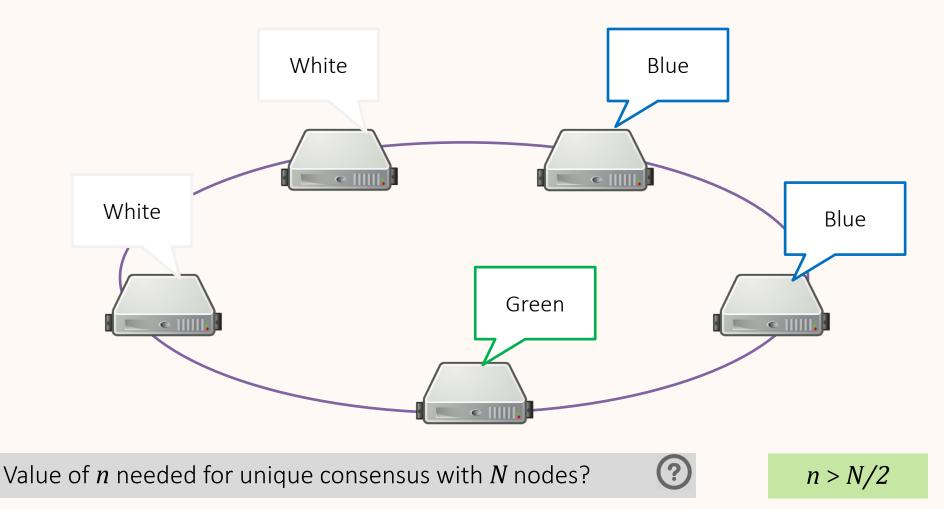
Quorum consensus: *n* nodes need to agree



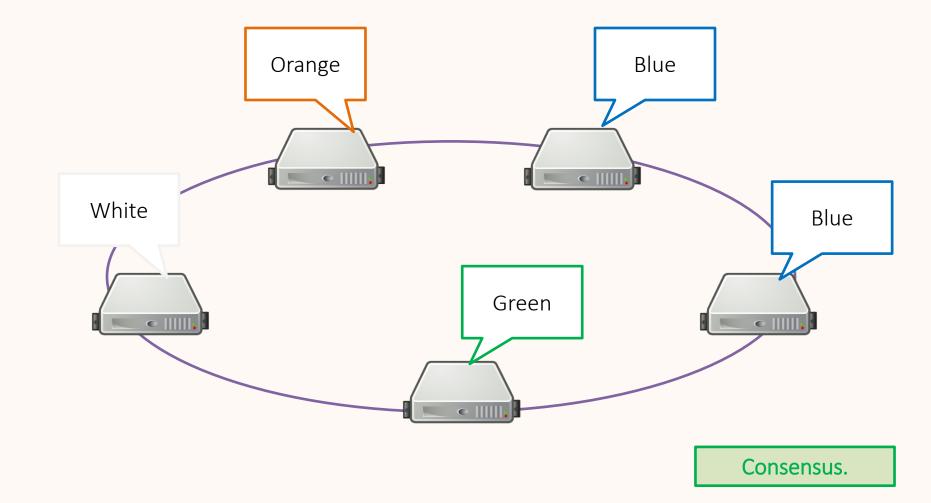
Quorum consensus: *n* nodes need to agree



Quorum consensus: *n* nodes need to agree



Consensus off: Take first answer



CP vs. AP?

Strong consensus: All nodes need to agree

Majority consensus: A majority of nodes need to agree

Plurality consensus: A plurality of nodes need to agree

Quorom consensus: "Fixed" *n* nodes need to agree

Consensus off: Take first answer

Scale?

More replication

Strong consensus: All nodes need to agree

Majority consensus: A majority of nodes need to agree

Plurality consensus: A plurality of nodes need to agree

Quorom consensus: "Fixed" *n* nodes need to agree

Consensus off: Take first answer

Less replication

Strong consensus: All nodes need to agree

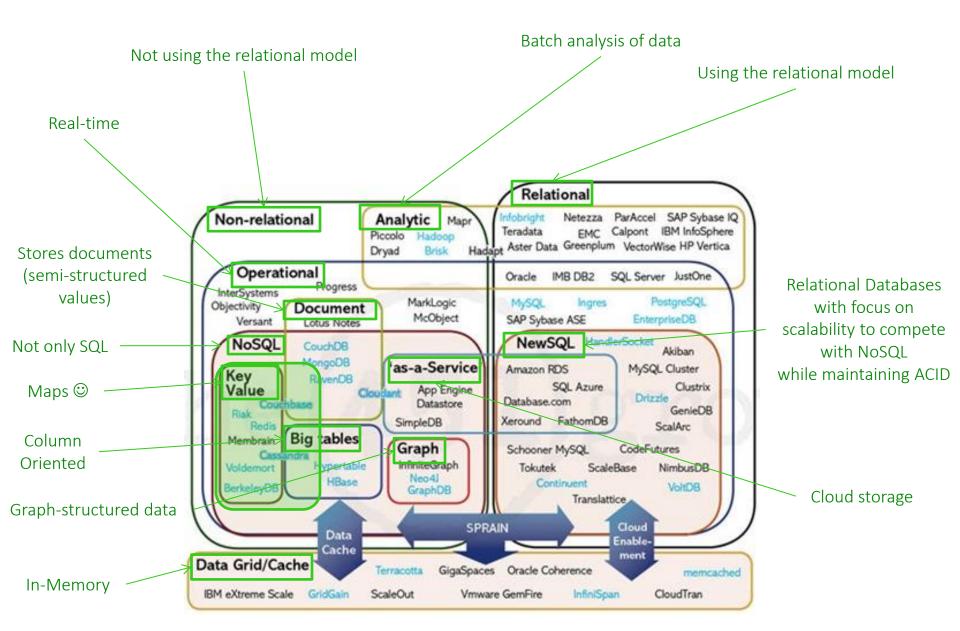
Majority consensus: A majority of nodes need to agree Choice is application dependent: Plurality Many NoSQL stores allow you to choose level of consensus/replication

Quorom consensus: "Fixed" *n* nodes need to agree

Consensus off: Take first answer

NOSQL: KEY–VALUE STORES

The Database Landscape



Key–Value Store Model

It's just a Map / Associate Array / Dictionary 😳

- put(key,value)
- get(key)
- delete(key)

Кеу	Value
Afghanistan	Kabul
Albania	Tirana
Algeria	Algiers
Andorra la Vella	Andorra la Vella
Angola	Luanda
Antigua and Barbuda	St. John's
•••	•••

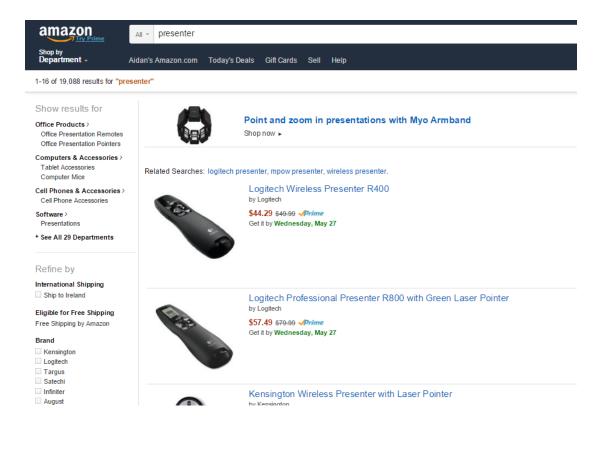
But You Can Do a Lot With a Map

Кеу	Value
country:Afghanistan	<pre>capital@city:Kabul,continent:Asia,pop:31108077#2011</pre>
country:Albania	<pre>capital@city:Tirana,continent:Europe,pop:3011405#2013</pre>
city:Kabul	country:Afghanistan,pop:3476000#2013
city:Tirana	country:Albania,pop:3011405#2013
•••	···
user:10239	<pre>basedIn@city:Tirana,post:{103,10430,201}</pre>

... actually you can model any data in a map (but possibly with a lot of redundancy and inefficient lookups if unsorted).

THE CASE OF AMAZON

Products Listings: prices, details, stock



Customer info: shopping cart, account, etc.

Shopping Cart Already a customer? subtotal = \$88.77 See more items like those in your Cart Make any changes below? Update Shopping Cart Items--To Buy Now Price: Qty: Item added The Principles of Beautiful Web Design - Jason Beaird; \$26.37 1 on May 22, Paperback You Save: 2009 Condition: New \$13,58 (34%) In Stock Save for later Delete ·Eligible for FREE Super Saver Shipping Add gift-wrap/note (Learn more) Item added Don't Make Me Think: A Common Sense Approach to \$26.40 1 on May 22, Web Usability, 2nd Edition - Steve Krug; Paperback You Save: 2009 Condition: New \$13.60 (34%) In Stock Save for later) Delete Eligible for FREE Super Saver Shipping

Add gift-wrap/note 🛄 (Learn more)

Recommendations, etc.:

Customers Who Bought This Item Also Bought



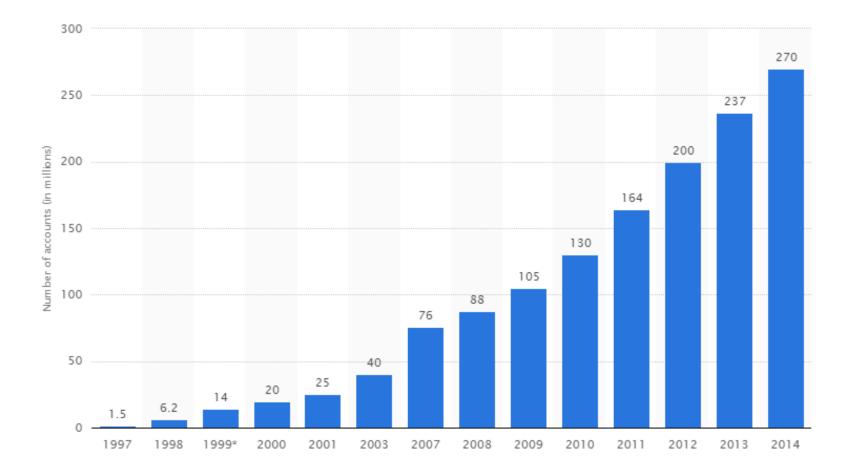


David Copperfield (Dover Thrift Editions) Charles Dickens (196) Paperback \$5.00



JANE EYRE Charlotte Bronte Charlotte Bronte (1,045) Paperback \$2.99

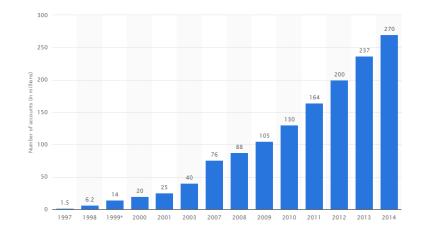
• Amazon customers:



amazon webservicesTM



Databases struggling ...



But many Amazon services don't need:

- SQL (a simple map often enough) or even:
- transactions, strong consistency, etc.

Key–Value Store: Amazon Dynamo(DB)

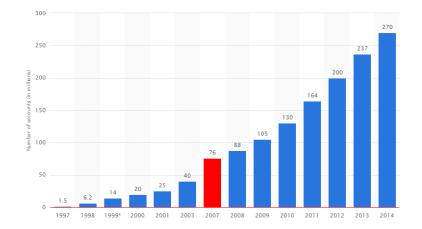
Dynamo: Amazon's Highly Available Key-value Store

Giuseppe DeCandia, Deniz Hastorun, Madan Jampani, Gunavardhan Kakulapati, Avinash Lakshman, Alex Pilchin, Swaminathan Sivasubramanian, Peter Vosshall and Werner Vogels

Amazon.com

ABSTRACT

Reliability at massive scale is one of the biggest challenges we face at Amazon.com, one of the largest e-commerce operations in the world; even the slightest outage has significant financial consequences and impacts customer trust. The Amazon.com platform, which provides services for many web sites worldwide, is implemented on top of an infrastructure of tens of thousands of servers and network components located in many datacenters One of the lessons our organization has learned from operating Amazon's platform is that the reliability and scalability of a system is dependent on how its application state is managed. Amazon uses a highly decentralized, loosely coupled, service oriented architecture consisting of hundreds of services. In this environment there is a particular need for storage technologies that are always available. For example, customers should be able to view and add items to their shopping cart even if disks are filling returned reture or flaming of deta nearther can being



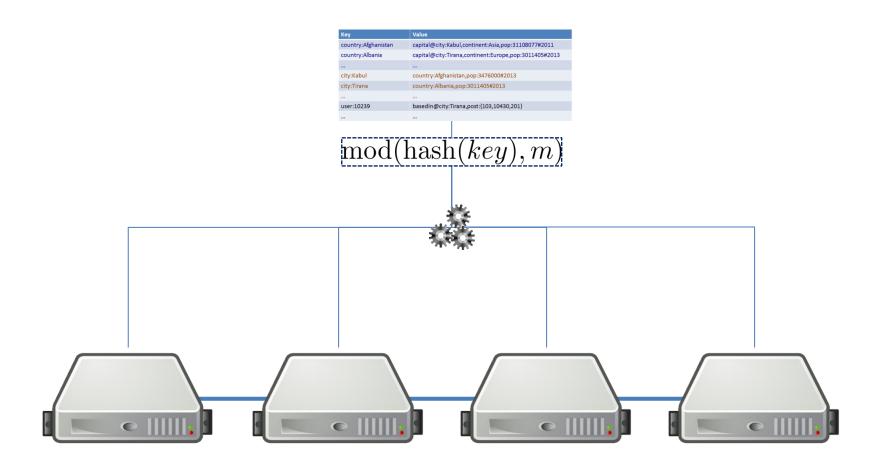
Goals:

- Scalability (able to grow)
- High availability (reliable)
- Performance (fast)

Don't need full SQL, don't need full ACID

Key–Value Store: Distribution

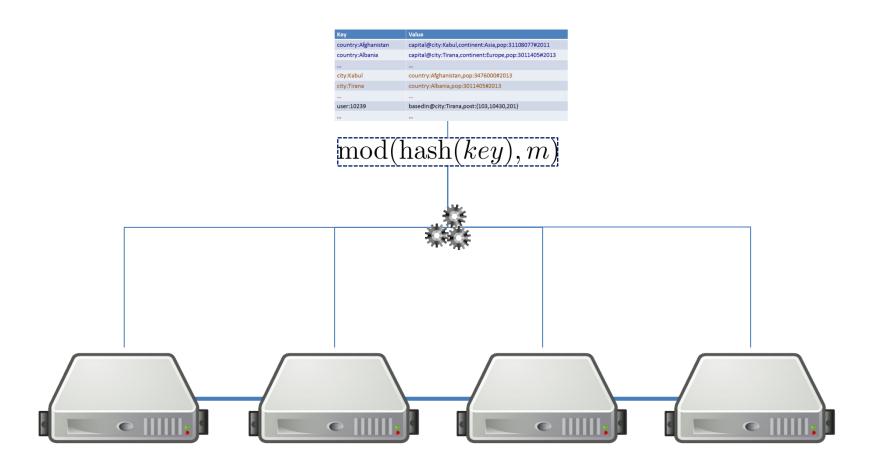
How might we distribute a key-value store over multiple machines?



Key–Value Store: Distribution

What happens if a machine leaves or joins afterwards?

How can we avoid rehashing everything?



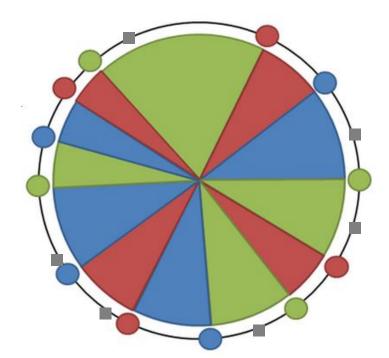
?

Consistent Hashing

Avoid re-hashing everything

- Hash using a ring
- Each machine picks *n* pseudo-random points <u>on</u> the ring
- Machine responsible for arc after its point
- If a machine leaves, its range moves to previous machine
- If machine joins, it picks new points
- Objects mapped to ring 🙂

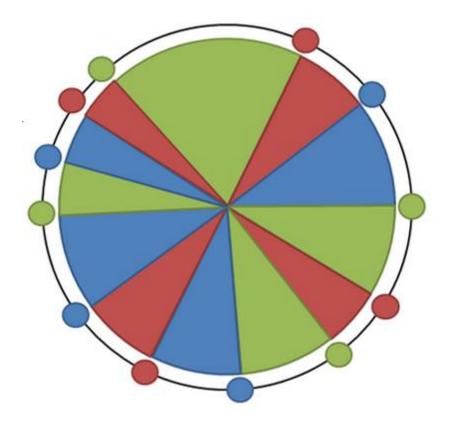
How many keys (on average) would need to be moved if a machine joins or leaves?



Amazon Dynamo: Hashing

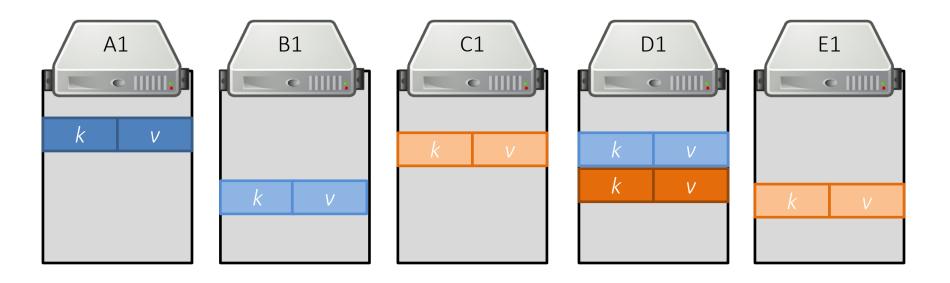


• Consistent Hashing (128-bit MD5)



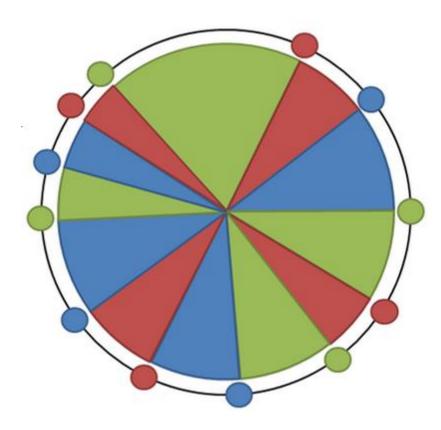
Amazon Dynamo: Replication

- A set replication factor (e.g., 3)
- Commonly primary / secondary replicas
 - Primary replica elected from secondary replicas in the case of failure of primary

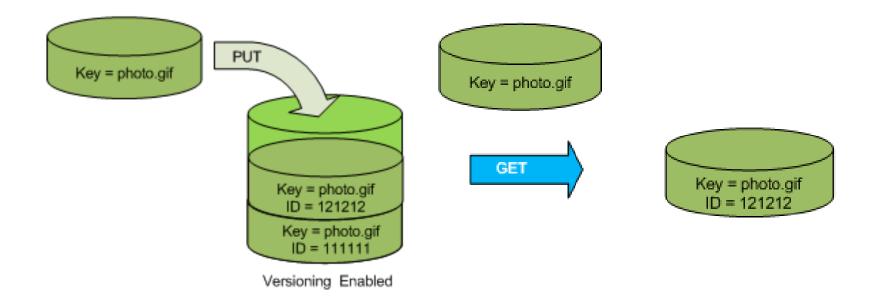


Amazon Dynamo: Replication

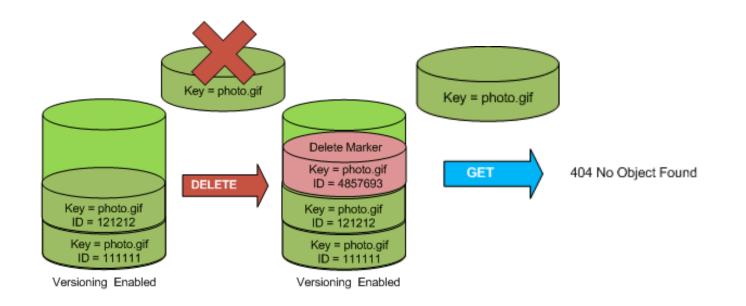
- Replication factor of *n*?
 - Easy: pick n next buckets (different machines!)



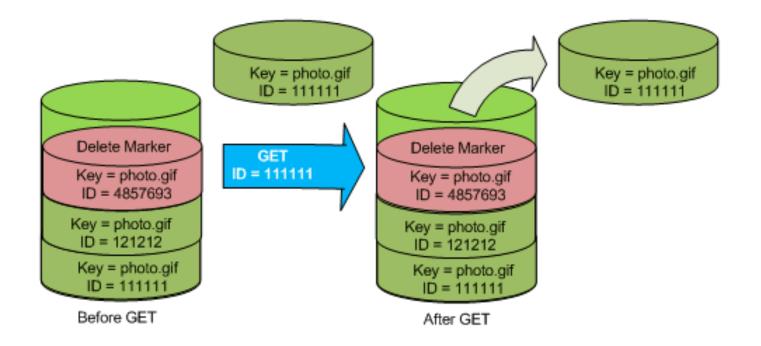
- Object Versioning (per bucket)
 - PUT doesn't overwrite: pushes version
 - GET returns most recent version



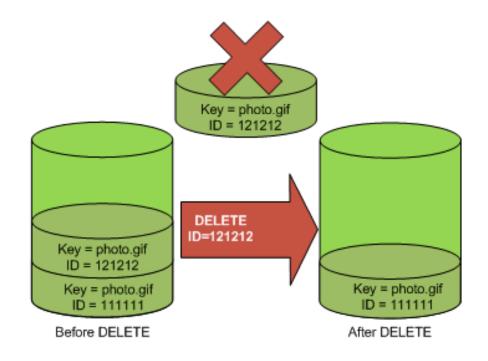
- Object Versioning (per bucket)
 - DELETE doesn't wipe
 - GET will return not found



- Object Versioning (per bucket)
 - GET by version



Object Versioning (per bucket)
 – PERMANENT DELETE by version ... wiped



Amazon Dynamo: Model

- Named table with primary key and a value
- Primary key is hashed / unordered

Countries						
Primary Key	Value					
Afghanistan	capital:Kabul,continent:Asia,pop:31108077#2011					
Albania	capital:Tirana,continent:Europe,pop:3011405#2013					

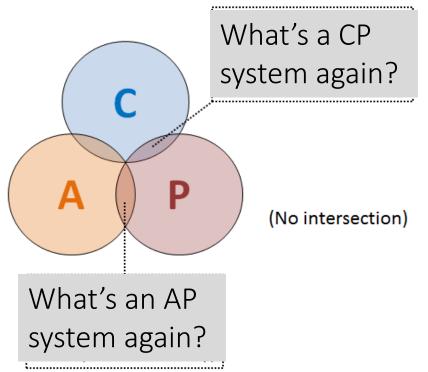
Cities						
Primary Key	Value					
Kabul	country:Afghanistan,pop:3476000#2013					
Tirana	country:Albania,pop:3011405#2013					

Amazon Dynamo: CAP

Two options for each table:

• **AP**: Eventual consistency, High availability

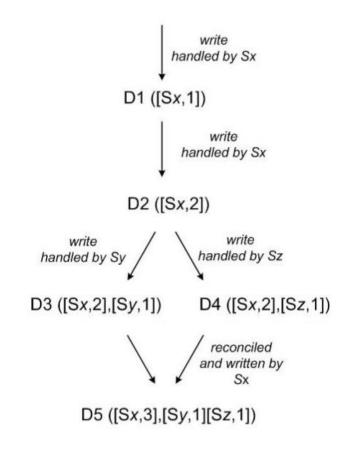
• **CP**: Strong consistency, Lower availability



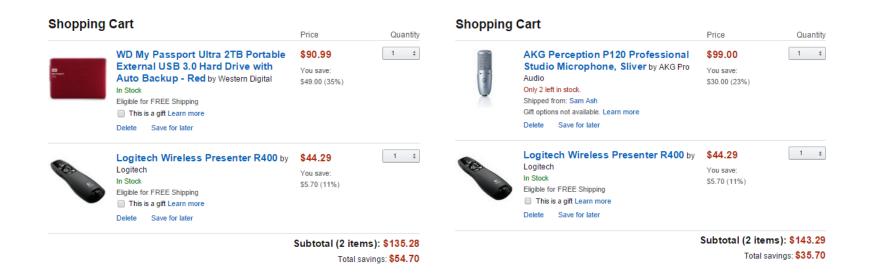
- Gossiping
 - Keep-alive messages sent between nodes with state
 - Dynamo largely decentralised (no master node)
- Quorums:
 - Multiple nodes responsible for a read (R) or write (W)
 - At least R or W nodes acknowledge for success
 - Higher R or W = Higher consistency, lower availability
- Hinted Handoff
 - For transient failures
 - A node "covers" for another node while it is down

- Vector Clock:
 - A list of pairs indicating a node and operation count

- Used to track branches of revisions



• Two versions of one shopping cart:



How best to merge multiple conflicting versions of a value (known as <u>reconciliation</u>)?

Application knows best

?

(... and must support multiple versions being returned)

Кеу	Value
country: Afghanistan	capital@city:Kabul,continent:Asia,pop:31108077#2011
country:Albania	capital@city:Tirana,continent:Europe,pop:3011405#2013
city:Kabul	country: Afghanistan, pop: 3476000#2013
city:Tirana	country: Albania, pop: 3011405#2013
user:10239	basedIn@city:Tirana,post:{103,10430,201,408}

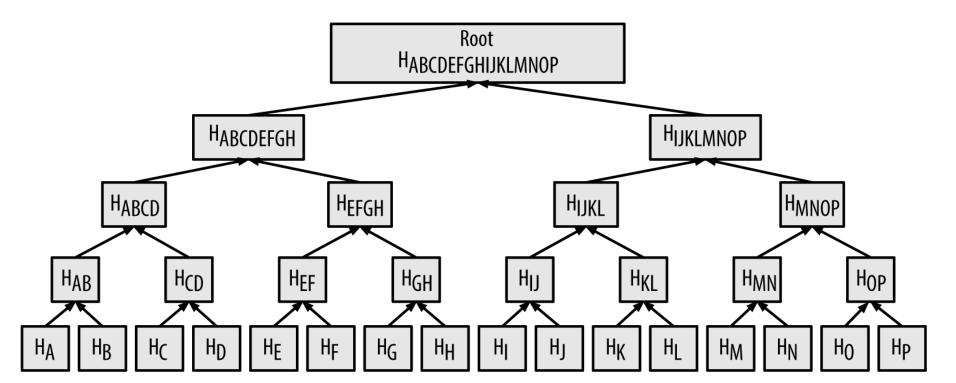
Кеу	Value
country: Afghanistan	capital@city:Kabul,continent:Asia,pop:31108077#2011
country: Albania	capital@city:Tirana,continent:Europe,pop:3011405#2013
city:Kabul	country: Afghanistan, pop: 3476000#2013
city:Tirana	country: Albania, pop: 3011405#2013
user:10239	basedIn@city:Tirana,post:{103,10430,201}

How can we efficiently verify that two copies of a block of data are the same (and find where the differences are)?



Amazon Dynamo: Merkle Trees

- Merkle tree: A hash tree
 - Leaf node compute hashes from data
 - Non-leaf nodes have hashes of their children
 - Find differences between two trees level-by-level



Merkle Trees also used in ...



Read More ...



Dynamo: Amazon's Highly Available Key-value Store

Giuseppe DeCandia, Deniz Hastorun, Madan Jampani, Gunavardhan Kakulapati, Avinash Lakshman, Alex Pilchin, Swaminathan Sivasubramanian, Peter Vosshall and Werner Vogels

Amazon.com

ABSTRACT

Reliability at massive scale is one of the biggest challenges we face at Amazon.com, one of the largest e-commerce operations in the world; even the slightest outage has significant financial consequences and impacts customer trust. The Amazon.com platform, which provides services for many web sites worldwide, is implemented on top of an infrastructure of tens of thousands of servers and network components located in many datacenters One of the lessons our organization has learned from operating Amazon's platform is that the reliability and scalability of a system is dependent on how its application state is managed. Amazon uses a highly decentralized, loosely coupled, service oriented architecture consisting of hundreds of services. In this environment there is a particular need for storage technologies that are always available. For example, customers should be able to view and add items to their shopping cart even if disks are failing network parter are famping or data centers are being























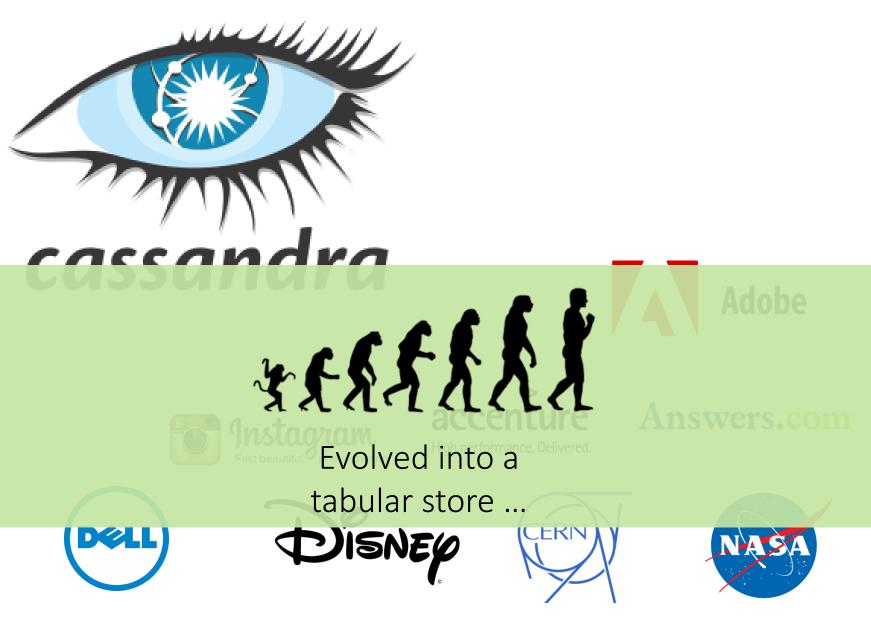


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TABULAR / COLUMN FAMILY

Key–Value = a Distributed Map

Countries						
Primary Key	Value					
Afghanistan	capital:Kabul,continent:Asia,pop:31108077#2011					
Albania	capital:Tirana,continent:Europe,pop:3011405#2013					

Tabular = Multi-dimensional Maps

	Countries									
Primary Key	capital	continent	pop-value	pop-year						
Afghanistan	Kabul	Asia	31108077	2011						
Albania	Tirana	Europe	3011405	2013						

Bigtable: The Original Whitepaper

MapReduce authors

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.

Abstract

Bigtable is a distributed storage system for managing structured data that is designed to scale to a very large size: petabytes of data across thousands of commodity servers. Many projects at Google store data in Bigtable, Sogle Earth, and Google Fiincluding ep indexn. nese applications place very different demands nance able, both in terms of data size (from URLs to on P ges to satellite imagery) an atency web ireme (fro ackend bulk processing t eal-time da ervi these varied demands, Des able has st SS provi flexible, high ce solutio or a fori these G products. In e descr se the sin s pape

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data represented in the unde dexed using row and column shows. Bigtable and reats d

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Section describes to data model in more detail, and Section 3 pointee proverview of the client API. Sec-

Bigtable used for ...



Bigtable: Data Model

"a sparse, distributed, persistent, multidimensional, sorted map."

- sparse: not all values form a dense square
- distributed: lots of machines
- persistent: disk storage (GFS)
- multi-dimensional: values with columns
- sorted: sorting lexicographically by row key
- map: look up a key, get a value

Bigtable: in a nutshell

Primary Key value only!

(row, column, time) \rightarrow value

 $(Afganistan, pop-value, t_4) \rightarrow 31108077$

Primary Key	capital		continent		pop	o-value	ро	o-year
			t ₁ Asia			31143292	+	2000
Afghanistan	t ₁	Kabul t ₁		Kabul t ₁	Asia	t ₂	31120978	L ₁
				t ₄	31108077	t4	2011	
Albania	+	Tiran	t ₁ E	t Europa	t ₁	2912380	t ₁	2010
Albania	t ₁	а		Europe	t ₃	3011405	t ₃	2013
	•••							

Bigtable: Sorted Keys

	Primary Key	capital		рс	op-value	pop-year		
				t ₁	31143292	+	2009	
	Asia:Afghanistan	t ₁	Kabul	t_2	31120978	t ₁	2009	
S				t ₄	31108077	t4	2011	
0	Asia:Azerbaijan							
R	•••				•••		•••	
T	Furana, Albania	+	Tinono	t ₁	2912380	t ₁	2010	
Ε	Europe:Albania	t ₁	Tirana	t ₃	3011405	t ₃	2013	
D	Europe:Andorra							

Benefits of sorted vs. hashed keys?



Range queries and ...

Bigtable: Tablets

	Primary Key	capital		pop-value		pop-year		
				t ₁	31143292	+	2000	
A	Asia:Afghanistan	t ₁	Kabul	t_2	31120978	t ₁	2009	
S				t ₄	31108077	t4	2011	
A	Asia:Azerbaijan		•••				•••	
			•••				•••	
	Europe:Albania	+	Tirana	t ₁	2912380	t ₁	2010	
U	Lui ope. Aibania	t ₁	i II alla	t ₃	3011405	t ₃	2013	
R	Europe:Andorra		•••	•••			•••	
0		•••	•••	•••			•••	
P F								

Benefits of sorted vs. hashed keys?



Range queries and ...

... locality of processing

A real-world example of locality/sorting

	Primary Key	la	nguage	title		links	
				t ₁	IMDb Home	+	
IMDb	com.imdb		en	t ₂	IMDB - Movies	t ₁	***
				t_4	IMDb	t_4	
	<pre>com.imdb/title/tt2724064/</pre>	t ₁	en	t ₂	Sharknado	t_2	
	<pre>com.imdb/title/tt3062074/</pre>	t ₁	en	t ₂	Sharknado II	t_2	
	•••				•••		•••
		t₁		t ₁	Wikipedia	t ₁	***
	org.wikipedia		multi	t ₃	Wikipedia Home	t ₃	
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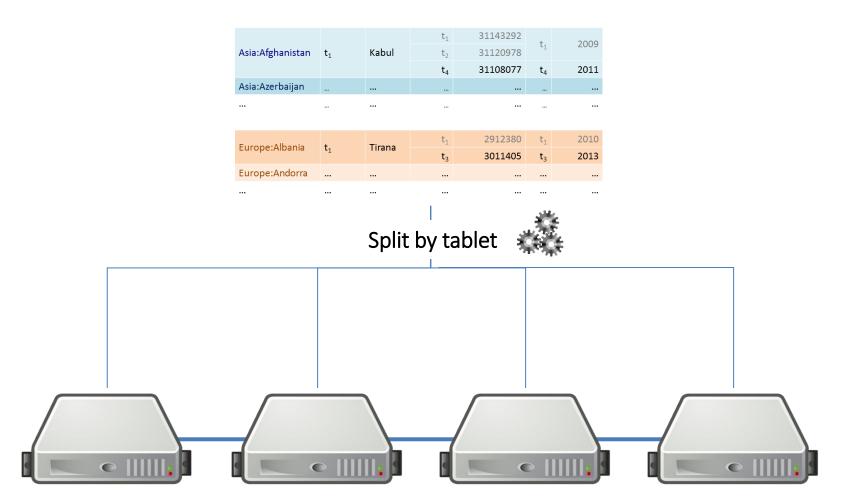
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org.wikipedia.ace

Bigtable: Distribution



Horizontal range partitioning

Bigtable: Column Families

pol:capital		dem	o:pop-value	demo:pop-year			
		t ₁	31143292	+	2009		
t ₁ Kabul	Kabul	Kabul	Kabul	t ₂	31120978	l ₁	2009
		t ₄	31108077	t ₄	2011		
+	Tirana	t ₁	2912380	t ₁	2010		
ι ₁	llidiid	t ₃	3011405	t ₃	2013		
	t ₁ t ₁	t ₁ Kabul t ₁ Tirana	$\begin{array}{c} t_{1} \\ t_{1} \\ t_{1} \\ t_{2} \\ t_{2} \\ t_{2} \\ t_{3} \\ t_{4} \\ t_{4} \\ t_{1} \\$	$\begin{array}{cccc} t_1 & & & t_1 & & & & \\ t_1 & & & & & \\ t_2 & & & & & \\ t_2 & & & & & \\ 100000000000000000000000000$	$ \begin{array}{cccc} & & & & & & & & & & & & & & & & & $		

...

. . .

• Group logically similar columns together

...

Accessed efficiently together

...

...

- Access-control and storage: column family level
- If of same type, can be compressed

Bigtable: Versioning

- Similar to Apache Dynamo
 - Cell-level
 - 64-bit integer time stamps
 - Inserts push down current version
 - Lazy deletions / periodic garbage collection
 - Two options:
 - keep last *n* versions
 - keep versions newer than t time

Bigtable: SSTable Map Implementation

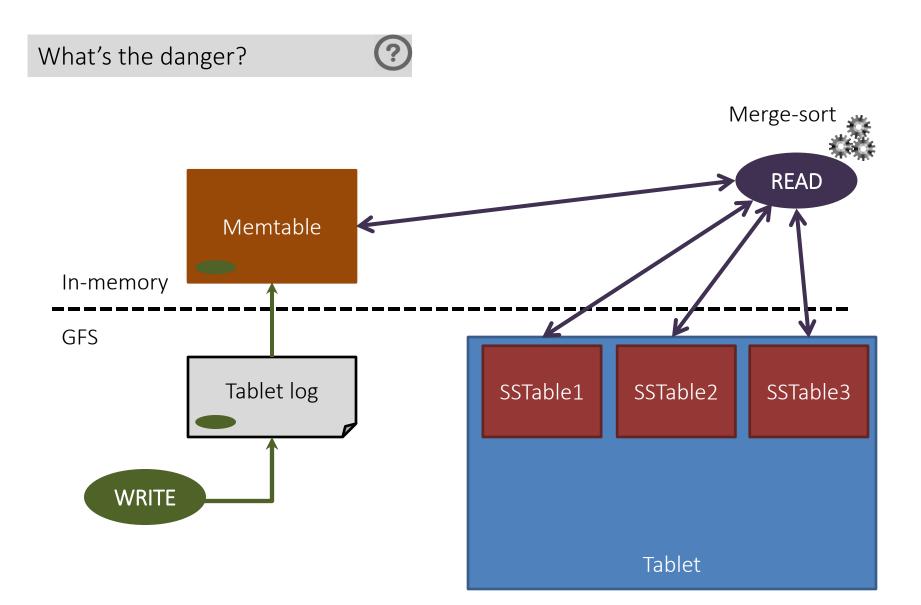
- 64k blocks (default) with index in footer (GFS)
- Index loaded into memory, allows for seeks
- Can be split or merged, as needed

6

	Primary Key	pol:ca	pol:capital		pop-value	demo:pop-year				
0				t ₁	31143292	+	2009			
	Asia:Afghanistan	t ₁	Kabul	t_2	31120978	t ₁	2009			
				t ₄	31108077	t4	2011			
	Asia:Azerbaijan									
							ا بتحصیت			
5536	Asia:Japan		•••							
	Asia:Jordan									
			•••							
	Block 0 / Offset 0 / Asia:Afghanistan									
Index:	Block 1 / Offset 65536 / Asia: Japan									

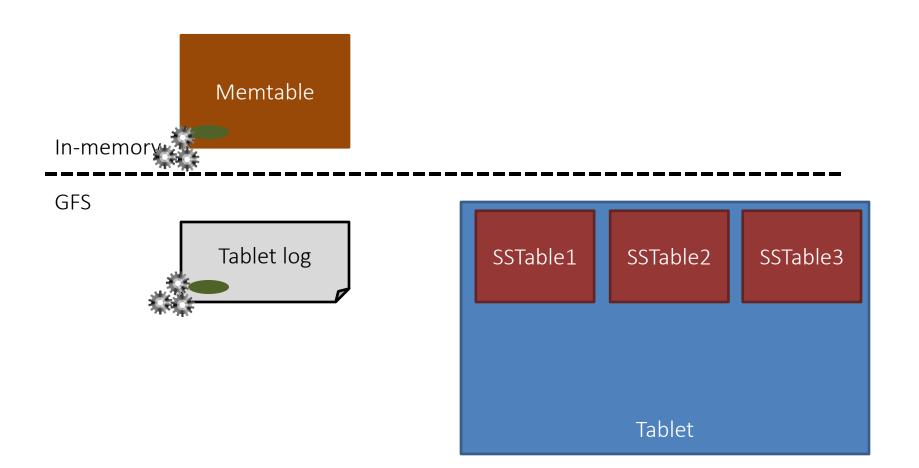
Writes?

Bigtable: Buffered/Batched Writes



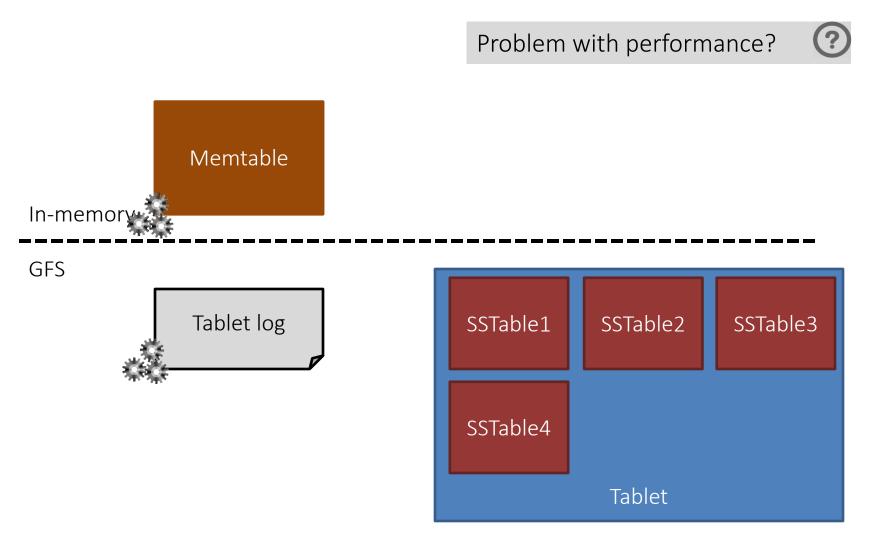


• If machine fails, Memtable redone from log



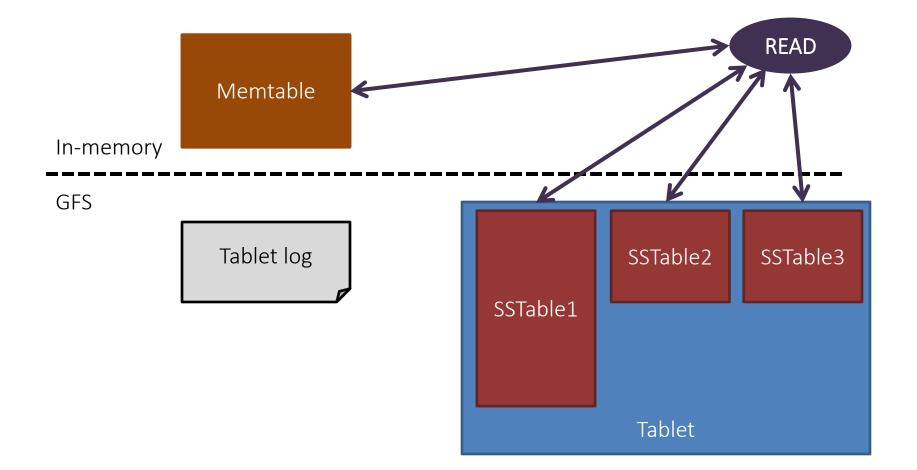
Bigtable: Minor Compaction

• When full, write Memtable as SSTable



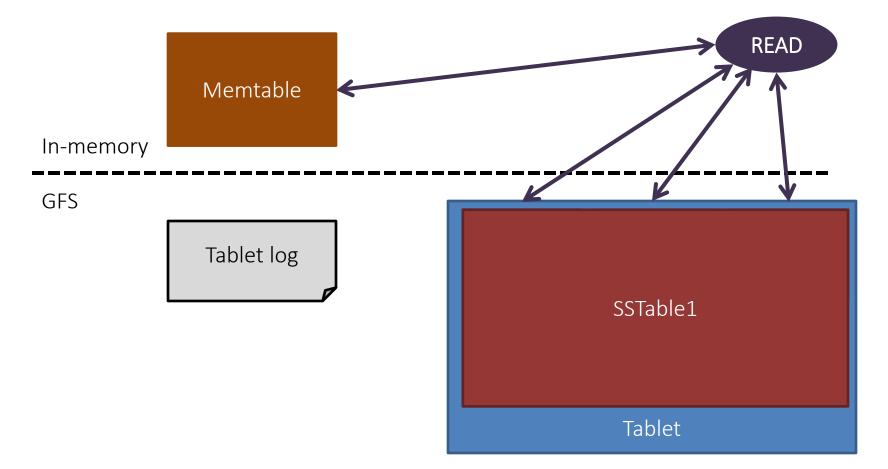
Bigtable: Merge Compaction

• Merge some of the SSTables (and the Memtable)



Bigtable: Major Compaction

- Merge all SSTables (and the Memtable)
- Makes reads more efficient!



Bigtable: A Bunch of Other Things

- Hierarchy and locks: how to find and lock tablets
- Locality groups: Group multiple column families together; assigned a separate SSTable
- Select storage: SSTables can be persistent or inmemory
- Compression: Applied on SSTable blocks; custom compression can be chosen
- Caches: SSTable-level and block-level
- Bloom filters: Find negatives cheaply ...

Read More ...

Google

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

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Google, Inc.

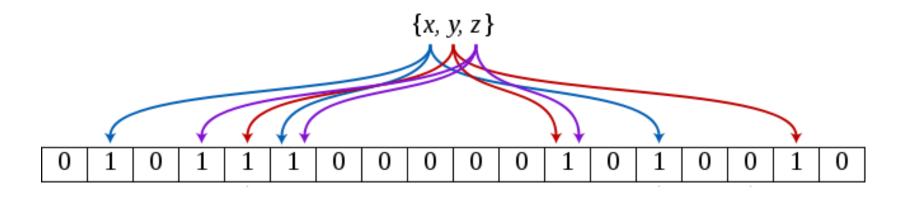
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Bigtable is a distributed storage system for managing structured data that is designed to scale to a very large size: petabytes of data across thousands of commodity servers. Many projects at Google store data in Bigtable, including web indexing, Google Earth, and Google Finance. These applications place very different demands on Bigtable, both in terms of data size (from URLs to web pages to satellite imagery) and latency requirements (from backend bulk processing to real-time data serving). Despite these varied demands, Bigtable has successfully provided a flexible, high-performance solution for all of these Google products. In this paper we describe the simple data model provided by Bigtable, which gives clients dynamic control over data layout and format, and we describe the design and implementation of Bigtable. achieved scalability and high performance, but Bigtable provides a different interface than such systems. Bigtable does not support a full relational data model; instead, it provides clients with a simple data model that supports dynamic control over data layout and format, and allows clients to reason about the locality properties of the data represented in the underlying storage. Data is indexed using row and column names that can be arbitrary strings. Bigtable also treats data as uninterpreted strings, although clients often serialize various forms of structured and semi-structured data into these strings. Clients can control the locality of their data through careful choices in their schemas. Finally, Bigtable schema parameters let clients dynamically control whether to serve data out of memory or from disk.

Section 2 describes the data model in more detail, and

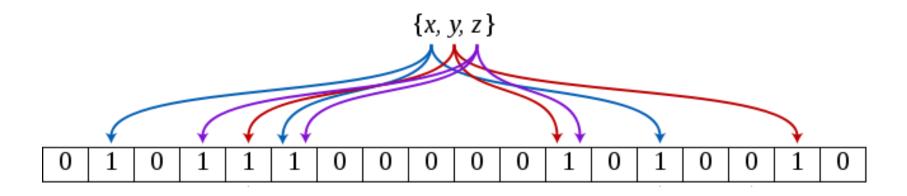
Aside: Bloom Filter

- Create a bit array of length *m* (init to 0's)
- Create *k* hash functions that map an object to an index of *m*
- Index *x*: set $m[hash_1(x)], ..., m[hash_k(x)]$ to 1



Aside: Bloom Filter

- Create a bit array of length *m* (init to 0's)
- Create k hash functions that map an object to an index of m
- Index x: set $m[hash_1(x)], ..., m[hash_k(x)]$ to 1



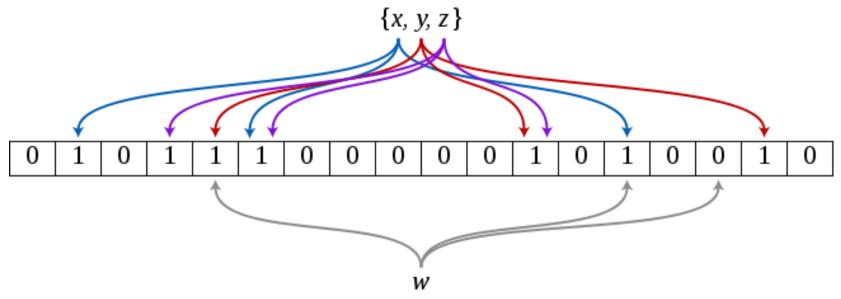
- Query *w*:
 - any m[hash₁(w)], ..., m[hash_k(w)] set to 0 ⇒
 - all $m[\text{hash}_1(w)], ..., m[\text{hash}_k(w)]$ set to $1 \Rightarrow$



Aside: Bloom Filter

Reject "empty" queries using very little memory!

- Create a bit array of length *m* (init to 0's)
- Create k hash functions that map an object to an index of m
- Index *x*: set *m*[hash₁(*x*)], ..., *m*[hash_k(*x*)] to 1



- Query *w*:
 - any m[hash₁(w)], ..., m[hash_k(w)] set to 0 ⇒ not indexed
 - all $m[\text{hash}_1(w)], ..., m[\text{hash}_k(w)]$ set to $1 \Rightarrow \text{might}$ be indexed

Tabular Store: Apache HBase



Tabular Store: Cassandra



Database Landscape

