

<u>Felix Gessert</u>, Norbert Ritter (22.05.2017)

Outline

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Foundations: Big Data, Scalability, Avaialbility

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The 4 Classes of NoSQL Databases



NoSQL Examples: concrete Architectures, Systems, APIs



- Literature
- Motivation
 - Big Data
 - NoSQL
- CAP Theorem
- 2-Phase-Commit
- NoSQL Triangle
- ACID vs BASE

Recommended Literature: NoSQL



Other Literature



ERHARD RAHM · GUNTER SAAKE KAI-UWE SATTLER

Verteiltes und Paralleles Datenmanagement

Von verteilten Datenbanken zu Big Data und Cloud

eXamen.pres

Description Springer Vieweg

Recommended Literature: Blogs

Martin Kleppmann

https://martin.kleppmann.com/



http://www.dzone.com/mz/nosql



http://www.nosqlweekly.com/



http://blog.baqend.com/

InfoQ

http://www.infoq.com/nosql/



http://highscalability.com/

The Database Explosion

Sweetspots



RDBMS

General-purpose ACID transactions



Wide-Column Store

Long scans over structured data



Graph Database Graph algorithms & queries



Parallel DWH

Aggregations/OLAP for massive data amounts

mongoDB

Document Store

Deeply nested data models



In-Memory KV-Store Counting & statistics



NewSQL

High throughput relational OLTP

*riak

Key-Value Store Large-scale session storage



Wide-Column Store

Massive usergenerated content

The Database Explosion

Cloud-Database Sweetspots



Realtime BaaS Communication and collaboration



Azure Tables

Wide-Column Store Very large tables



Managed NoSQL **Full-Text Search** Amazon RDS

Managed RDBMS General-purpose ACID transactions



DynamoDB

Wide-Column Store

Massive usergenerated content

Google Cloud Storage

Object Store Massive File Storage



Managed Cache

Caching and transient storage



Backend-as-a-Service Small Websites and Apps



Hadoop-as-a-Service **Big Data Analytics**







As of 2011, the global size of data in healthcare was estimated to be **150 EXABYTES** [161 BILLION GIGABYTES]

30 BILLION

every month

-

PIECES OF CONTENT are shared on Facebook

F G G

By 2014, it's anticipated there will be 420 MILLION WEARABLE, WIRELESS HEALTH MONITORS

mill

Variety

DIFFERENT

FORMS OF DATA

4 BILLION+ HOURS OF VIDEO

are watched on YouTube each month



400 MILLION TWEETS

are sent per day by about 200 million monthly active users



Hype Cycle





Data flood

Climate Research: The *Deutsche Klimarechenzentrum (DKRZ)* stores **60 PB** climate data.

Archiving: The Internet Archive stores **10 PB** of archived websites.

Gaming: World of Warcraft needs **1.3 PB** for storing the game state. Steam delivers **over 30 PB** of data per month.

Movies: The CGI-effects in Avatar (2009) needed **over 1 PB** storage for rendering.

Supercomputing: The Blue Waters Supercomputer is planned to have a storage capacity of **500 PB**.

Particle Physics: In search of the Higgs-Boson CERN gathered **200 PB** of data.

Email: In May 2013 Microsoft announced that for the migration of Hotmail to oulook.com **over 150 PB** user data were transferred.



Dropping storage costs





Big Data Defined

Big Data has two sides:

Big Data

Big Data Management

- OLTP
- Often referred to as "NoSQL"
- e.g. MongoDB, HBase, Cassandra

Big Data Analytics

- OLAP
- Often referred to as "Big Data"
- e.g. Hadoop, Storm

Architectural Change



Architectural Change





Two main motivations:



NoSQL Databases

- "NoSQL" term coined in 2009
- Interpretation: "Not Only SQL"
- Typical properties:
 - Non-relational
 - Open-Source
 - Schema-less (schema-free)
 - Optimized for distribution (clusters)
 - Tunable consistency

NoSQL-Databases.org:

Current list has over 150 NoSQL systems Wide Column Store / Column Families

Hadoop / HBasc AFt: Java / any writer, Protocol: any write call, Quey Nethod: MapReduce Java / any coxe, Replication: MPS Replication, Writen in: Java, Concurrency 1, Misc: Links: 3 Bools (J. 2, 3)

Cassandra maskicy selable, aphilone fee son matorica arbitratic and the superior and the sonmatorica arbitratic readwite superior arose multiple data centres e dios valuability sons. All' Casy Menos. CRL and Theffe realization peer-to-peer without in Java Theffe realization peer-to-peer without in Java competition. Statistica superior primary second intervent second readwite sons and the superior sons intervent second readwite sons and the superior sons competition. Management of the superior sons and competition. Superior sons and the superior sons and competition. Superior sons and the superior sons and competition. Superior sons and the superior sons and the superior sons and the superior sons and the superior sons and sons and the superior sons and sons and the superior sons and sons and the superior sons and sons and the superior sons and the superior sons and the sons and the superior sons and the superior sons and the sons and the superior sons and the superior sons and the sons and the superior sons and the superior sons and the sons and the superior sons and the superior sons and the sons and the superior sons and the superior sons and the sons and the superior sons and the superior sons and the sons and the superior sons and the superior sons and the sons and the superior sons and the superior sons and the sons and the superior sons and the superior sons and the sons and the superior sons and the superior sons and the sons and the superior sons and the superior sons and the sons and the superior sons and the superior sons and the sons and the superior sons and the sup

Hypertable API: Thrift (Java, FHP, Perl, Python, Ruby, etc.), Protocol: Thrift (Java, FHP, Perl, Python, Ruby, API: Replication, HDPS Replication, Concurrency, HVCC, Consistency Model: Fully consistent Misc High performance C+- implementation of Geogle's Bigable. <u>2</u> Commercial support

Accumulo Accumulo is based on BigErabic and is built on too of Hadro<u>on</u> Tookcorp, and Thirling It features improvements on the Bafasic access in the form of cellbased access control improved compression and a sorveide pregramming mechanism that can modify registrate pairs at various points in the case management process.

Amazon SimpleDB Mise: not open source / part of AVS, Book (will be outperformed by DynamoDB ?!) Cloudata Google's Big table clone like HBase. » Article

Clouders Professional Software & Services based on Haddoo. Haddoo. HPCC from <u>Lexisticuis, info, anticle</u> Stratosphere (research system) massive parallel & flexible.

Stratosphere (research system) massive parallel a flexible execution, MR generalization and extendion (paper, poster). (Openheptune, (base, KDI) Document Store

MongoDB APE BSOR, Protocol: C, Quey Method: dynamic object-based language & MapReduce, Replication: Master Slave & Auto-Sharding Writen

Consolutions 5 and 2011 a manufacture APL protocol (Dray 247 AUL) most languages hoteout (Dray 247 AUL) most languages hoteout Homeacher REST interface for cluster conf management (Mice) in CC-4- Briang Interface), Registration Peer to Peer, fully consistent, Mice Transparent topology changes during transparent topology changes during caching hurdets, commercially supported version available; Univ. 2016, and/of

CouchDB APE JSON, Protocol: REST, Query Michod: MapReduccR of JavaScript Funcs, Replication: Master Master, Written in: Erlang, Concurrency: MVCC, Misc

Links: <u>> 3 Couch08 books</u>, <u>> Couch Lounge</u> (partitioning / clustring), <u>> Dr. Dobbs</u>

Rethinking AFF probati-based (ucy Nened) unified charable cucy ingragase (inc. jOtks, sub-cucrics, MapReduce, GroupedkapReduce) Redication Sync and Async Master Slave with portable acknowledgements Darating pulled range-based, Witch in C-x, Concurrent, MPCC Misc legistuctures storage engine with concurrent MPCC Misc strage consister

RavenDB Net solution. Provides HTTP/JSON access. LING outries a Sharding supported. <u>a Mise</u>

MarkLogic Server (Itenare-commercial AFE (SON, Xall, Java Fotocols: HTTP, RESTQuey lichos: Fuil Text Scarch, XPath, XQuey, Range, Goospatial Million in: C+- Concurreny: Shared-nothing cluster, MVCC Mise: Petaplosciable, (double), ACD sharedons, subsharing, failour, masto slave replication, server with ACLs. Developer Community

Cluster science of the oper-connecting AP, Mall, Phile grant MRT reduces the THP, BST, nakes TEP/IP Outy Mitmost full text scarch, Xall, range and Xpath curries White in Case Consumer, ACIDcompliant, transactional, multi-master cluster Misc: Petabytic-scalable colument store and full text scarch engine. Information ranking. Keplication. Cloudable

ThruDB (please help provide more facts!) Uses Apache <u>Thrift</u> to internate multiple backend databases as BerkeleyOB, Olsk, MySQL, S3.

Terrastore APE Java & http://rotocol.http://anguage Java, Gorying: Range queries, Predicates, Replication Partitioned with consistent hashing Consistency Per-record strict consistency Misc Based on Toracota

JasDB Liphoncipht open source document database written in Java for high portemance, rung innemnoy, supports Android. APP: JSON, Java Quey Nituned: REST Obstas Style Query language, Java fluent Query API Concurrency, Atomic document writtes Indoces:

cventually consistent indexes RaptorDB (SON based, Document store database with

complied ...nct map functions and automatic hybrid bitmap indexing and LINQ query filters SisoDB A Document Store on top of SQL-Server.

SisoDB A Document Store on top of SQL-Server. SDB For small online databases, PHP / JSON interface, implemented in PHP.

djondb djon0B API: BSDN, Protocol: C++, Query Method: dynamic queries and map/reduce, Eriver: Java, C++, PHP Misc. ACID compliant, Full shell console over pogle viš engine, djondo requirements are submitted by users, and existin (Javar, GB) and comparediate post existin (Javar, GB) and comparediate.

Big Data Analytics

Idea: make existing massive, unstructured data amounts usable



- Structured data (DBs)
- Log files
- Documents, Texts, Tables
- Images, Videos
- Sensor data
- Social Media, Data Services

- Statistics, Cubes, Reports
- Recommender
- Classificators, Clustering
- Knowledge

Scale-up vs Scale-out

Scale-Up (*vertical* scaling):



Scale-Out (*horizontal* scaling):

Same Hardware

Connected by

network

Schema-free Data Modeling

RDBMS: **NoSQL DB:** Item[Price] -Item[Discount] SELECT Name, Age FROM Customers Implicit schema Customers Explicit schema

Paradigm Shift



Paradigm Shift

Shift towards distributed computing architectures





Sharding (aka Partitioning, Fragmentation)

- Horizontal distribution of data over server nodes
- > Paritioning strategies: Hash-based vs. Range-based
- Difficulty: Multi-Shard-Operations (join, aggregation)



Sharding (aka Partitioning, Fragmentation)

- Horizontal distribution of data over server nodes
- Paritioning strategies: Hash-based vs. Range-based
- Difficulty: Multi-Shard-Operations (join, aggregation)



Sharding

Hash-based Sharding

- Builds hash of data values (e.g. over the key) to determine a partition (shard) for a data item (tuple)
- **Pro**: Perfectly even distribution
- Contra: No data locality data items are pseudorandomly scattered over partitions

Range-based Sharding

- Assigns ranges defined over fields (shard keys) to partitions
- Pro: Data locality preserved (for shard keys)
- Contra: distribution might grow uneven → repartitioning/balancing required

Traditional Sharding

Example: Tumblr

- Caching
- Sharding from application

Moved towards:

- Redis
- HBase



Replication

- Stores N copies of each data item
- Consistency model: synchronous vs asynchronous
- Coordination: Multi-Master, Master-Slave



Replication

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- Consistency model: synchronous vs asynchronous
- Coordination: Multi-Master, Master-Slave



Replication: consistency models

Asynchronous

- Writes are acknowledged immdediately
- Performed through *log shipping* or *update propagation*
- **Pro**: Fast writes, no coordination needed
- **Contra**: Replica data potentially stale (*inconsistent*)

Synchronous

- The node accepting writes synchronously propagates updates/transactions before acknowledging
- **Pro**: Consistent
- Contra: needs a commit protocol (more roundtrips), unavaialable under certain network partitions

Replication: coordination

Master-Slave (Primary Copy)

- Only a dedicated master is allowed to accept writes, slaves are read-replicas
- **Pro**: reads from the master are consistent
- Contra: master is a bottleneck and SPOF

Multi-Master (Update anywhere)

- The server node accepting the writes synchronously propagates the update or transaction before acknowledging
- Pro: fast and highly-available
- Contra: either needs complicated coordination protocols (e.g. Paxos) or is inconsistent

Synchronous Replication: 2PC


Error scenarios (timeouts)

In **INITIAL**:

No consequence

In **WAIT**:

• Abort

In ABORT oder COMMIT:

 Resend commit/abort and wait for all responses



Error scenarios (timeouts)

In **INITIAL**:

Coordinator probably crashed →
 Abort (*"Presumed-Abort-Protocol"*)

In **WAIT**:

Wait for message from coordinator



2PC is not available



Commit protocols

- Provide atomic propagation of writes or commits
- Most prominent implementation: 2-Phase-Commit

R	Read-RMs,	W	Read/Write-	- <i>RMs,</i> N=R+W
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Commit protocol	Messages	Property
1-Phase-Commit	2N	Not always possible
Linear 2PC	2N+1	Not parallel
Hierarchical and normal 2PC	4N-2R	Might block indefinitely
3-Phase-Commit	6N-4R	No consistency guarantee
Paxos-Commit	3N+2F(N+1)+1	F failures tolerated
Distributed 2PC	N ²	No 2nd phase

CAP-Theorem



- Classifies distributed databases
- Only 2 out of 3 properties are achievable at a time:
 - **Consistency**: all clients have the same view on the data
 - Availability: every request to a nonfailed node most result in correct response
 - Partition tolerance: the system has to continue working, even under arbitrary network partitions

Eric Brewer, ACM-PODC Keynote, Juli 2000



Gilbert, Lynch: Brewer's Conjecture and the Feasibility of Consistent, Available, Partition-Tolerant Web Services, SigAct News 2002

CAP-Theorem: simplified proof

Intuition for the impossibility of simultaneously achieving **C**, **A** and **P** at once:



Value is replicated to two nodes

CAP-Theorem: simplified proof

Failure-free reading and writing:



CAP-Theorem: simplified proof

Problem: when a network partition occurs, either consistency or availability have to be given up



Network partition

CAP-Theorem: Wrap-up



NoSQL triangle





PACELC – an alternative CAP formulation

Idea: Classify system according to their heaviour during network partitions



Abadi, Daniel. "Consistency tradeoffs in modern distributed database system design: CAP is only part of the story."

Negative Results In Distributed Computing

Asychronous Network, Unreliable Channel

Atomic Storage

Impossible: CAP Theorem

Consensus

Impossible:

2 Generals Problem



Asychronous Network, Reliable Channel

Atomic Storage

<u>Possible</u>: Attiya, Bar-Noy, Dolev (ABD) Algorithm

Consensus

Impossible:

Fisher **L**ynch **P**atterson (FLP) Theorem

Negative Results

Consensus Algorithms

- Consensus:
 - Agreement: No two processes can comput different decisions
 - Validity (Non-triviality): If all initial values are same, nodes must commit that value
 Liveness

Safety

Properties

Property

- Termination: Nodes commit eventually
- No algorithm *guarantees* termination (FLP)
- Algorithms:
 - Paxos (e.g. Google Chubby, Spanner, Megastore, Cassandra Lightweight Transactions)
 - **Raft** (e.g. etcd service)
 - Zookeeper Atomic Broadcast (ZAB)

Negative Results

Correctness/Serializability

Distributed ACID and availability are incompatible:



- Weaker isolations levels are possible:
 - RAMP Transactions (P. Bailis, A. Fekete, A. Ghodsi, J. M. Hellerstein, und I. Stoica, "Scalable Atomic Visibility with RAMP Transactions", SIGMOD 2014)
- Consequence: trade-offs are important

Typical Trade-offs

Read Performance	Write Performance
Latency	Durability
Synchronous replication	Asynchronous replication
Row-based	Column-based
Transactions	Availability
REST	RPC
Commodity servers	High-end hardware
Normalisation	Denormalisation
Schemas	Schemafreeness

Client-Centric Consistency Models

 Define models that relax strong consistency (=linearizability) in different aspects



Read Your Writes (RYW)

Definition: Once the user has written a value, subsequent reads will return this value (or newer versions if other writes occurred in between); the user will never see versions older than his last write.



ttps://blog.acolyer.org/2016/02/26/distributed-consistencyand-session-anomalies/



Monotonic Reads (MR)

Definition: Once a user has read a version of a data item on one replica server, it will never see an older version on any other replica server



https://blog.acolyer.org/2016/02/26/distributed-consistencyand-session-anomalies/ Wiese, Lena. Advanced Data Management: For SQL, NoSQL, Cloud and Distributed Databases. De Gruyter, 2015.

Montonic Writes (MW)

Definition: Once a user has written a new value for a data item in a session, any previous write has to be processed before the current one. I.e., the order of writes inside the session is strictly maintained.



Writes Follow Reads (WFR)

Definition: When a user reads a value written in a session after that session already read some other items, the user must be able to see those *causally relevant* values too.



https://blog.acolyer.org/2016/02/26/distributed-consistencyand-session-anomalies/ Wiese, Lena. Advanced Data Management: For SQL, NoSQL, Cloud and Distributed Databases. De Gruyter, 2015.

PRAM and Causal Consistency

- Combinations of previous session consistency guarantess
 - PRAM = MR + MW + RYW
 - Causal Consistency = PRAM + WFR
- All consistency level up to causal consistency can be guaranteed with high availability
- Example: Bolt-on causal consistency



Bailis, Peter, et al. "Bolt-on causal consistency." Proceedings of the 2013 ACM SIGMOD, 2013.

Bounded Staleness

• Either **time-based**:

t-Visibility (Δ -atomicity): the inconsistency window comprises at most t time units; that is, any value that is returned upon a read request was up to date t time units ago.

Or version-based:

k-Staleness: the inconsistency window comprises at most k versions; that is, lags at most k versions behind the most recent version.

Both are *not* achievable with high availability



NoSQL Storage Management In a Nutshell



NoSQL Storage Management In a Nutshell



Low Performance High Performance **RR**: Random Reads **RW**: Random Writes **SR**: Sequential Reads **SW**: Sequential Writes

Local Secondary Indexing

Partitioning By Document



Local Secondary Indexing

Partitioning By Document



Global Secondary Indexing

Partitioning By Term



Global Secondary Indexing

Partitioning By Term



Wrap-up



- High data volumes, unstructured sources and new kinds of applications triggered BigData and NoSQL technologies
- Shared Nothing architectures for horizontal scalability
 - **Replication** enables read scalability and fault tolerance
 - Sharding enables write scalability and data volume scalability
- **CAP Theorem**: Consistency, Availability and Partition Tolerance cannot be achieved at the same time
 - **BASE** (Basically available, soft-state, eventually consistent) paradigm as an alternative to ACID
- 2-Phase-Commit (2PC): popular protocol for atomic commitment; without availability guarantee
- **Consistency** can be relaxed in various ways

Outline

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Foundations: Big Data, Scalability, Avaialbility

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The 4 Classes of NoSQL Databases

- Key-Value stores
- Wide-Column stores
- Document stores
- Graph databases
- Other classes



NoSQL Examples: concrete Architectures, Systems, APIs



Key-Value Stores

- Data model: (key) -> value
- Interface: CRUD (Create, Read, Update, Delete)



Examples: Amazon Dynamo (AP), Riak (AP), Redis (CP)

Wide-Column Stores

- Data model: (rowkey, column, timestamp) -> value
- Interface: CRUD, Scan



 Examples: Cassandra (AP), Google BigTable (CP), HBase (CP)

Document Stores

- Data model: (collection, key) -> document
- Interface: CRUD, Querys, Map-Reduce



 Examples: CouchDB (AP), Amazon SimpleDB (AP), MongoDB (CP)

Graph Databases

- Data model: G = (V, E): Graph-Property Modell
- Interface: Traversal algorithms, querys, transactions



Examples: Neo4j (CA), InfiniteGraph (CA)

Graph Databases

- Data model: G = (V, E): Graph-Property Modell
- Interface: Trave
 Interface: Trave

Examples: Neo4j (CA), IIIIIIICoraph (CA)
Search Platforms

Data model: vectorspace model, docs + metadata Examples: Solr, ElasticSearch



Object-oriented Databases

- Data model: Classes, objects, relations (references)
- Interface: CRUD, querys, transactions



Examples: Versant (CA), db4o (CA), Objectivity (CA)

Object-oriented Databases

- Data model: Classes, objects, relations (references)
- ▶ Interface: CRU

Properties -

-not scalable -strong coupling between programming language and database



Examples: Versant (CA), db4o (CA), Objectivity (CA)

XML databases, RDF Stores

- Data model: XML, RDF
- Interface: CRUD, querys (XPath, XQuerys, SPARQL), transactions (some) -not scalable
 Examples: MarkLogi (Mdefg) used legroGraph (CA) -specialized data

model

XML databases, RDF Stores

- > Data model: XML, RDF
- Interface: CRUF transactions (s
- Examples: Ma

-not scalable -not widely used -specialized data model rys, SPARQL), aph (CA)

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Distributed File System

Data model: files + folders



Big Data Frameworks

- Data model: arbitrary (frequently unstructured)
- Examples: Hadoop, Spark, Flink, DryadLink, Pregel



Wrap-up



- 4 core NoSQL classes
 - Key-Value Stores: store opaque key-value pairs
 - Document Stores: store nested, rich, schema-free documents
 - Wide-Column Stores: extensible table data model
 - Graph Databases: graph-property-model (vertices and edges)
- Other NoSQL-related systems: Object-oriented databases, Search platforms, XML databases, Big Data Frameworks, Distributed File Systems

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Foundations: Big Data, Scalability, Avaialbility

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The 4 Classes of NoSQL Databases

- MapReduce (Hadoop)
- Dynamo (Riak)
- BigTable (HBase)
- MongoDB
- Others



NoSQL Examples: concrete Architectures, Systems, APIs

Cloud Databases



- Modelled after: Googles GFS (2003)
- Master-Slave Replication
 - Namenode: Metadata (files + block locations)
 - Datanodes: Save file blocks (usually 64 MB)
- Design goal: Maximum Throughput and data locality for Map-Reduce



Hadoop

- For many synonymous to Big Data Analytics
- Large Ecosystem
- Creator: Doug Cutting (Lucene)
- Distributors: Cloudera, MapR, HortonWorks
- Gartner Prognosis: By 2015 65% of all complex analytic applications will be based on Hadoop
- Users: Facebook, Ebay, Amazon, IBM, Apple, Microsoft, NSA



Hadoop
Model:
Batch-Analytics Framework
License:
Apache 2
Written in:
Java



MapReduce: Word Count



MapReduce: Example

Constructing a reverse-index







Summary: Hadoop Ecosystem



- Hadoop: Ecosystem for Big Data Analytics
- Hadoop Distributed File System: scalable, shared-nothing file system for thoughput-oriented workloads
- Map-Reduce: Paradigm for performing scalable distributed batch analysis
- Other Hadoop projects:
 - **Hive**: SQL(-dialect) compiled to YARN jobs (Facebook)
 - Pig: workflow-oriented scripting language (Yahoo)
 - Mahout: Machine-Learning algorithm library in Map-Reduce
 - Flume: Log-Collection and processing framework
 - Whirr: Hadoop provisioning for cloud environments
 - Giraph: Graph processing à la Google Pregel
 - Drill, Presto, Impala: SQL Engines



Popularity

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

Rang	DBMS	Modell	Punkte	Rang	DBMS	Modell	Punkte
1.	Oracle	Relational DBMS	1514,90	14.	Memcached	Key-Value Store	30,73
2.	MySQL	Relational DBMS	1334,94	15.	HBase	Wide Column Store	25,78
3.	Microsoft SQL Server	Relational DBMS	1286,22	16.	Informix	Relational DBMS	24,73
4.	PostgreSQL	Relational DBMS	199,39	17.	Hive	Relational DBMS	22,16
5.	DB2	Relational DBMS	177,04	18.	CouchDB	Document Store	15,93
6.	Microsoft Access	Relational DBMS	149,66	19.	Firebird	Relational DBMS	14,55
7.	MongoDB	Document Store	137,49	20.	Netezza	Relational DBMS	11,44
8.	Sybase	Relational DBMS	88,41	21.	dBASE	Relational DBMS	10,44
9.	SQLite	Relational DBMS	87,81	22.	Elasticsearch	Suchmaschine	9,51
10.	Teradata	Relational DBMS	51,11	23.	Sphinx	Suchmaschine	9,02
11.	Solr	Suchmaschine	46,43	24.	Riak	Key-Value Store	8,99
12.	Cassandra	Wide Column Store	37,64	25.	Neo4j	Graph DBMS	8,83
13.	Redis	Key-Value Store	34,22				

Scoring: Google/Bing results, Google Trends, Stackoverflow, job offers, LinkedIn



NoSQL foundations

- BigTable (2006, Google)
 - Consistent, Partition Tolerant
 - Wide-Column data model
 - Master-based, fault-tolerant, large clusters (1.000+ Nodes),
 HBase, Cassandra, HyperTable, Accumolo
- **Dynamo** (2007, Amazon)
 - Available, Partition tolerant
 - Key-Value interface
 - Eventually Consistent, always writable, fault-tolerant
 - Riak, Cassandra, Voldemort, DynamoDB



DeCandia, Giuseppe, et al. "Dynamo: Amazon's highly available key-value store."







Dynamo (AP)

- Developed at Amazon (2007)
- Sharding of data over a ring of nodes
- Each node holds multiple partitions
- Each partition N-times replicated







Consistent Hashing

 Naive approach: Hash-partitioning (e.g. in Memcache, Redis)



Consistent Hashing

Solution: Consistent Hashing – mapping of data to nodes is stable under topology changes



Reading and Writing

- > An arbitrary node acts as a coordinator
- **N**: number of replicas
- **R**: number of nodes that need to confirm a read
- W: number of nodes that need to confirm a write



Versioning and Consistency

- $R + W \leq N \Rightarrow$ no consistency guarantee
- ▶ $R + W > N \Rightarrow$ newest value included in any read
- Vector Clocks used for versioning



R + W> N does not imply linearizability

Consider the following execution:



CRDTs

Convergent/Commutative Replicated Data Types

- Goal: avoid manual conflict-resolution
- Approach:
 - **State-based** commutative, idempotent merge function
 - **Operation-based** broadcasts of commutative upates
- Example: State-based Grow-only-Set (G-Set)

$$S_{1} = \{\}$$

$$S_{1} = \{x\}$$

$$S_{1} = \{x\}$$

$$S_{1} = merge(\{x\}, \{y\})$$

$$= \{x, y\}$$

$$S_{2} = \{y\}$$

$$S_{2} = \{y\}$$

$$S_{2} = merge(\{y\}, \{x\})$$

$$= \{x, y\}$$

$$S_{2} = merge(\{y\}, \{x\})$$

$$S_{2} = merge(\{y\}, \{x\})$$

$$S_{3} = \{x, y\}$$

$$S_{4} = merge(\{y\}, \{x\})$$

$$S_{5} = merg$$

Zawirski "Conflict-free Replicated Data Types"

Riak (AP)

- Open-Source Dynamo-Implementation
- Extends Dynamo:
 - Keys are grouped to **Buckets**
 - KV-pairs may have metadata and links
 - Map-Reduce support
 - Secondary Indices, Update Hooks, Solr Integration
 - REST-API



: Minimum Mini	K
Riak	
Model:	
Key-Value	
License:	
Apache 2	
Written in:	
Erlang und C	

Summary: Dynamo and Riak



- Consistent Hashing: hash-based distribution with stability under topology changes (e.g. machine failures)
- Parameters: N (Replicas), R (Read Acks), W (Write Acks)
 - N=3, R=W=1 \rightarrow fast, potentially inconsistent
 - $^{\circ}$ N=3, R=3, W=1 \rightarrow slower reads, most recent object version contained
- Available and Partition-Tolerant
- Vector Clocks: concurrent modification can be detected, inconsistencies are healed through the application
- API: Create, Read, Update, Delete (CRUD) on key-value pairs
- **Riak**: Open-Source Implementation of the Dynamo paper

Redis (CA)

- Remote Dictionary Server
- In-Memory Key-Value Store
- Asynchronous Master-Slave Replication
- Data model: rich data structures stored under key
- Tunable persistence: logging and snapshots
- Single-threaded event-loop design (similar to Node.js)
- Optimistic batch transactions (*Multi blocks*)
- Very high performance: >100k ops/sec on one machine
- Redis Cluster adds sharding



Data structures

String, List, Set, Hash, Sorted Set



Example Redis Data Structure: lists

(Linked) Lists:



Example Redis Use-Case: Twitter





Classification: Redis Techniques



Google BigTable (CP)

- Published by Google in 2006
- Original purpose: storing the Google search index

A Bigtable is a sparse, distributed, persistent multidimensional sorted map.

Data model also used in: HBase, Cassandra, HyperTable, Accumolo


Wide-Column Data Modelling

Storage of crawled web-sites ("Webtable"):



Architecture



Range-based Sharding



Master

Storage: Sorted-String Tables

- **Goal**: Append-Only IO when writing (no disk seeks)
- Achieved through: Log-Structured Merge Trees
- Writes go to an in-memory memtable that is periodically persisted as an SSTable as well as a commit log
- Reads query memtable and all SSTables





Apache HBase (CP)

- Open-Source Implementation of BigTable
- Hadoop-Integration
 - Data source for Map-Reduce
 - Uses Zookeeper and HDFS
- Data modelling challenges: key design, tall vs wide
 - **Row Key**: only access key (no indices) \rightarrow key design important
 - Tall: good for scans
 - Wide: good for gets, consistent (*single-row atomicity*)
- No typing: application handles serialization
- Interface: REST, Avro, Thrift

п	DASE
HBase	
Model:	
Wide-Colu	mn
License:	
Apache 2	
Written in:	
Java	

HBase Storage

r3

r4

r5

Logical to physical mapping:



r1:cf2:c1:t1:<value>
r2:cf2:c2:t1:<value>
r3:cf2:c2:t2:<value>
r3:cf2:c2:t1:<value>
r5:cf2:c1:t1:<value>
HFile cf2

r1:cf1:c1:t1:<value>
r2:cf1:c2:t1:<value>
r3:cf1:c2:t1:<value>
r3:cf1:c1:t2:<value>
r5:cf1:c1:t1:<value>
HFile cf1



Example: Facebook Insights





Summary: BigTable, HBase



- ► Data model: (*rowkey*, *cf*: *column*, *timestamp*) → *value*
- API: CRUD + Scan(start-key, end-key)
- Uses distributed file system (GFS/HDFS)
- Storage structure: Memtable (in-memory data structure) + SSTable (persistent; append-only-IO)
- Schema design: only primary key access → implicit schema (key design) needs to be carefully planned
- **HBase**: very literal open-source implementation BigTable
- **Cassandra**: combination of Dynamo and BigTable ideas

Classification: HBase Techniques



Apache Cassandra (AP)

- Published 2007 by Facebook
- Idea:
 - BigTable's wide-column data model
 - Dynamo ring for replication and sharding
- Cassandra Query Language (CQL): SQL-like query- and DDL-language
- ► Compound indices: partition key (shard key) + clustering key (ordered per partition key) → Limited range queries
- Secondary indices: hidden table with mapping \rightarrow queries with simple equality condition



Classification: Cassandra Techniques



MongoDB (CP)

- ▶ From hu**mongo**us ≅ gigantic
- Tunable consistency
- Schema-free document database
- Allows complex queries and indexing
- Sharding (either range- or hash-based)
- Replication (either synchronous or asynchronous)
- Storage Management:
 - Write-ahead logging for redos (journaling)
 - Memory-mapped storage files, buffer management handled by operating system (paging)

mongoDB
MongoDB
Model:
Document
License:
GNU AGPL 3.0
Written in:
C++

Data Modelling





Sharding und Replication



Classification: MongoDB Techniques



Outline

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•	Concession in the local division in the loca
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Foundations: Big Data, Scalability, Avaialbility

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The 4 Classes of NoSQL Databases



NoSQL Examples: concrete Architectures, Systems, APIs



- Database-as-a-Service
- Backend-as-a-Service

Cloud Databases



Database-as-a-Service

- Cloud databases with a pay-per-use pricing model
- Managed Database Service: Existing DBMS deployed and managed in the cloud
 - Managed NoSQL System (e.g. MongoHQ, Redis2Go)
 - Managed RDBMS (e.g. Amazon Relational Database Service)
- Proprietary Database Service: special DBMS built for cloud environments (e.g. Amazon DynamoDB)
- Object Stores: cloud-based file storage (e.g. Amazon S3)
- Backend-as-a-Service: Database + Implementation of standard app concerns (e.g. user management, push)

Real terrors Advector and terrorsents



Presentation is loading

The Latency Problem





If perceived speed is such an import factor



...what causes slow page load times?

State of the art Two bottlenecks: latency und processing



Network Latency

The underlying problem of high page load times



I. Grigorik, High performance browser networking.
 O'Reilly Media, 2013.

Network Latency The underlying problem of high page load times



I. Grigorik, High performance browser networking O'Reilly Media, 2013.

The low-latency vision

Data is served by ubiquitous web-caches



The Problem with today's caching

Changes invalidate cached data



Our Research

Keep Data up-to-date through Cache Sketches



Bacend Build a faster web.

Backend-as-a-Service

Feature Sets



Frontend



Compatible with:



Frontend



Development

On Baqend

Dashboard



Create Schema, configure, browse data, etc.

CLI

annes@bdi:~≯ badendneib	
Usage: baqend [command] [o	ptions] <args></args>
Commands:	
login [options] register open [app] dashboard deploy [options] [app] logout [options] typings [options] <app> start [name] [dir]</app>	Logs you in and lo Registers an accou Opens the url to y Opens the url to t Deploys your baqen Removes your store Generates addition clones the starter
Type in one of the above c	ommands followed by

Develop, deploy and test frontend und backend Code

REST & SDK

4. ۲	scriptja 0
	<pre>function leaveMessage(name, message) {</pre>
	//Create new message object
	<pre>var msg = new DB.Message();</pre>
	//Set the properties
	msg.name = name;
	msg.message = message;
	<pre>msg.date = new Date();</pre>
	<pre>msg.insert().then(showMessages);</pre>
	}
11	
12	<pre>function showMessages() {</pre>
13	DB.Message.find()
14	<pre>.descending("date")</pre>
15	.limit(30)
16	.resultList()

Website logic: load site, get data, login, etc.

Orestes & Bagend

Learn more

If you are interested in topics combining web/mobile with scalable data management:



Bachelor and Master thesis topics http://tiny.cc/orestes (frequently updated)



Hiwi/student positions

Tasks: building real applications using cutting edge technology (e.g. ES6, Angular, React, MongoDB, Redis, Node.js,...)

Contact me directly or at fg@baqend.com

Summary



- Variety of different NoSQL systems:
 - HDFS and Hadoop: Map-Reduce platform for batch analytics
 - Dynamo and Riak: KV-store with consistent hashing
 - **Redis**: replicated, in-memory KV-store
 - BigTable, HBase, Cassandra: wide-column stores
 - MongoDB: sharded and replicated document store
- Cloud Databases
 - Database-as-a-Service: managed (NoSQL) database provided as a pay-per-use service
 - Orestes and Baqend: Backend-as-a-Service research project and startup with the goal of solving the web's latency problem