CS315: DATABASE SYSTEMS NOSQL AND BIG DATA SYSTEMS

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- NoSQL aims to provide
 - Scalability
 - Flexibility
 - Naturalness
 - Distribution
 - Performance

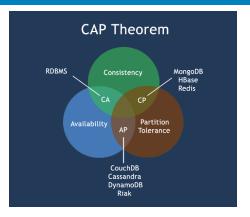
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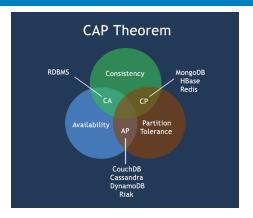
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- NewSQL

CAP Theorem



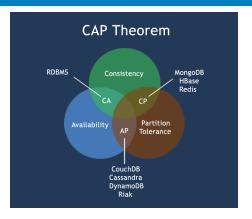
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- All of C, A, P cannot be satisfied simultaneously
- More a hypothesis than a theorem

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- Basically Available: System guarantees availability
- Soft state: State of system is soft, i.e., it may change without input to maintain consistency
- Eventual consistency: Data will be eventually consistent without any interim perturbation
 - Sacrifices strong (immediate) consistency

Types

- Main types of NoSQL data stores:
 - Columnar families
 - Key-value stores
 - Bigtable systems
 - Document databases
 - Graph databases

Columnar Storage

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- A single disk block (or a set of consecutive blocks) stores a single column family
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- Two main types
 - Columnar relational models
 - Key-value stores and/or big tables

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- Example: Cassandra, CouchDB, Tokyo Cabinet, Redis

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- Example: BigTable, HBase, Cassandra, HyperTable, SimpleDB

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- Example: Neo4J, HyperGraph, Infinite Graph, Titan, FlockDB

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- Trend is for NoSQL as cloud computing and big data relies on it
- Many NoSQL systems are increasingly using features of RDBMS
- New paradigm of scalability with transaction support is NewSQL

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- When data is bigger than most standard machines can store or most algorithms can handle

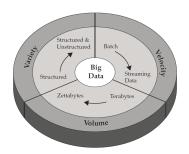
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 - Newer tools
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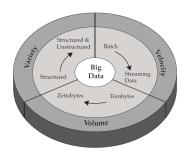
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 - Newer techniques
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 - Newer architectures
- Allows solving newer problems
 - Can also solve older problems better

Properties of Big Data



- 3 V's: volume, variety, velocity
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- Variety: Data can be semi-structured or unstructured as well; how to query
- Velocity: Data can arrive at real time and can be streaming

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- Extended V's: veracity, validity, visibility, variability

Enablers of Big Data

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- Improved processing power
- Improved data
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- Increased capital
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- Operations: Querying, indexing, analytics
 - Data mining, Information retrieval
 - Machine learning: Mahout on top of Hadoop

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- Databases have become robust and stable