

# Big Data Infrastructures

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Lecture 5 – NoSQL

# On Today's Menu...

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## Go BIG!

- Parallel DBMS
- CAP
- NoSQL intro
- Column-Family Stores
- Lab!
  - Hadoop bundle
  - HBase

# What's wrong with my old DBMS?

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- Managing Big Data is hard...
  - ... extremely hard
  - Traditional DBMSs are 30 years old, were not meant for Big Data
    1. **New queries** (analytics, clustering, prediction, etc.)
    2. **New data types** (text, images, social graphs, sensor data, etc.)
    3. Impractical logical guarantees (**ACID**)



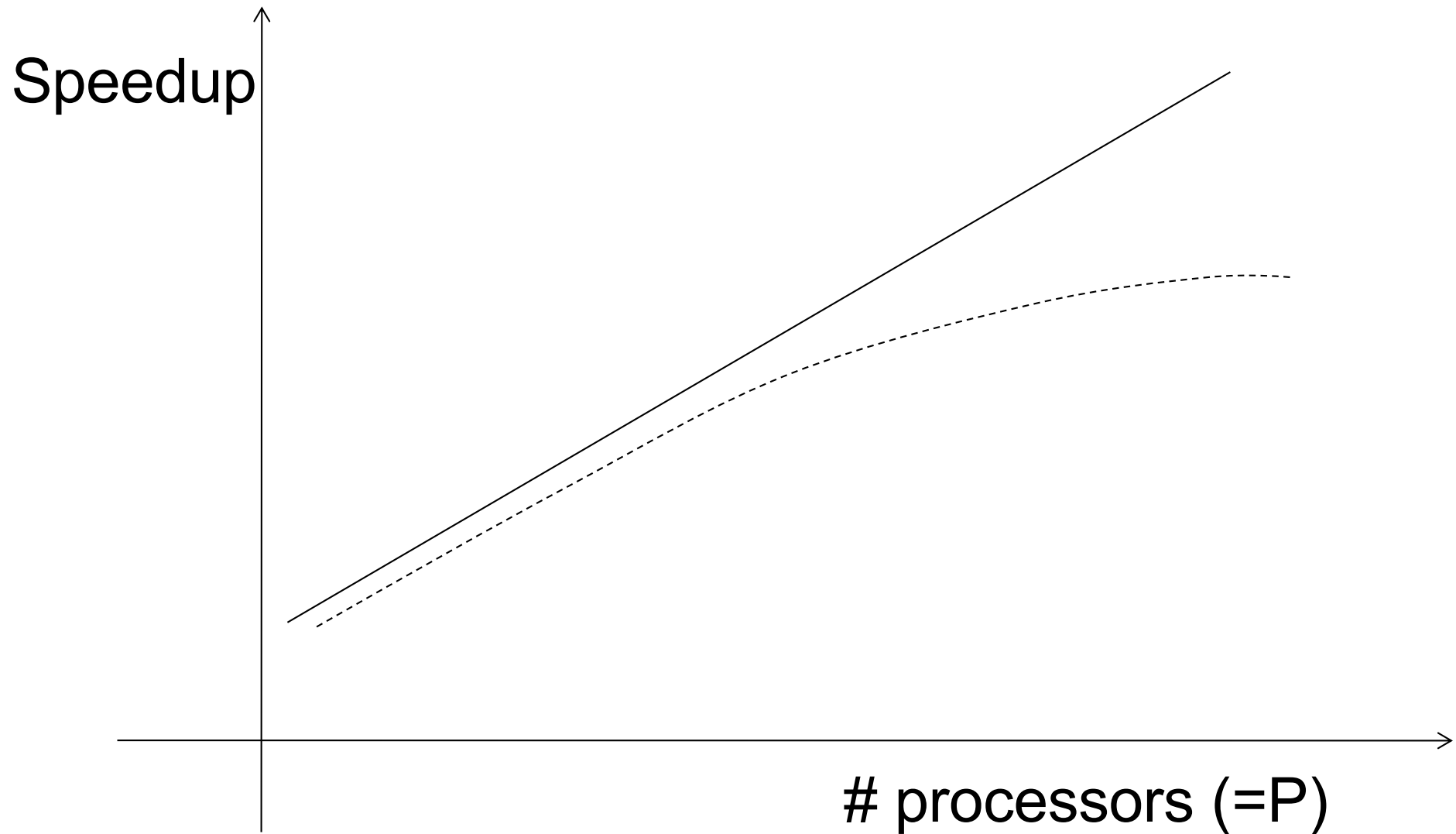
# Parallel DBMSs

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- Goal
  - Improve performance by executing multiple operations in parallel
- Key benefit
  - Cheaper to scale than relying on a single increasingly more powerful processor
- Key challenges
  - ACID compliance
  - Ensure overhead and contention do not kill performance

# Linear v.s. Non-linear Speedup

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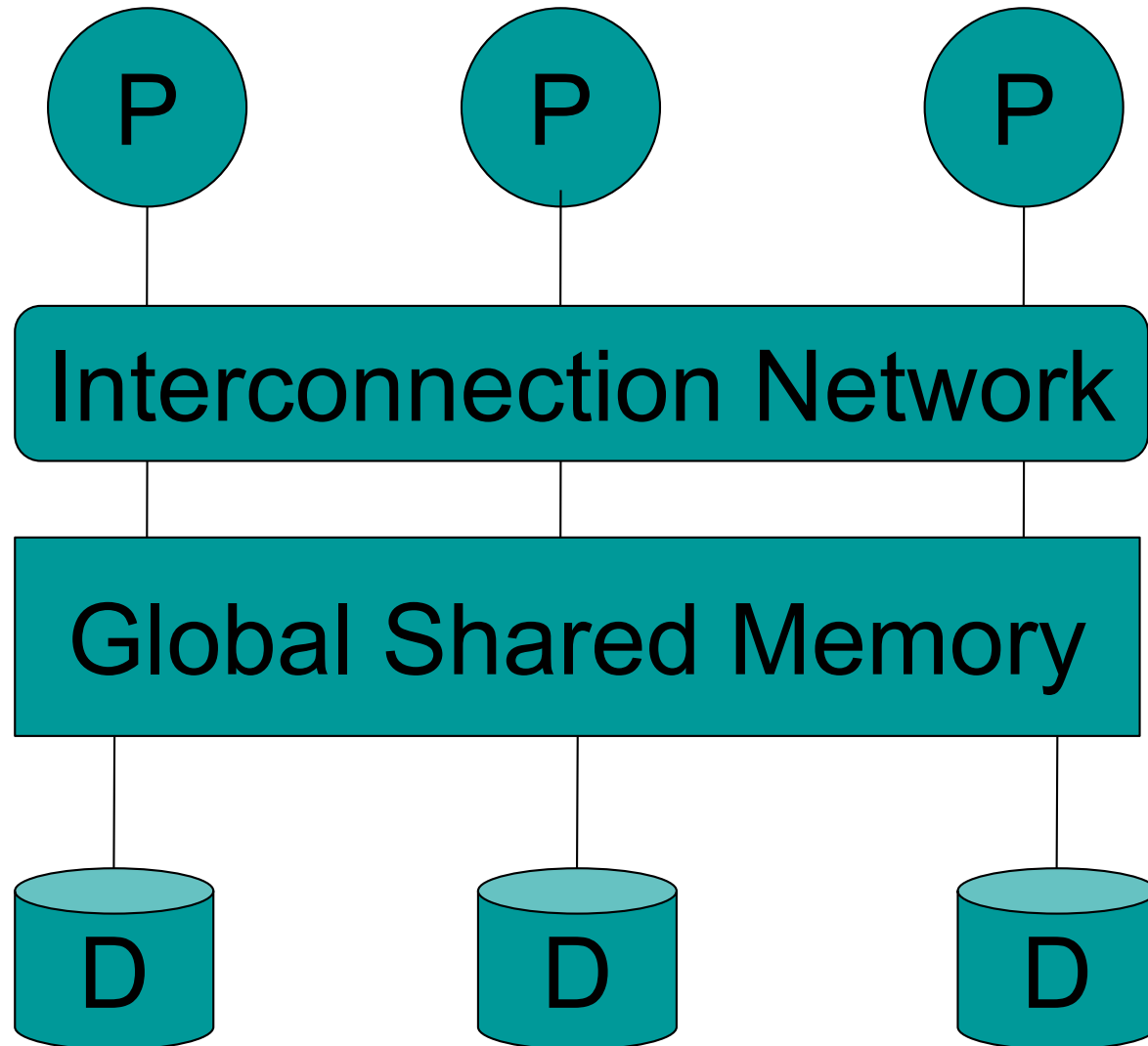
# Architectures for Parallel Databases

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- Shared memory
- Shared disk
- Shared nothing

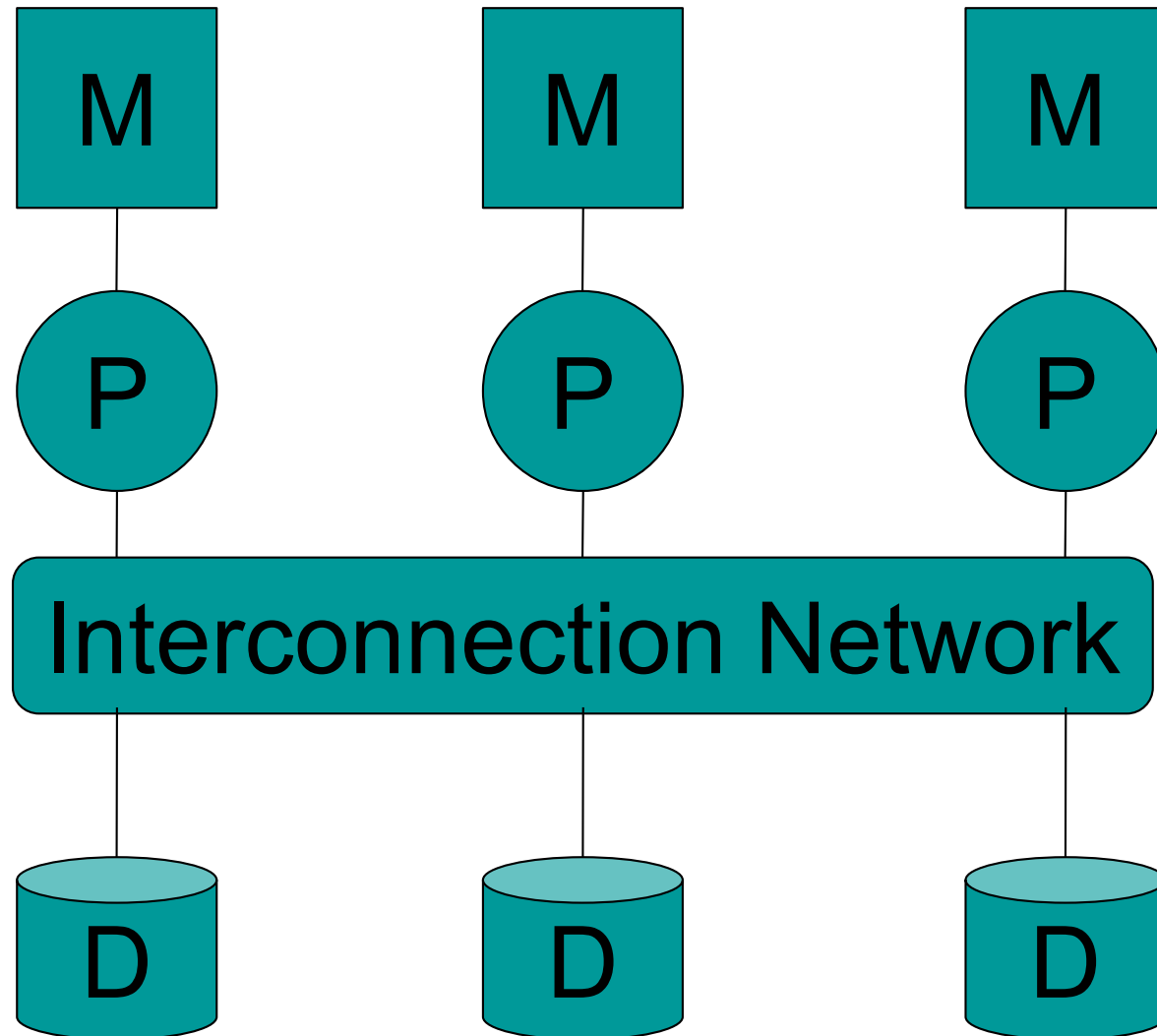
# Shared Memory

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# Shared Disk

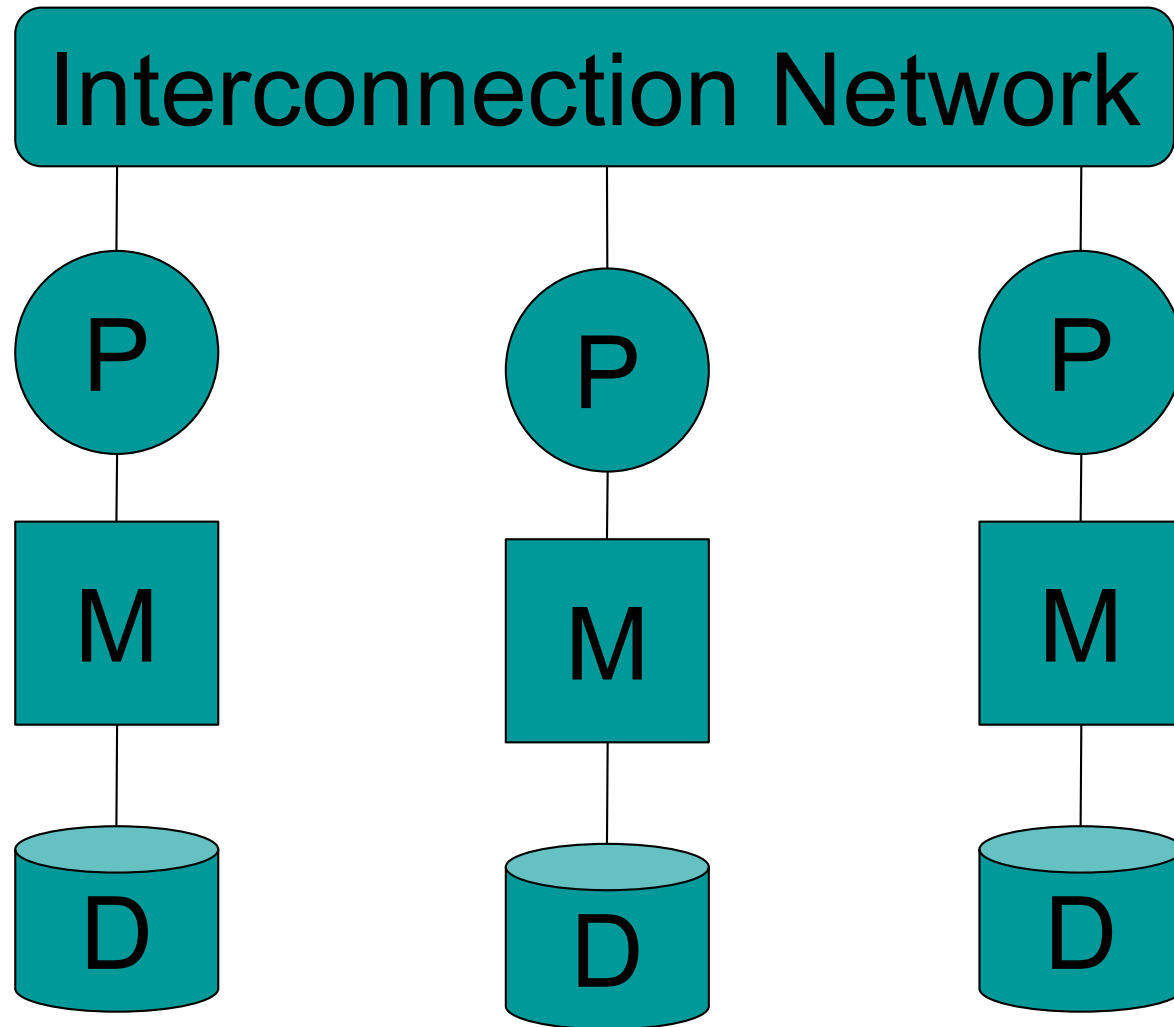
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# Shared Nothing

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# Shared Nothing

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- Most scalable architecture
  - Minimizes interference by minimizing resource sharing
  - Can use commodity hardware
- Also most difficult to program and manage
- Processor = server = node
- $P$  = number of nodes

We will focus on shared nothing

# Horizontal Data Partitioning

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- A.k.a. *Sharding* (mySQL, Google)
- Typical shared-nothing parallelization
- Relation  $R$  split into  $P$  chunks  $R_0, \dots, R_{P-1}$ , stored at the  $P$  nodes
- **Round robin**: tuple  $t_i$  to chunk  $(i \bmod P)$
- **Hash based partitioning on attribute  $A$** :
  - Tuple  $t$  to chunk  $h(t.A) \bmod P$
- **Range based partitioning on attribute  $A$** :
  - Tuple  $t$  to chunk  $i$  if  $v_{i-1} < t.A < v_i$

# Parallel Selection

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Compute  $\sigma_{A=v}(R)$ , or  $\sigma_{v1 < A < v2}(R)$

- On a conventional database: cost =  $B(R)$
- Q: What is the cost on a parallel database with  $P$  servers?
  - Round robin
  - Hash partitioned
  - Range partitioned

# Parallel Selection

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- Answer:
  - Round robin:  $B(R)$ ; all servers do the work in parallel
  - Hash:  $B(R)/P$  for  $\sigma_{A=v}(R)$ ; one server works only  
 $B(R)$  for  $\sigma_{v_1 < A < v_2}(R)$ ; all servers work in parallel
  - Range: (assuming relatively small range)  
 $B(R)/P$ ; one server works only

# Data Partitioning Revisited

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What are the pros and cons ?

- Round robin
  - Good load balance but always needs to read all the data
- Hash based partitioning
  - Good load balance but works only for equality predicates and full scans
- Range based partitioning
  - Works well for range predicates but can suffer from data skew

# Parallel Group By

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- Compute  $\gamma_{A, \text{sum}(B)}(R)$
- Step 1: server  $i$  partitions chunk  $R_i$  using a hash function  $h(t.A) \bmod P$ :  $R_{i0}, R_{i1}, \dots, R_{i,P-1}$
- Step 2: server  $i$  sends partition  $R_{ij}$  to server  $j$
- Step 3: server  $j$  computes  $\gamma_{A, \text{sum}(B)}$  on  $R_{0j}, R_{1j}, \dots, R_{P-1,j}$

# Parallel Join

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- Simplest implementation:
- Step 1
  - For all servers in  $[0, k]$ , server  $i$  partitions chunk  $R_i$  using a hash function  $h(t.A) \bmod P$ :  $R_{i0}, R_{i1}, \dots, R_{i, P-1}$
  - For all servers in  $[k+1, P-1]$ , server  $j$  partitions chunk  $S_j$  using a hash function  $h(t.A) \bmod P$ :  $S_{j0}, S_{j1}, \dots, S_{j, P-1}$
- Step 2:
  - Server  $i$  sends partition  $R_{iu}$  to server  $u$
  - Server  $j$  sends partition  $S_{ju}$  to server  $u$
- Steps 3: Server  $u$  computes the join of  $R_{iu}$  with  $S_{ju}$



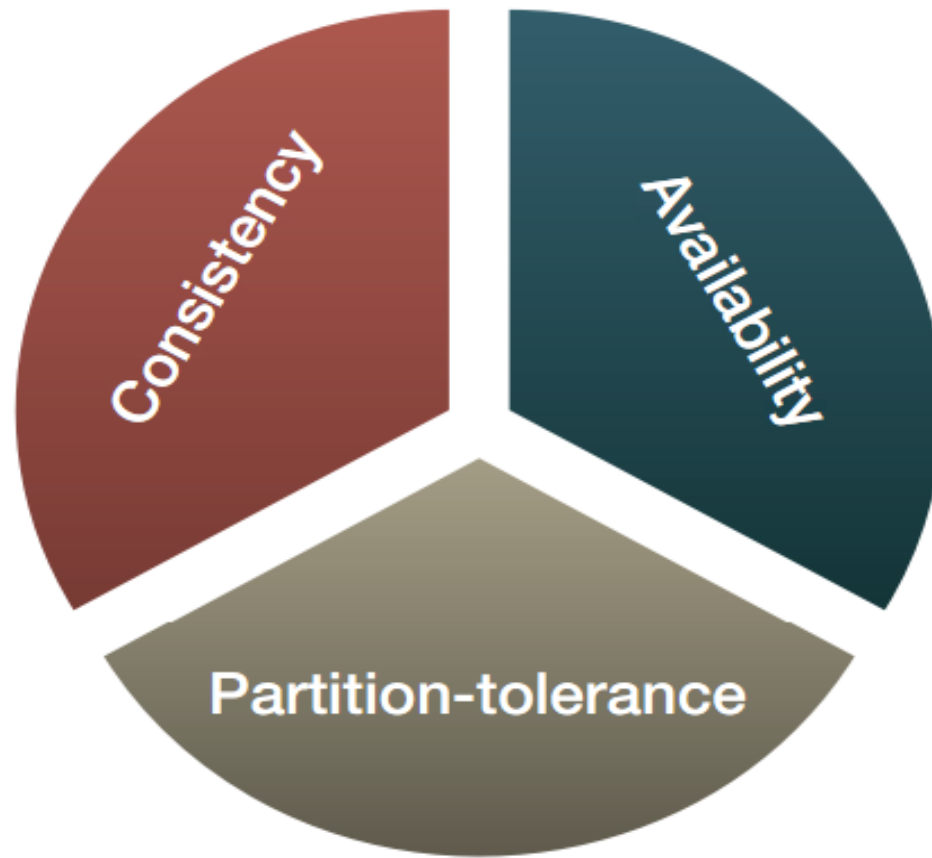
# ACID Properties (Standard DB)

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- **Atomicity**: Either all changes performed by transaction occur or none occurs
- **Consistency**: A transaction as a whole does not violate integrity constraints (only valid tuples are written)
- **Isolation**: Transactions appear to execute one after the other in sequence
- **Durability**: If a transaction commits, its changes will survive failures
- Q: Benefits & drawbacks of providing ACID transactions?

# CAP Properties

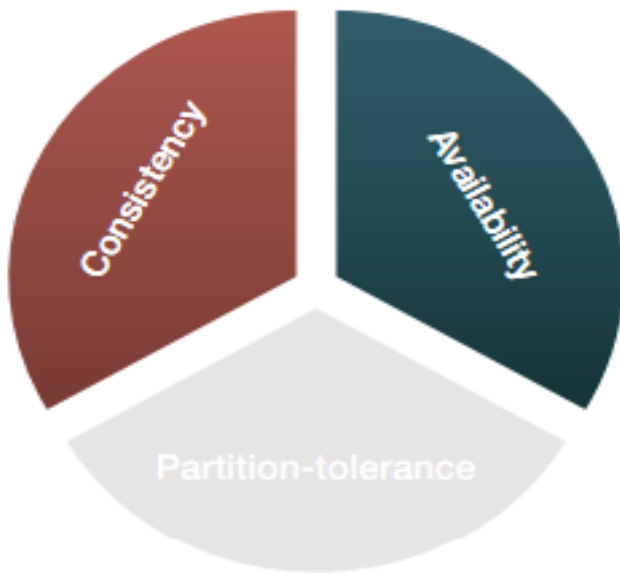
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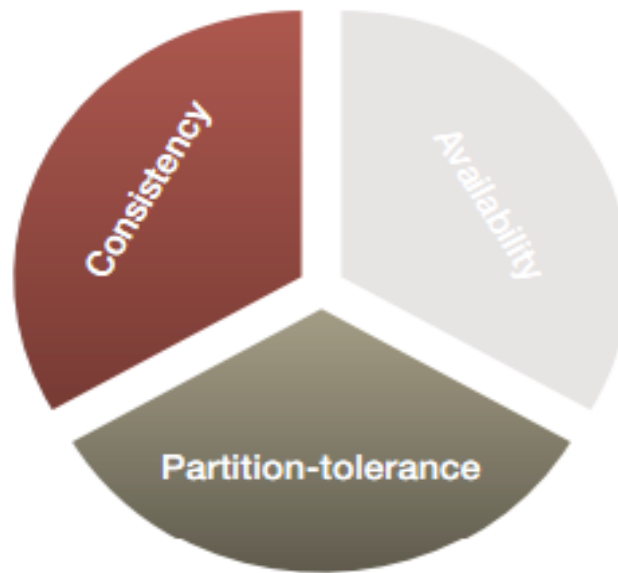
# CAP Conjecture

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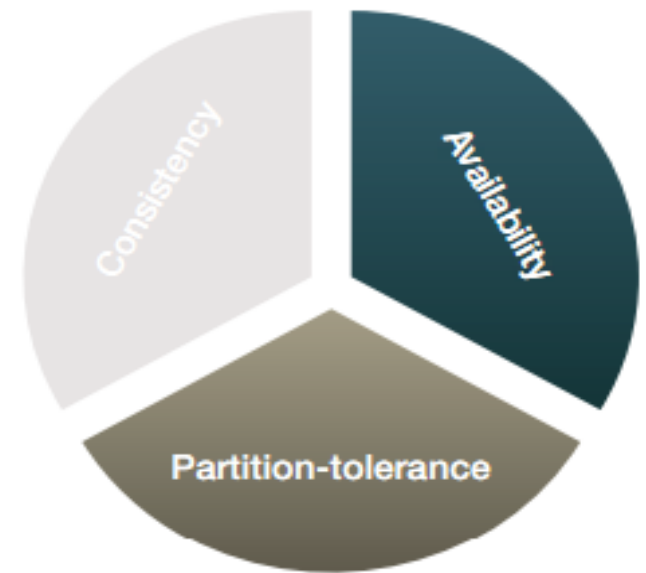
- It is **impossible** for a distributed computer system to simultaneously provide all three guarantees
  - Pick **at most two** properties



CA



CP



AP

# CAP Tradeoffs

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- While it is impossible to provide all three properties, any two of those three properties can be achieved!  
**Trivial** examples for the asynchronous model:
  - CA: centralized RDBMS
  - CP: ignore all incoming requests
  - AP: always return initial value

# Visual Guide to Recent Systems

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**CA:**

RDBMSs  
(MySQL,  
Postgres,  
Oracle etc.)  
Aster Data,  
Greenplum,  
Vertica

**A**

**AP:**

Amazon Dynamo,  
LinkedIn Voldemort,  
Facebook Cassandra,  
SimpleDB,  
CouchDB

**C**

**P**

**CP:** Google BigTable, Hbase, Berkeley  
DB, MemcachDB, MongoDB

*<http://blog.nahurst.com/visual-guide-to-nosql-systems>; classification subject to discussion...*

# Weak Consistency Models

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- Following the CAP theorem, systems started to appear providing **weaker consistency** models
    - failures are unavoidable in large scale systems
    - availability is a must for many services
    - compromise on consistency!
  - Example: t-Connected Consistency (Lynch)
    - in the presence of no partitions, the system is consistent
    - in the presence of partitions, stale data can be returned
    - once a partition heals, there is a time limit on how long it takes for consistency to return
- ⇒ **“Eventual” consistency in many noSQL systems**

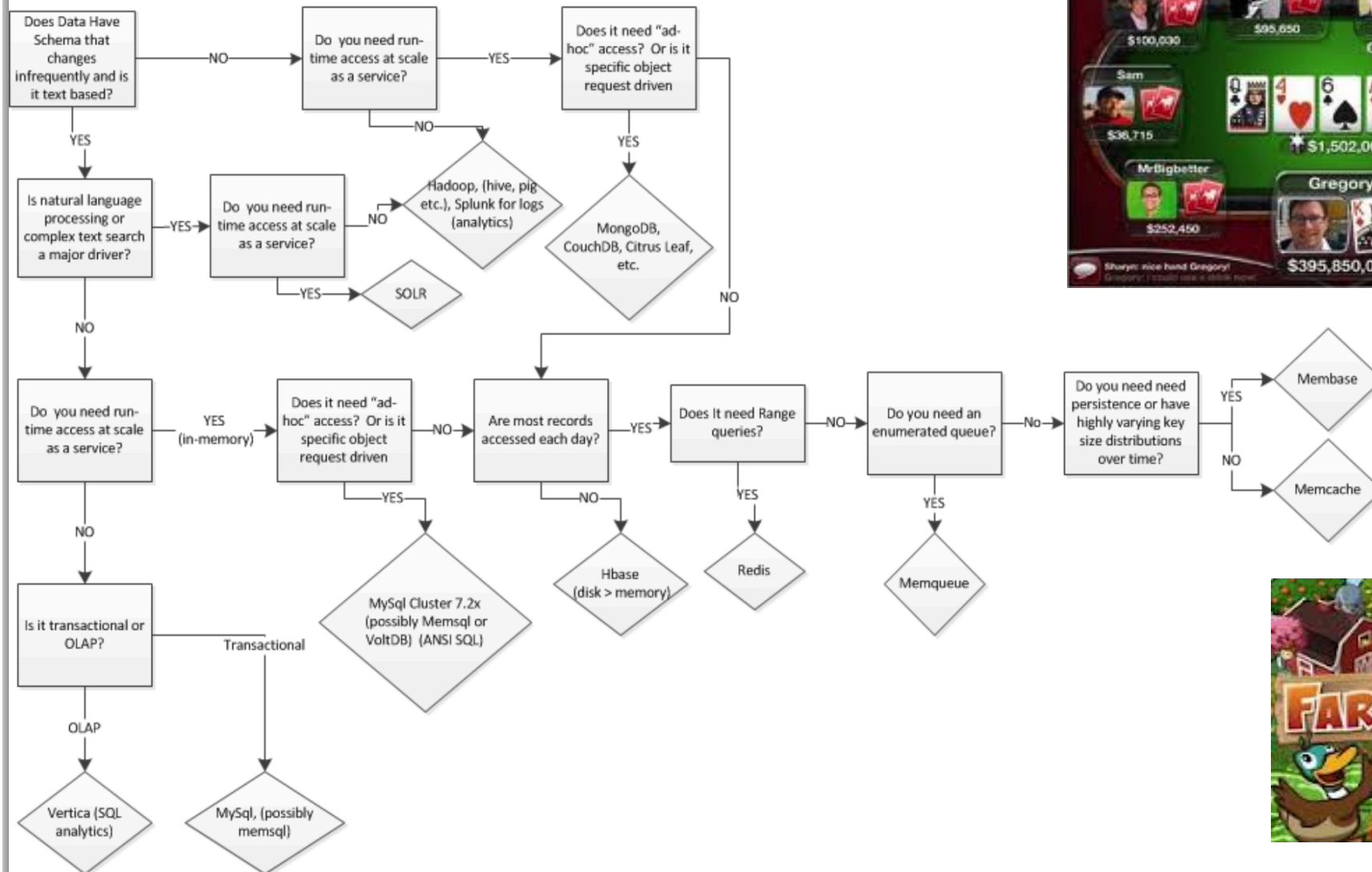
# NoSQL / NewSQL Solutions

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- The end of one-size-fits-all! [Stonebraker]
- Specialized solutions to ensure efficiency
  - Premium Data Warehousing [e.g., Teradata]
  - Column-stores [e.g., Vertica]
  - Wide columns [e.g., Cassandra]
  - Document Stores [e.g., MongoDB]
  - Graphs [e.g., neo4j]
  - Arrays [e.g., SciDB]
  - Streams [e.g., Storm]
  - Etc.

# A Concrete Example: Zynga

Dan's Scalable Database Decision Matrix at Zynga





# Key-Value (**Column-Family**) Store: Google BigTable

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- **Many different types of data to manage today**
  - **Structured data**
    - All data conforms to a strict schema. Ex: business data
  - **Semi-structured data**
    - Some structure in the data but implicit and/or irregular
    - Ex: resume, ads, the Web in general
  - **Unstructured data**
    - All other data. Ex: text, sound, video, images
    - They actually do have some structure, but not for DBMSs!

# Column-Family Store

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- Distributed storage system storing (complex) key-value pairs
  - Key: (row+column) / value: (String)
- Designed to
  - Hold **widely heterogeneous semi-structured data**
  - Scale to thousands of servers
  - Store up to several hundred terabytes (maybe even petabytes)
  - Perform backend bulk processing
  - Perform real-time data serving
- To scale, Bigtable has a **limited set of features and data types**

# Bigtable Data Model

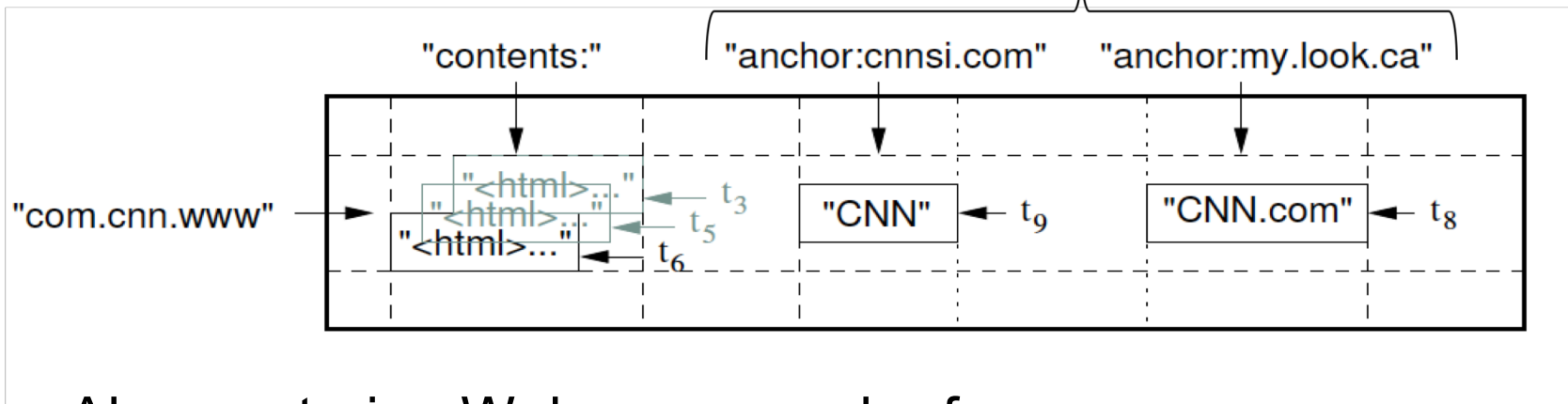
- **Sparse, multidimensional sorted map**

`(row:string, column:string, time:int64) → string`

Notice how everything but time is a string

- Example:

Columns are grouped into families



- Above: storing Web pages and references

# Other Key Facts about Big Table

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- Read/writes of data under single row key is atomic
  - Only single-row transactions!
- Data is stored in lexicographical order
  - Improves data access locality
- Column families are unit of access control
- Data is versioned (old versions can be garbage-collected)
  - Example: most recent three crawls of each page, with times
- Current open-source systems (Apache Cassandra, Hadoop's **HBase**, etc.) are directly inspired from BigTable