CS315: DATABASE SYSTEMS NOSQL AND BIG DATA SYSTEMS

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NoSQL is

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- It is not only SQL (originated as no-SQL, though)

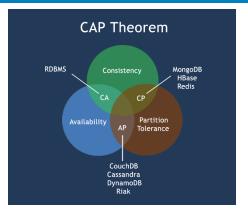
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 - Atomicity: Either all operations of a transaction are reflected or none are reflected
 - Consistency: If a database is consistent before the execution of the transaction, it must be consistent after it
 - Isolation: Although multiple transactions may execute concurrently, each transaction must be unaware of others
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- Later changed since RDBMS is too powerful to always ignore
- NewSQL

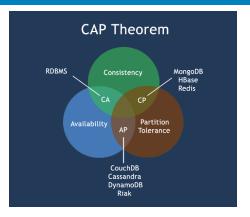
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- BASE is to counter ACID

Types

- Main types of NoSQL data stores:
 - Columnar families
 - Key-value stores
 - Bigtable systems
 - Ocument 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: MongoDB, CouchDB

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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

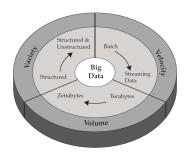
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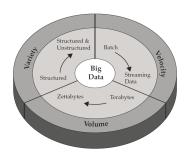
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 - Newer techniques
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 - Newer architectures
- Allows solving newer problems
 - Can also solve older problems better

Properties of Big Data



- 3 V's: volume, variety, velocity
- Volume: When data is extremely large in size, how to load it, index it or query it
- 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

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- Improved processing power
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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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