# Do Relational Databases Belong in the Cloud?

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# How do you model data in the cloud?

## **Relational Model**

A query operation on a relation (table) produces another relation (table).

Based on the relational algebra and calculus, a query engine can produce provably correct results.

# Declarative Language Allows Optimization

Architectural Assumption: Data Outlasts Implementation Data Separate From Code

## **Consistency Required**

Transactional consistency No specification of insert, update or delete. Non clustered indices consistent with data Design consistency Denormalized data must be kept consistent Lossless join decompositions Transactional Consistency Means Holding Database Locks

# Holding Locks Interferes With Availability and Scalability

# Do Availability and Consistency Conflict?

Laws of Physics Technology Limits Economics

# Laws of Physics

# Latency Exists

Speed of light in fiber optic cable: 124,000 miles per second Ideal ping Japan to Boston takes 100 ms. Fetch 10 images for a web site: 1 second Ignores Latency of the operation

## Bandwidth is Not Cheap

Shannon's Law: C = B log<sub>2</sub> (1 + S / N) Capacity = bit / second Bandwidth (hertz) S/N \* 5 to double capacity given bandwidth

## Latency is Not Bandwidth

Size of the shovel vs. how fast you can shovel

Infinite shovel capacity(bandwidth) is limited by how fast one can shovel (latency).

#### Great Bandwidth Terrible Latency

#### Buy a two terabyte disk drive

Drive with it from Boston to New York

### You can only move data so fast

### You can only move so much data

**Technology Limits** 

## Connectivity is Not Always Available

Cell phone Data Center Outages Equipment Upgrades Data redundancy to improve reliability Offline mode on client for availability

## Expensive to Move Data

Data naturally lives in multiple places Computational Power gets cheaper faster than network bandwidth Cheaper to compute where data is instead of moving it

Cheaper to compute where data is instead of moving it Distributed Computing Economics Jim Gray

## Economics Dictate Scale Out, Not Up

Cheap, commodity hardware argues for spreading load across multiple servers

Relational Databases were not designed to be run on clusters (shared disk subsystem)

# Wind up Building a Distributed System

# Can the relational database scale?

# Traditionally, focus was on optimizing specific problems

Optimize Insert/Update or Read?

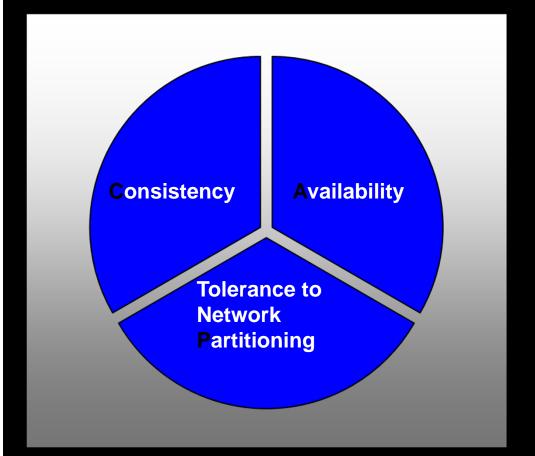
Data intensive relational applications: frequent small read / writes large size reads, but infrequent writes Problems:

Heavy workloads with frequent writes Scanning over large indices for queries Dirty reads can mean inconsistent data

#### What does it mean to scale?

Large Number of Users Geographic Distribution Hugh Amounts of Data To Scale a Distributed System Focus on Data, Not Just Computation

## **CAP** Theorem

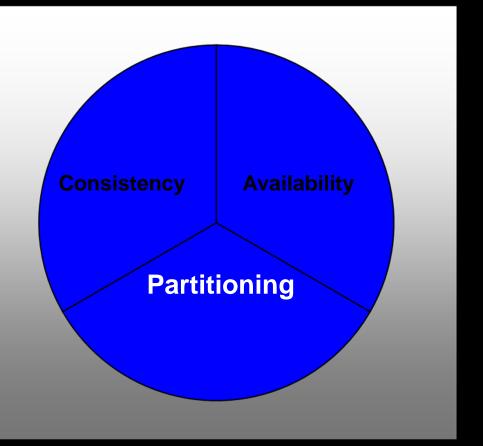


Can Have Any Two

Eric Brewer UC Berkeley, Founder Inktomi

http://www.cs.berkeley.edu/~brewer/cs262b-2004/PODC-keynote.pdf

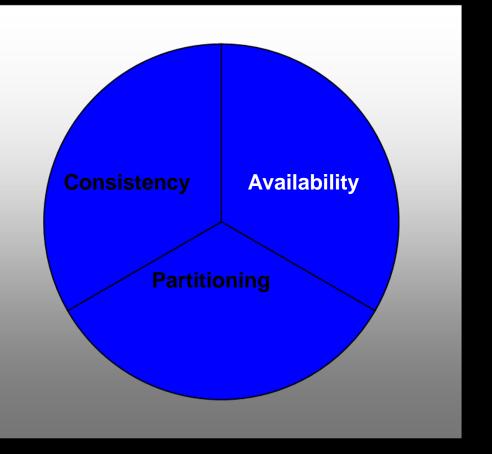
### **Consistency and Availability**



Single site Database Database Cluster LDAP

Two phase commit Validate Cache

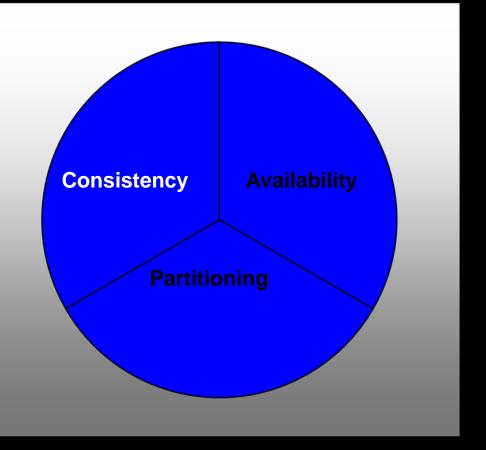
# **Consistency and Partitioning**



Distributed Database Distributed Locking

Pessimistic Locking Minority Partitions invalid

## Availability and Partitioning



Forfeit Consistency

Google Big Table Amazon Simple DB Azure Storage Tables

Optimistic Locking Can Denormalize

## CAP Does *Not* Imply:

Never give up on Durability Atomicity within a Partition Inconsistency should be the exception Partition Everywhere No ACID within a Partition Give up on Declarative Languages such as SQL

## Then...

#### If we give up Consistency, how do we Partition?

If we Partition how do we recover system invariants?

# **Classic Ways to Partition**

# **Distributed Objects**

#### **Distributed Objects Fail**

Separate Address Space Disparate Lifetimes Location is Not Transparent RPC Model Fails Cannot Hide Network

## **Distributed Transactions**

Relational Model works with single node/ cluster

Complexity of relations

Query plans with hundreds of options which query analyzer evaluates at runtime

Normalization

**ACID Transactions** 

Quick hardware scale up difficult

Two Phase Commit works with infinite time

## **Better Ways to Partition**

**Non-Relational Approach** Key Value / Tuple Store **Document Store Column Family Store Graph Store Relational Approach** Sharding NewSQL

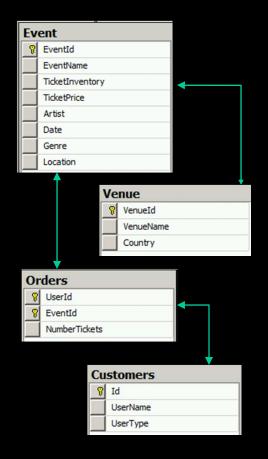
# For Better Partitioning, Look at Data Model

Relational: Given the structure of the data, what kind of questions can I ask? Non Relational: Given the questions I want to ask, how do I structure the data?

# Model Application Specific Questions

# The aggregate is the unit of atomicity in a NoSql Data Model

# Relational vs. Aggregate



Venue {	
Name	
Country	<b>y</b>
Event	•
{	
L	Name
	Ticket Inventory
	Artist
	Date
	Genre
	Location
}	
}	
S	
Customers	
{	
Name	
Orders	[]
Event N	
	Tickets
1	1 TORCEO
S	

Prioritized Query Restrictions
1. How many tickets are left for an event? *date, location, event*2. What events occur on which date? *date, artist, location*3. When is a particular artist coming to town? *artist, location*

- 4. When can I get a ticket for a type of event? *genre*
- 5. Which artists are coming to town? *artist, location*

# **Query Analysis**

Most common combination: artist *or* date / location Most common query: event / date / location

Partition based on location or venue Allows for geographic sensitivity

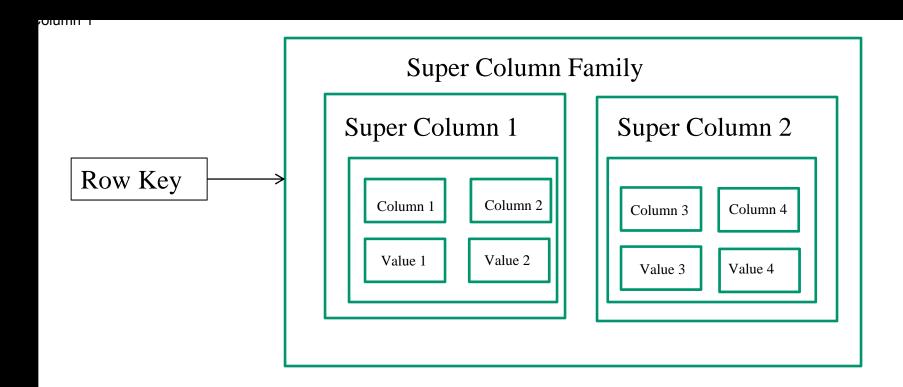
Partitioning may or may not imply denormalization

# Each NoSql Data Model Treats Aggregates Differently

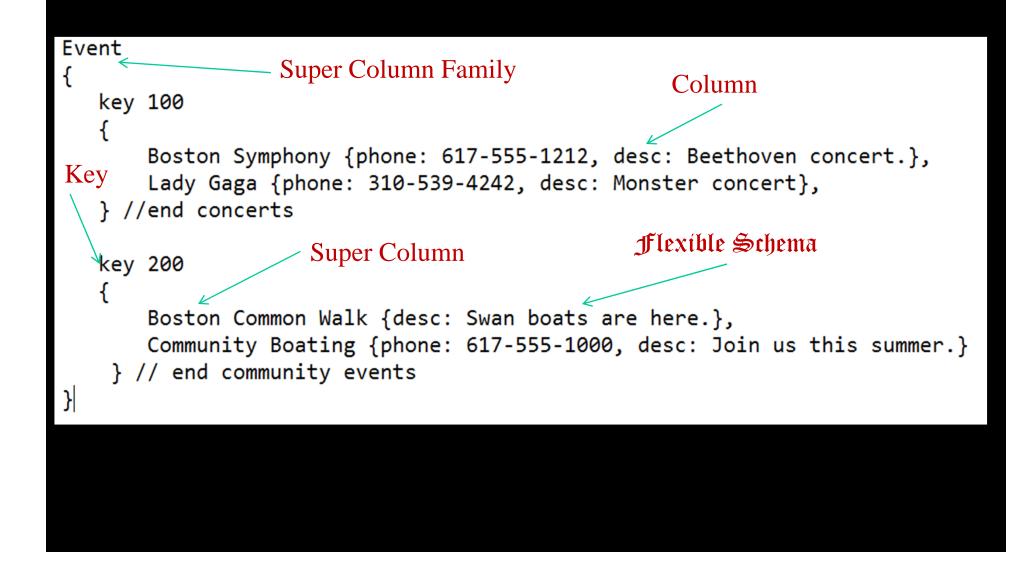
#### In general....

Code has integrity constraints Code handles joined queries No standard among vendors (lock in) Key-Value treats the aggregate as opaque Might have a opaque set of attributes Key is the index to the aggregate Ordered Key-Value allows for range queries Only the application knows the schema Column Family is a Two Level Aggregate Keys are first level Aggregates are the second level Aggregate is composed of other aggregate Reads are common, Writes rare

# Column Family Data Model (Cassandra)



# Example



# Document Database has aggregate of arbitrary complexity with an index on attribute data.

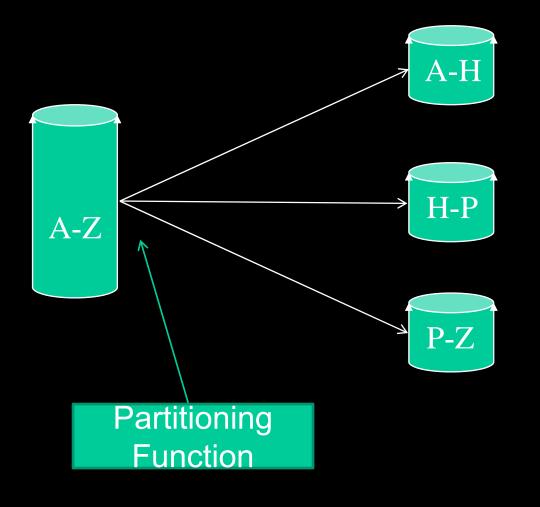
# Mechanics of Relational Database Partitioning

# Find Independent Units of Data

# Separate Transactions From Queries



## **Transactional Units Across Databases**



**Partitioning Mechanisms** 

Horizontal Partitioning
Divide table rows across databases
Vertical Partitioning
Divide table columns across databases
Different tables in different databases
Reference data can be copied
Queries scan less data

Horizontal Partitioning Each table contains identical columns Data is partitioned into different databases. Each part is referred to as a *shard*. Table is a single logical entity for updates and queries Indices for a shard must be in the same shard Sharding strategy based on use or query patterns **Implementing Horizontal Partitions** 

- Function that converts sharding property into a database location
- Primary keys unique across all shards Shards hand out distinct ranges Shard id is part of primary key Pool hands out unique identifiers No secondary keys across shards No distributed transactions across databases May need to UNION query results

# **Vertical Partitioning**

Divide table columns across databases Primary key identical for a given "row" Data may or may not be normalized A join across the partitions recreates the "row"

# Vertical Partitioning Strategy

Columns used in different queries go in different partitions

Different business processes "own" a table.

Leads to service oriented approach

Design business processes to avoid cross table joins

Transactions within service boundary

## **Implementing Vertical Partitions**

Primary or foreign keys may be used to recreate the row

No secondary keys across databases

Secondary indices in different partitions might diverge Normalize columns not frequently used No distributed transactions

# NewSQL

#### **New Relational Database Architectures**

Examples:

In-memory databases Google Spanner In-memory Data Model equivalent to relational short lived transactions index look ups (no table scans) repeated queries with different parameters

## **Google Spanner**

Globally distributed relational database Synchronizes with atomic and GPS clocks Uses Paxos protocol for consensus

# Availability or Consistency ?

What is the Cost of an Apology?

Amazon Airline reservations Stock Trades Deposit of a Bank Check Deleting a photo from Flickr or Facebook

#### Sometimes the cost is too high

Authentication SAML tokens expire Launching a nuclear weapon

#### **Businesses Apologize Anyway**

Vendor drops the last crystal vase Check bounces Double-entry bookkeeping requires compensation at least 13<sup>th</sup> century Eventually make consistent (partition healing)

### Software State ≠ State of the World

Software approximates the state of the world Best guess possible Could be wrong Other computers might disagree

## How consistent?

**Business Decision** 

What is the cost to get it absolutely right? What is the cost of lost business? Computers can remember their guesses Can replicate to share guesses May be cheaper to forget, and reconcile later

#### **Design For Eventual Consistency**

Decouple unrelated application functionality Focus on atomic or invariant business operations, not database reads or writes. No distributed transactions Asynchronous processing

# **Eventual Consistency**

Different computations might come to different conclusions

Define message based workflows for ultimate reconciliation and replication of results

### Not the Whole Story

# Databases are not the best integration technology Object-Relational Mismatch Certain problems match other data models

# Services, not Data, Outlast Implementation

# Application or Service Specific Databases

# Case Study: Amazon Four Day Outage

#### Facts

April 21, 2011

One Day of Stabilization, Three Days of Recovery Problems: EC2, EBS, Relational Database Service Affected: Quora, Hootsite, Foursquare, Reddit Unaffected: Netflix, Twillo

# Netflix Explicitly Architected For Failure

Although more errors, higher latency, no increase in customer service calls or inability to find or start movies.

### **Key Architectural Decisions**

Stateless Services Data stored across isolation zones Could switch to hot standby Had Excess Capacity (N + 1) Handle large spikes or transient failures Used relational databases only where needed. Could partition data Degraded Gracefully

### Data Architecture

Separate databases:

User, Accounts, Feedback, Transactions Split by primary access path No business logic in database CPU intensive work in service tier Referential Integrity, Joins, Sorting Avoids deadlock

## **Degraded Gracefully**

Fail Fast, Aggressive Timeouts
Can degrade to lower quality service
no personalized movie list, still can get list of available movies
Non Critical Features can be removed.

## Suggested Reading

"Life Beyond Distributed Transactions: An Apostate's View" by Pat Helland

## Conclusions

Scalability means Users, Bandwidth, Geography Partitioning Changes the Data Model Service Orientation Changes the Data Model **Design for Eventual Consistency** No need for scalability or service orientation, **Relational Model works** Unified Data Model makes it hard to meet rapid change.