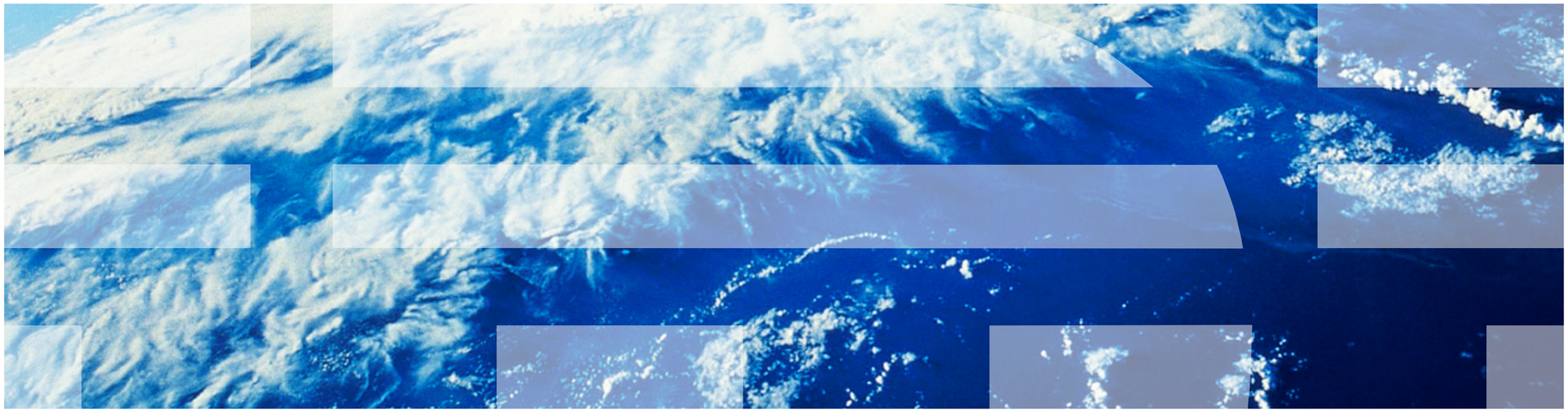
Lecture 2



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  - Modern datacenter design: standard hardware, replicated in racks (cabinets), rows, deployed in football stadium-sized warehouses

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- Schema evolution
  - API schema
  - Case studies [1, 2]

Row/Cluster

- 30+ racks

Network Topology

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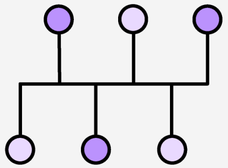
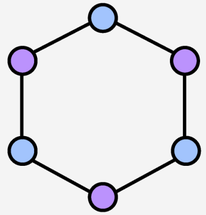
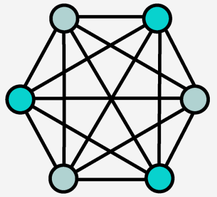
Bus



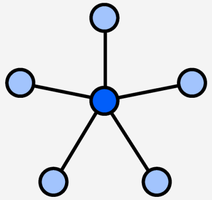
Ring



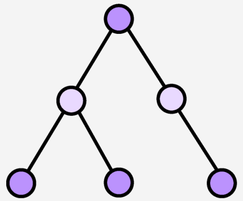
Mesh



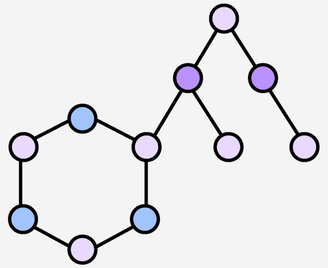
Star



Tree



Hybrid



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- Each of these have different latencies, throughput
  - Higher in hierarchy -> higher throughput

Multipath routing

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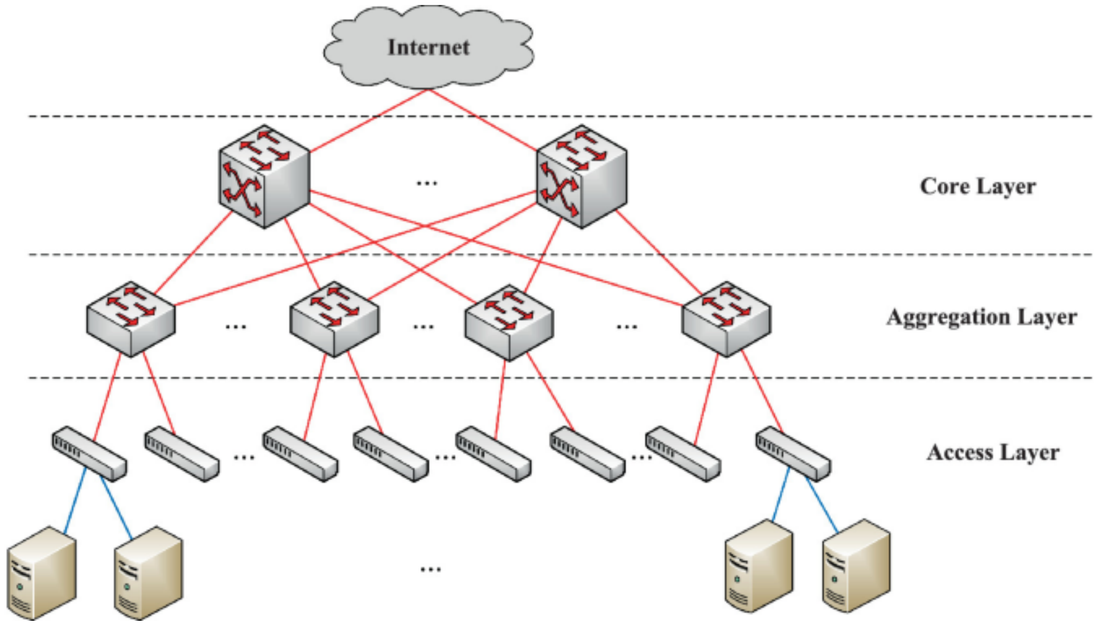

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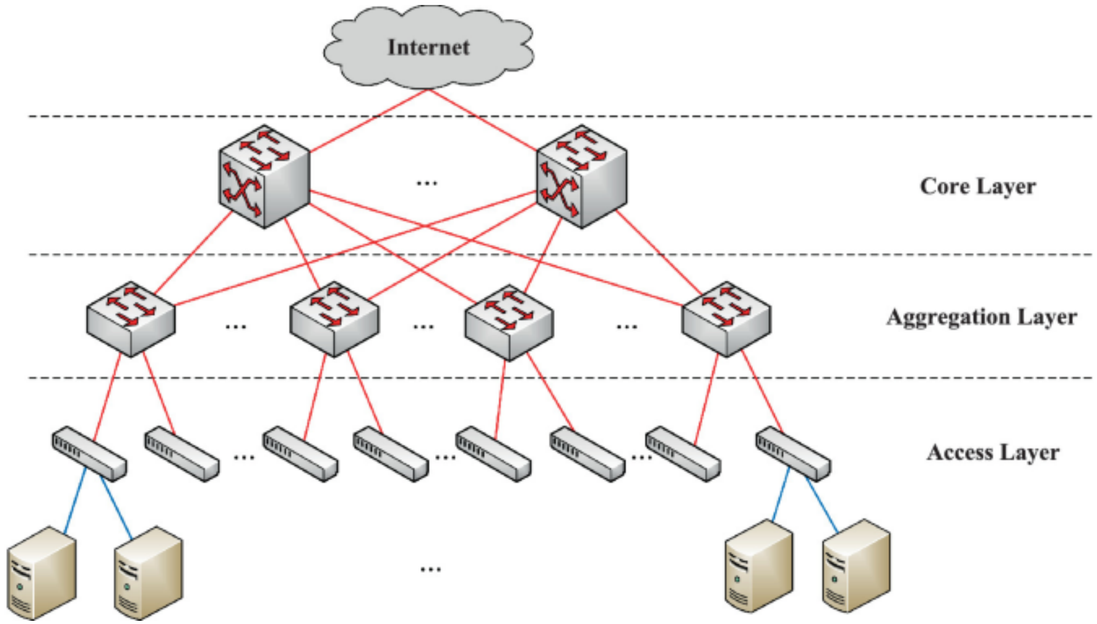

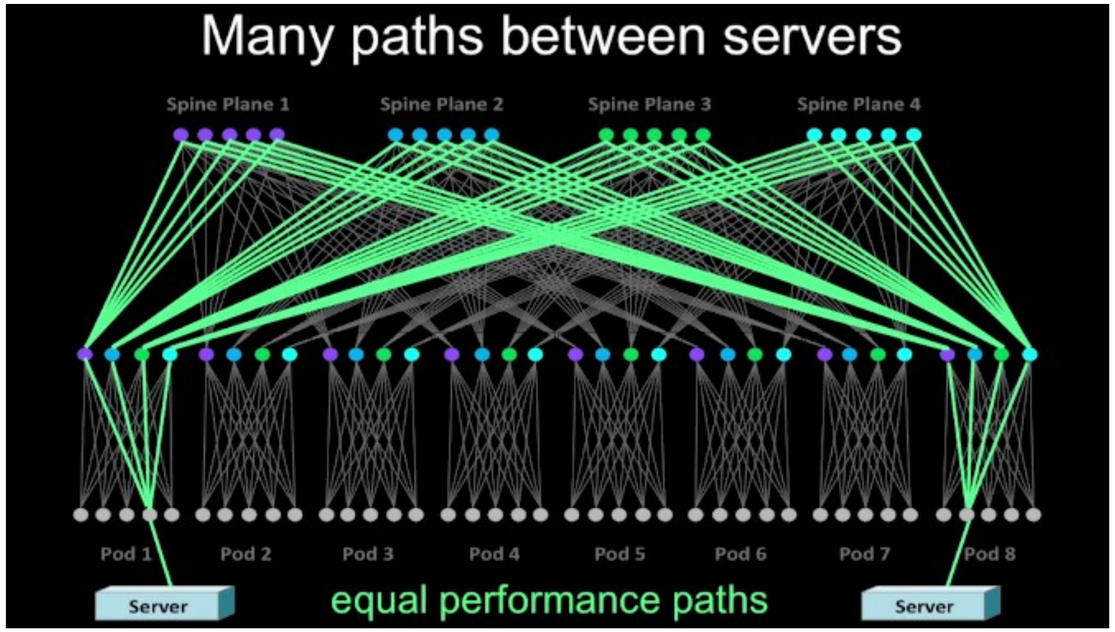

Power Usage Effectiveness (PUE)

- Early data centers built with off-the-shelf components
  - Standard servers
  - HVAC unit designs from malls

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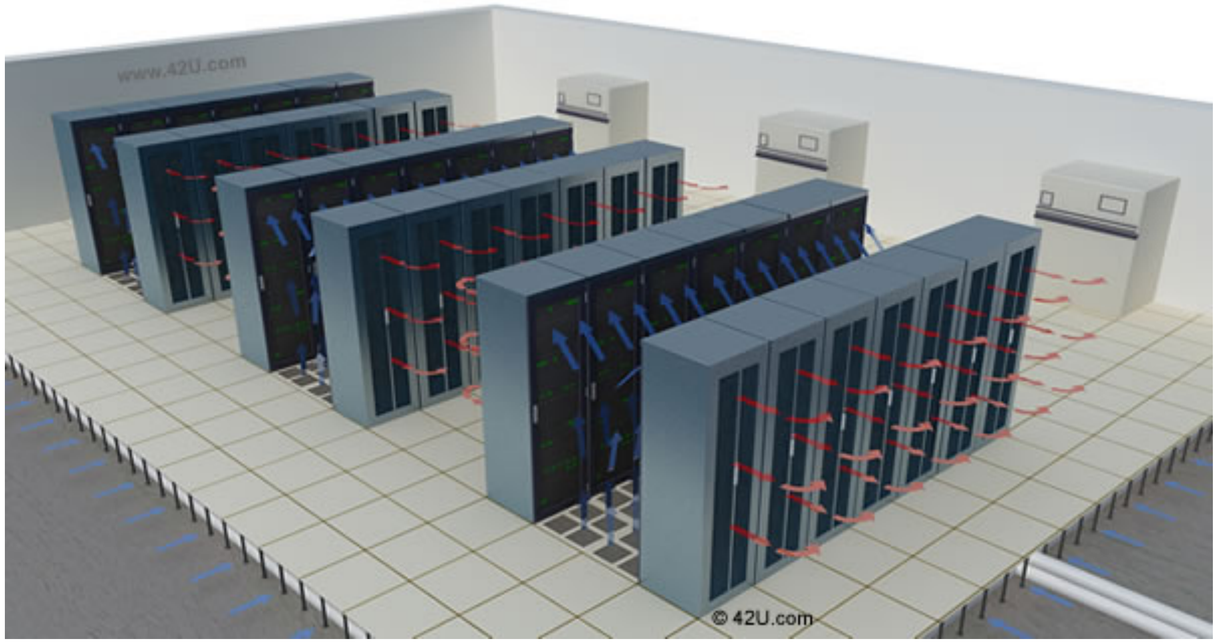
- Average PUE for AWS datacenters in 2024: 1.15 (only 15% from optimal!)
- Some can be 1.04
- Power is about 25% of monthly operating cost
  - And is (one of) the limiting factor in how large the datacenter can be

Energy Efficient Data Centers

- Better power distribution - Fewer transformers



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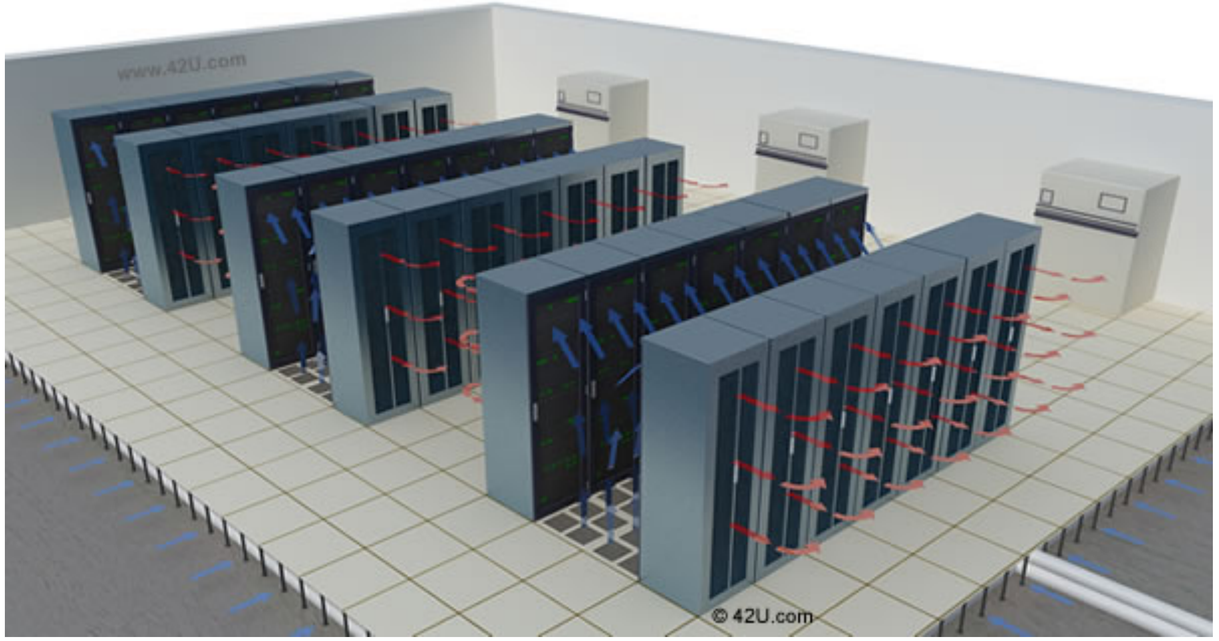

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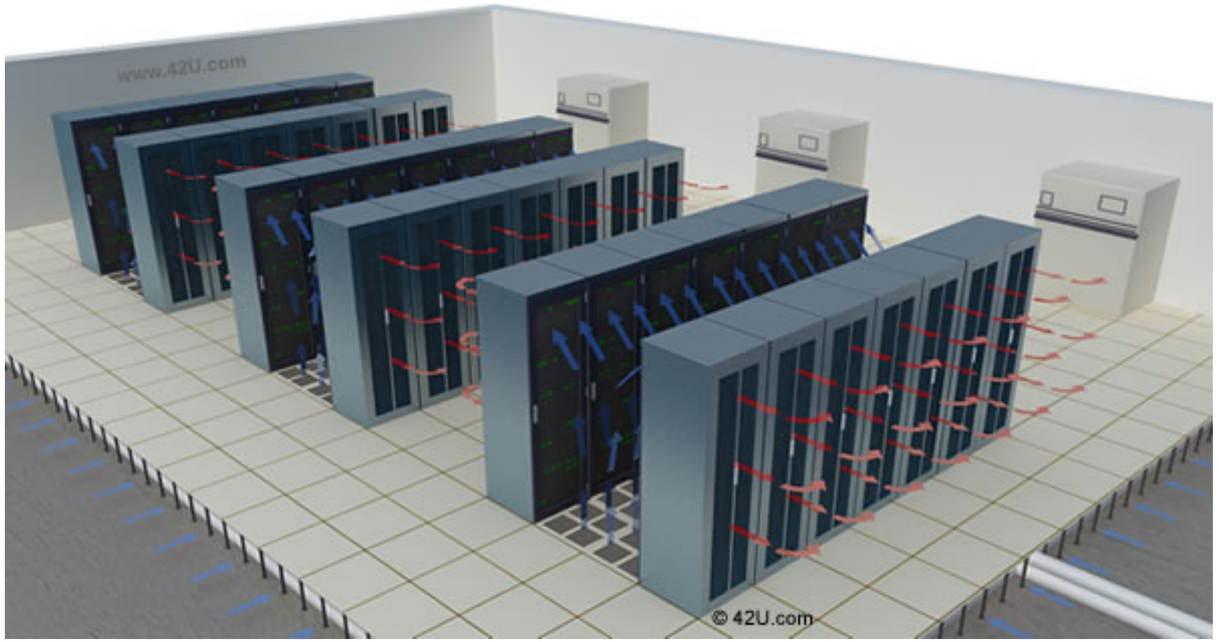

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SEP 27, 2025

By Laura Sharman

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→ **Reliability must come from software!**

Failures in first year for a new data center (Jeff Dean)

~thousands of hard drive failures

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Cloudflare 1.1.1.1 incident on July 14, 2025

2025-07-15


Ash Pallarito


Joe Abley

8 min read

On 14 July 2025, Cloudflare made a change to our service topologies that caused an outage for 1.1.1.1 on the edge, resulting in downtime for 62 minutes for customers using the 1.1.1.1 public DNS Resolver as well as intermittent degradation of service for Gateway DNS.

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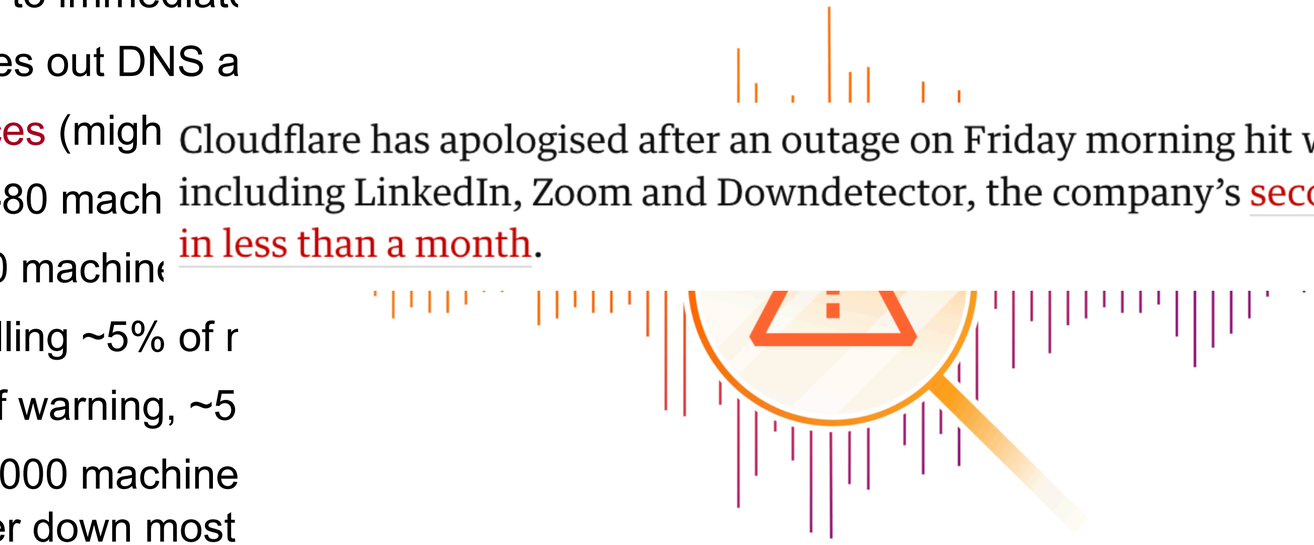

Cloudflare has apologised after an outage on Friday morning hit websites including LinkedIn, Zoom and Downdetector, the company's second outage in less than a month.

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- We will cover these topics more deeply in the second half of the class

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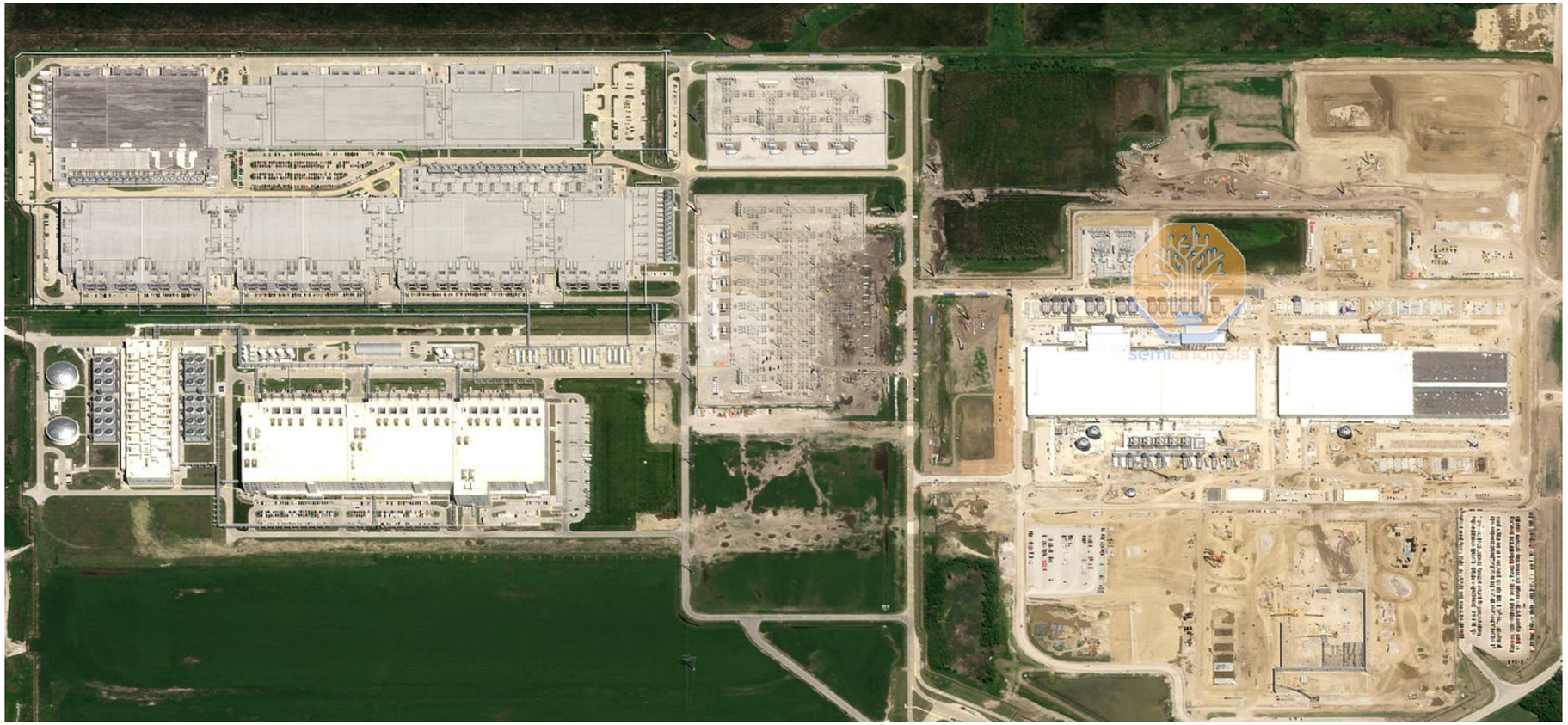
- Available labor pool
- Politics
  - Crime and corruption
  - Tax breaks
  - AI regulations

Google Data Center - Council Bluffs, Iowa, USA



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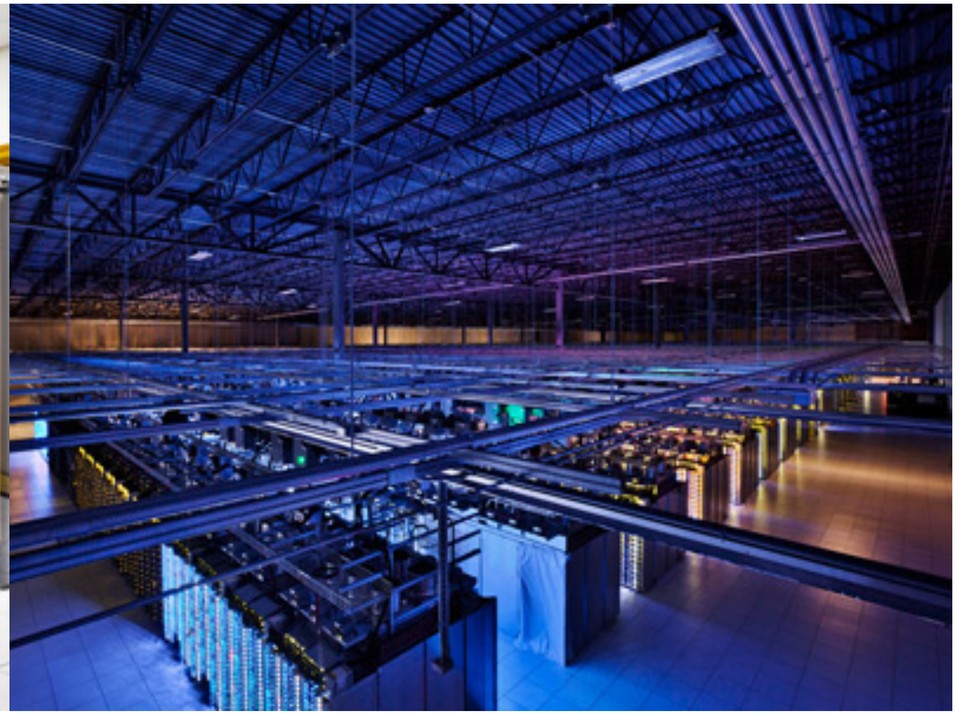
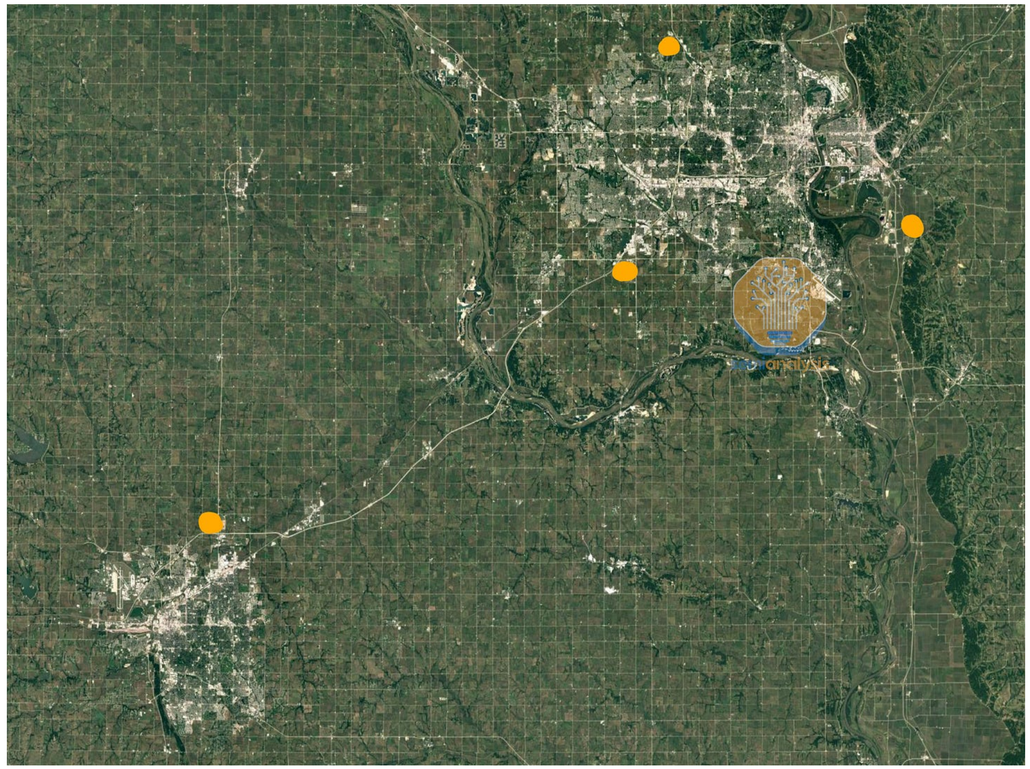
Google data center pictures: Council Bluffs



Datacenter “megasites”

- Four Google datacenter sites within a 50-mile radius of each other, in the Iowa/Nebraska region
- May reach GW of total power consumption



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General application guidance

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  - Respects quotas
  - Provides telemetry for observation and adjustment

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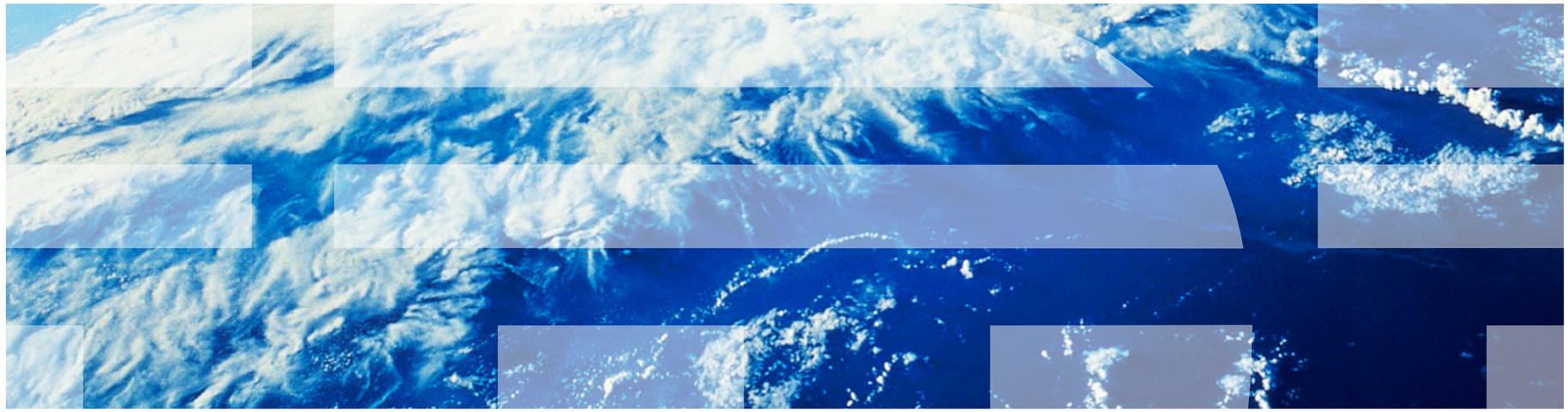
Summary

- It’s easy as data scientists (or software engineers) to lose sight that our code actually runs somewhere **physically**
- The cloud is not some abstract concept: these are huge physical sites consuming power equivalent to entire cities
- AI is accelerating the construction of new data centers
- Datacenter sustainability (especially in the age of AI) is going to be extremely important in the coming years

Borrowed from Shiva Shivakumar and Theodoros Rekatsinas

Computer Systems for Data Science
Topic 2

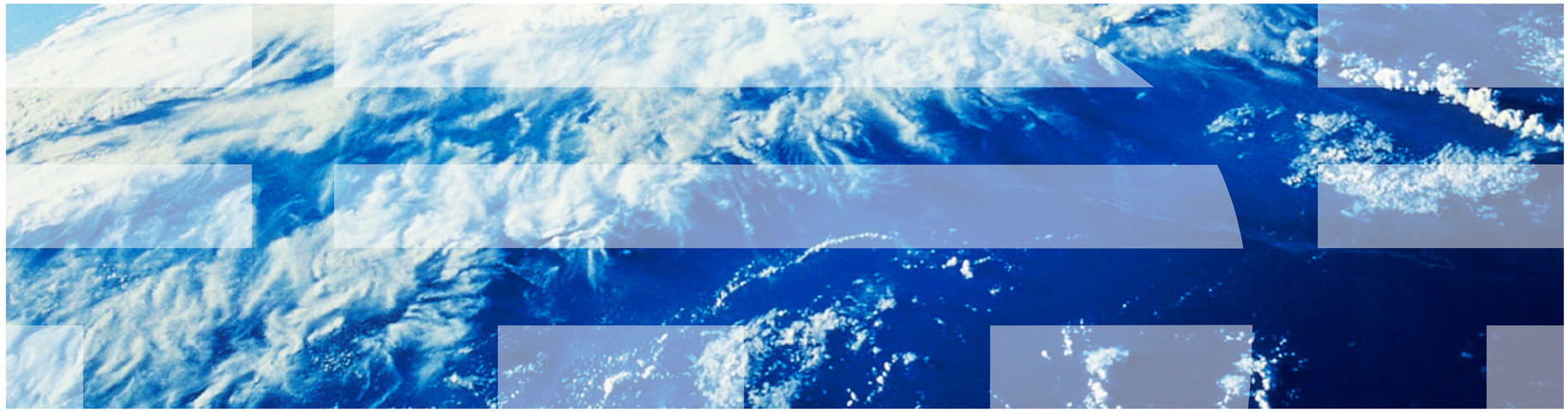
Relational Model and SQL



What we'll cover in this topic

- **Intuition**
  - Basic relational model
  - Map-filter-reduce concept
- **Intro to SQL**
  - Schemas, query structure of SELECT-FROM-WHERE, JOINs

Relational Model: Intuition



A Motivating Example

A basic Course Management System (CMS):

Entities or Relation (e.g., Students, Courses)

Relationships (e.g., Alice is enrolled in CSEE 4121)

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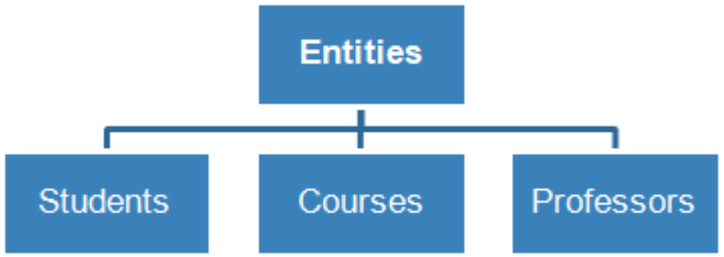

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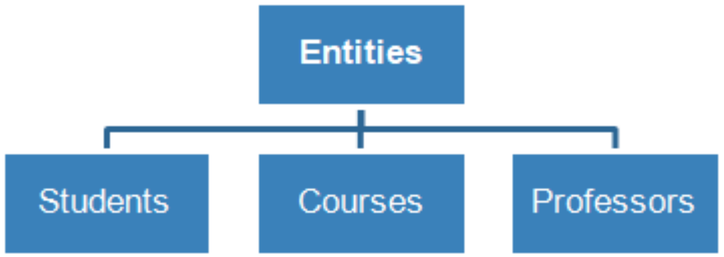

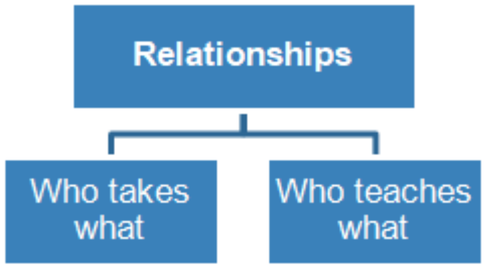

Intuition: Spreadsheet Tables

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Data Independence

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   - Protection from changes in the logical structure of the data

2. Do you need to care which disks/machines are the data stored on?

   – **Physical Data Independence**
   - Protection from Physical Layout Changes

Python Operating on Lists

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Basic types

- Int
- Long
- String

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Map + Filter

- map(function, list)
- filter(function, list)

Map applies function to input list
Filter returns sub list that satisfies filter condition

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Filter returns sub list that satisfies filter condition

Reduce/Aggregate
- reduce(…)

Reduce runs a computation on a list and returns a result
E.g., SUM, AVG, MAX

SQL Queries on Tables (Lists of Rows)

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SELECT c1, c2
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WHERE condition;
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SELECT SUM(c1*c2)
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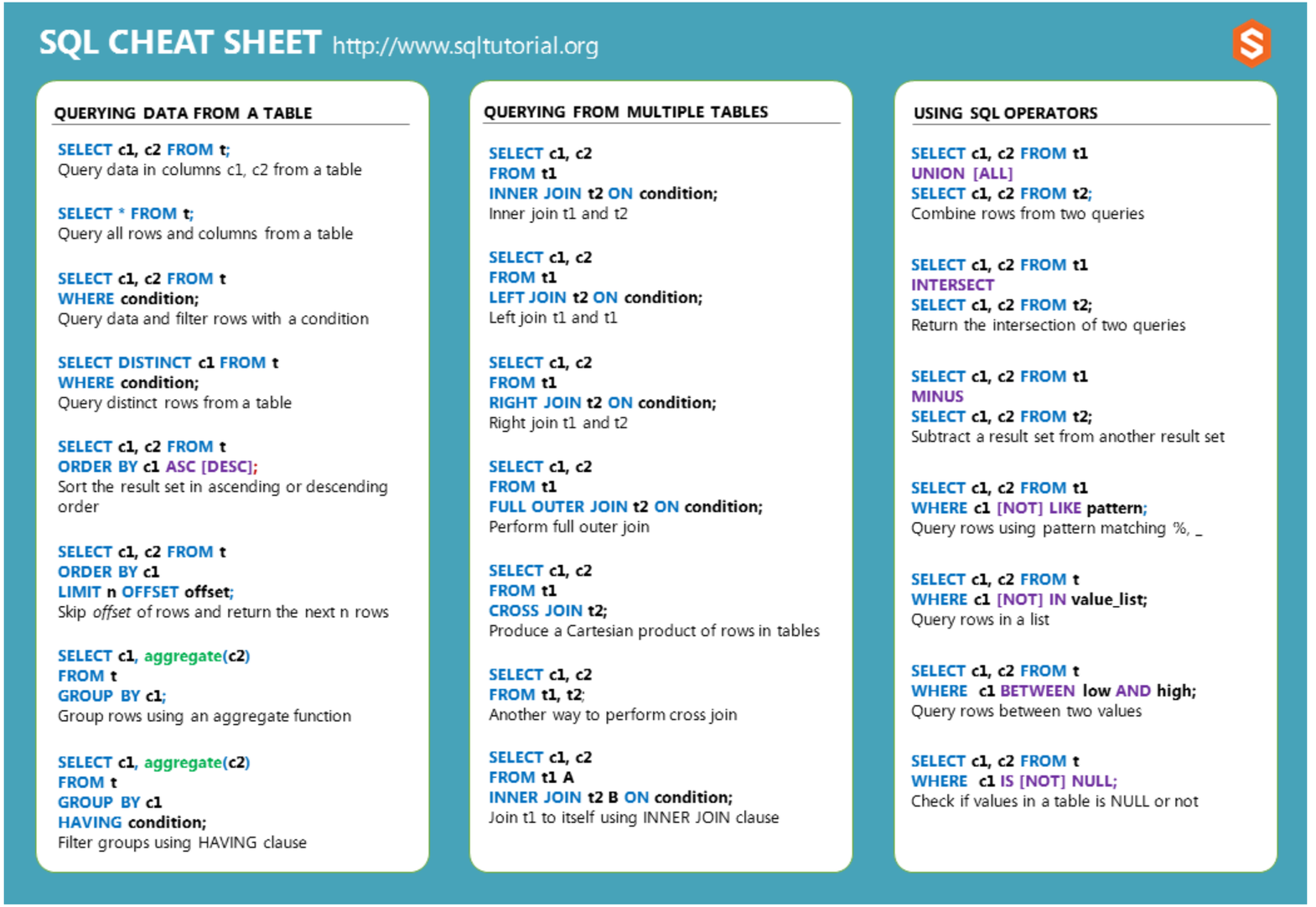
Map-Filter-Reduce pattern: Same simple/powerful idea in MapReduce, Hadoop, Spark, etc.

SQL Cheat Sheet (www.sqltutorial.org/sql-cheat-sheet)



SQL CHEAT SHEET http://www.sqltutorial.org

QUERYING DATA FROM A TABLE

```
SELECT c1, c2 FROM t;
```
Query data in columns c1, c2 from a table

```
SELECT * FROM t;
```
Query all rows and columns from a table

```
SELECT c1, c2 FROM t
WHERE condition;
```
Query data and filter rows with a condition

```
SELECT DISTINCT c1 FROM t
WHERE condition;
```
Query distinct rows from a table

```
SELECT c1, c2 FROM t
ORDER BY c1 ASC [DESC];
```
Sort the result set in ascending or descending order

```
SELECT c1, c2 FROM t
ORDER BY c1
LIMIT n OFFSET offset;
```
Skip *offset* of rows and return the next n rows

```
SELECT c1, aggregate(c2)
FROM t
GROUP BY c1;
```
Group rows using an aggregate function

```
SELECT c1, aggregate(c2)
FROM t
GROUP BY c1
HAVING condition;
```
Filter groups using HAVING clause

QUERYING FROM MULTIPLE TABLES

```
SELECT c1, c2
FROM t1
INNER JOIN t2 ON condition;
```
Inner join t1 and t2

```
SELECT c1, c2
FROM t1
LEFT JOIN t2 ON condition;
```
Left join t1 and t1

```
SELECT c1, c2
FROM t1
RIGHT JOIN t2 ON condition;
```
Right join t1 and t2

```
SELECT c1, c2
FROM t1
FULL OUTER JOIN t2 ON condition;
```
Perform full outer join

```
SELECT c1, c2
FROM t1
CROSS JOIN t2;
```
Produce a Cartesian product of rows in tables

```
SELECT c1, c2
FROM t1, t2;
```
Another way to perform cross join

```
SELECT c1, c2
FROM t1 A
INNER JOIN t2 B ON condition;
```
Join t1 to itself using INNER JOIN clause

USING SQL OPERATORS

```
SELECT c1, c2 FROM t1
UNION [ALL]
SELECT c1, c2 FROM t2;
```
Combine rows from two queries

```
SELECT c1, c2 FROM t1
INTERSECT
SELECT c1, c2 FROM t2;
```
Return the intersection of two queries

```
SELECT c1, c2 FROM t1
MINUS
SELECT c1, c2 FROM t2;
```
Subtract a result set from another result set

```
SELECT c1, c2 FROM t1
WHERE c1 [NOT] LIKE pattern;
```
Query rows using pattern matching %, _

```
SELECT c1, c2 FROM t
WHERE c1 [NOT] IN value_list;
```
Query rows in a list

```
SELECT c1, c2 FROM t
WHERE c1 BETWEEN low AND high;
```
Query rows between two values

```
SELECT c1, c2 FROM t
WHERE c1 IS [NOT] NULL;
```
Check if values in a table is NULL or not

Other data models

Other data models

Key-Value — The simplest model: every piece of data is stored as a key mapped to a value (which can be anything—string, JSON, binary blob). No schema, no relationships. Examples: Redis, DynamoDB, etcd. Great for caching, session storage, and simple lookups where you always know the key.

Document — Stores semi-structured documents (typically JSON or BSON) that can have nested fields and varying structures. Unlike relational tables, each document can have different fields. Examples: MongoDB, CouchDB, Firestore. Good for content management, user profiles, and applications where schema flexibility matters.

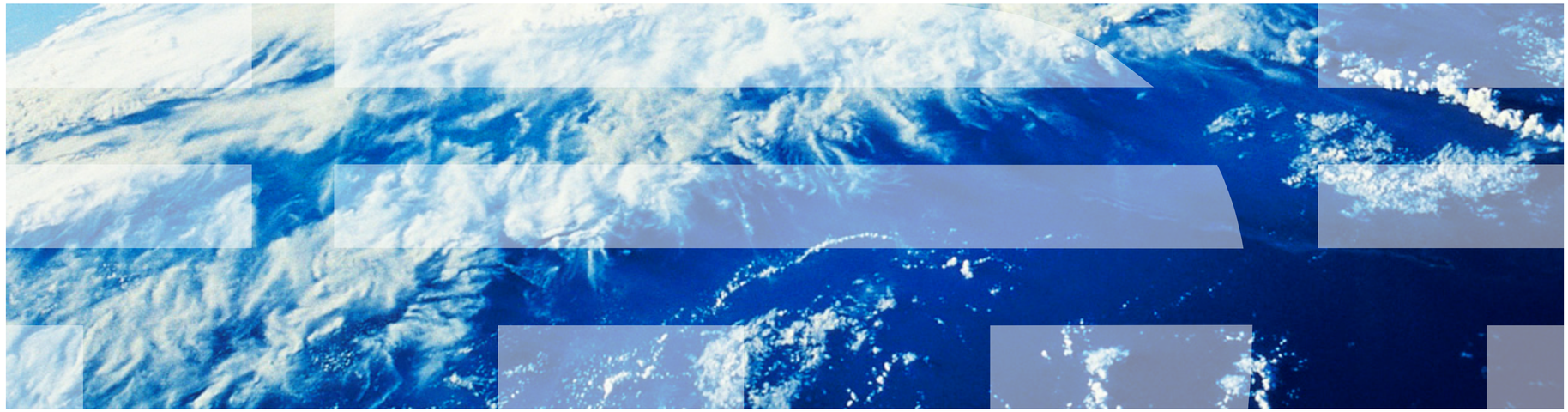
Wide-Column / Column-Family — Data is organized by columns rather than rows, with rows that can have different columns. Optimized for queries over large datasets where you typically read specific columns across many rows. Examples: Cassandra, HBase, Google Bigtable. Common for time-series data, analytics, and write-heavy workloads.

Graph — Models data as nodes (entities) and edges (relationships), with properties on both. Traversing relationships is a first-class operation rather than an expensive join. Examples: Neo4j, Amazon Neptune, TigerGraph. Ideal for social networks, fraud detection, and recommendation engines.

Time-Series — Optimized specifically for timestamped data points, with efficient compression and time-based queries. Examples: InfluxDB, TimescaleDB, Prometheus. Used for metrics, IoT sensor data, and monitoring.

Vector — Stores high-dimensional embeddings and supports similarity search (nearest neighbor queries). Examples: Pinecone, Milvus, pgvector. Essential for AI applications like semantic search and RAG systems.

Intro to SQL



SQL Introduction

- SQL is a standard language for querying and manipulating data

- SQL is a **very high-level** programming language
  - This works because it is optimized well!

SQL stands for
Structured
Query
Language

SQL is a…

- Data Manipulation Language (DML)
  - Query one or more tables
  - Insert/delete/modify tuples in tables

- Data Definition Language (DDL)
  - Define relational schemata
  - Create/alter/delete tables and their attributes

Basic Set Algebra Concepts

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- List: [1, 1, 2, 3] Ordered, duplicates

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- Cross-product:
  - {1, 1, 2, 3} * {y, z} = {1, y}, {1, y}, {2, y}, {3, y}, {1, z}, {1, z}, {2, z}, {3, z}

Tables in SQL

Product

PName	Price	Manuf
Gizmo	$19.99	GizmoWorks
Powergizmo	$29.99	GizmoWorks
SingleTouch	$149.99	Canon
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A **relation** or **table** is a multiset of tuples/rows having the attributes specified by the schema

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An **attribute** (or **column**) is a typed data entry present in each tuple in the relation

*Attributes must have an **atomic** type in standard SQL, i.e. not a list, set, etc.*

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A **tuple** or **row** or **record** is a single entry in the table having the attributes specified by the schema

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The number of tuples is the **cardinality** of the relation

The number of attributes is the **arity** of the relation

Data Types in SQL

Atomic types:

- Characters: CHAR(20), VARCHAR(50)
- Numbers: INT, BIGINT, SMALLINT, FLOAT
- Others: MONEY, DATETIME…

Every attribute must have an atomic type

Table Schemas

Product(Pname: *string*, Price: *float*, Category: *string*, Manufacturer: *string*)

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A **key** is a **minimal subset of attributes** that acts as a unique identifier for tuples in a relation

- A key is an implicit constraint on which tuples can be in the relation
- i.e. if two tuples agree on the values of the key, then they must be the same tuple!

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1. Which would you select as a key?

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Students(cuid:string, name:string, gpa: float)

1. Which would you select as a key?
2. Is a key always guaranteed to exist?

Declaring Schema

Students(cuid: *string,* name: *string,* gpa: *float*)

```
CREATE TABLE Students (
  cuid CHAR(20),
  name  VARCHAR(50),
  gpa  float,
  PRIMARY KEY (cuid),
)
```

NULL and NOT NULL

NULL and NOT NULL

- To say “does not have value,” we use NULL

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143	Jim	NULL

Say, Jim just enrolled in his first class.

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General Constraints

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- We can actually specify arbitrary assertions
  E.g. “*There cannot be 25 people in the DB class*”

- In practice, we don’t specify many such constraints. Why?
  Performance!

Usually we do something ugly (or avoid doing something convenient) for the sake of performance

Summary of Schema Information

- Schema and Constraints are how databases understand the semantics (meaning) of data

- SQL supports general constraints:

  Keys are most important

API Schema

- Translation layer between external clients and internal database schema
- Same logical entity might be represented differently
  - (e.g., database splits User across multiple tables, but API returns a single unified User object)
- API can hide sensitive database details or expose computed/ aggregated data not directly stored
- Database schema can change without breaking the API if the translation layer is updated accordingly

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- Defines the structure of data in transit
  - request/response formats, endpoints, parameters
- Optimized for usability, clarity, and client needs
- External contract - publicly exposed interface that clients depend on
- Uses language-agnostic formats
  - (JSON, XML, Protocol Buffers) with type systems
- Changes must maintain backward compatibility or use versioning

Protocol Buffers

- API Schema definition language
- Provides libraries for convenience
- Comparable to JSON and XML
  - But better!
- Binary on the wire

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```
edition = "2023";

package tutorial;

message Person {
  string name = 1;
  int32 id = 2;
  string email = 3;

  enum PhoneType {
    PHONE_TYPE_UNSPECIFIED = 0;
    PHONE_TYPE_MOBILE = 1;
    PHONE_TYPE_HOME = 2;
    PHONE_TYPE_WORK = 3;
  }

  message PhoneNumber {
    string number = 1;
    PhoneType type = 2;
  }

  repeated PhoneNumber phones = 4;
}

message AddressBook {
  repeated Person people = 1;
}
```

Uber Blog Explore EN Search

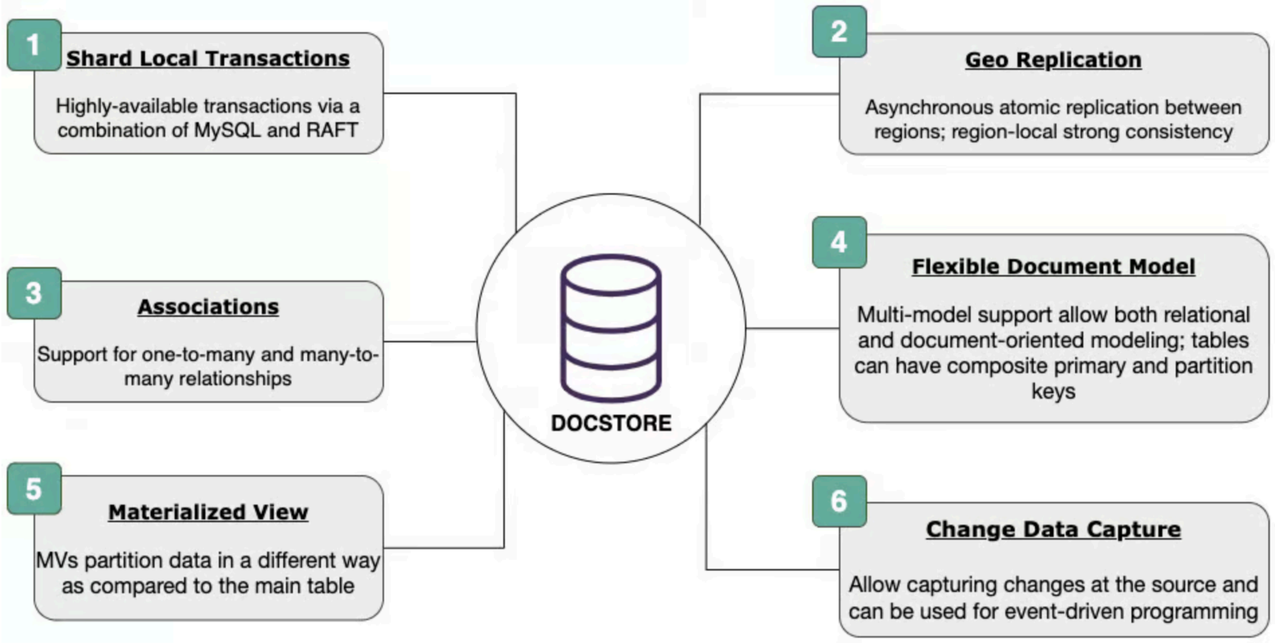
Engineering

Overview Backend Culture Data / ML Mobile Security Uber AI Web

Engineering

Evolving Schemaless into a Distributed SQL Database

February 23, 2021 / Global



- Flexible schema, not no schema!
- Centralizing the complexity of consistency
- Operational reality may not be “beautiful”

https://www.uber.com/blog/schemaless-sql-database/

Uber Blog

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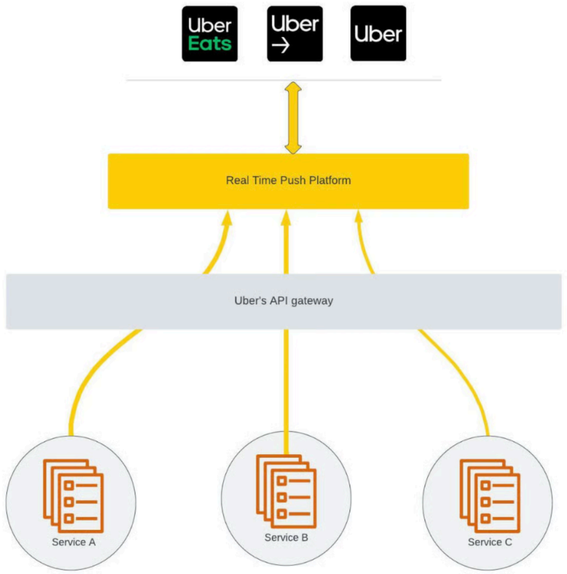
Engineering

Engineering, Backend, Mobile

Uber's Next Gen Push Platform on gRPC

August 16, 2022 / Global



In our last blog post we talked about how we went from polling for refreshing the app to a push-based flow to build our app experience.

- Not request/response but streaming
- From REST-like to RPC-like
- Transport is as important as anything else
- Don't reinvent the wheel

https://www.uber.com/blog/ubers-next-gen-push-platform-on-grpc/