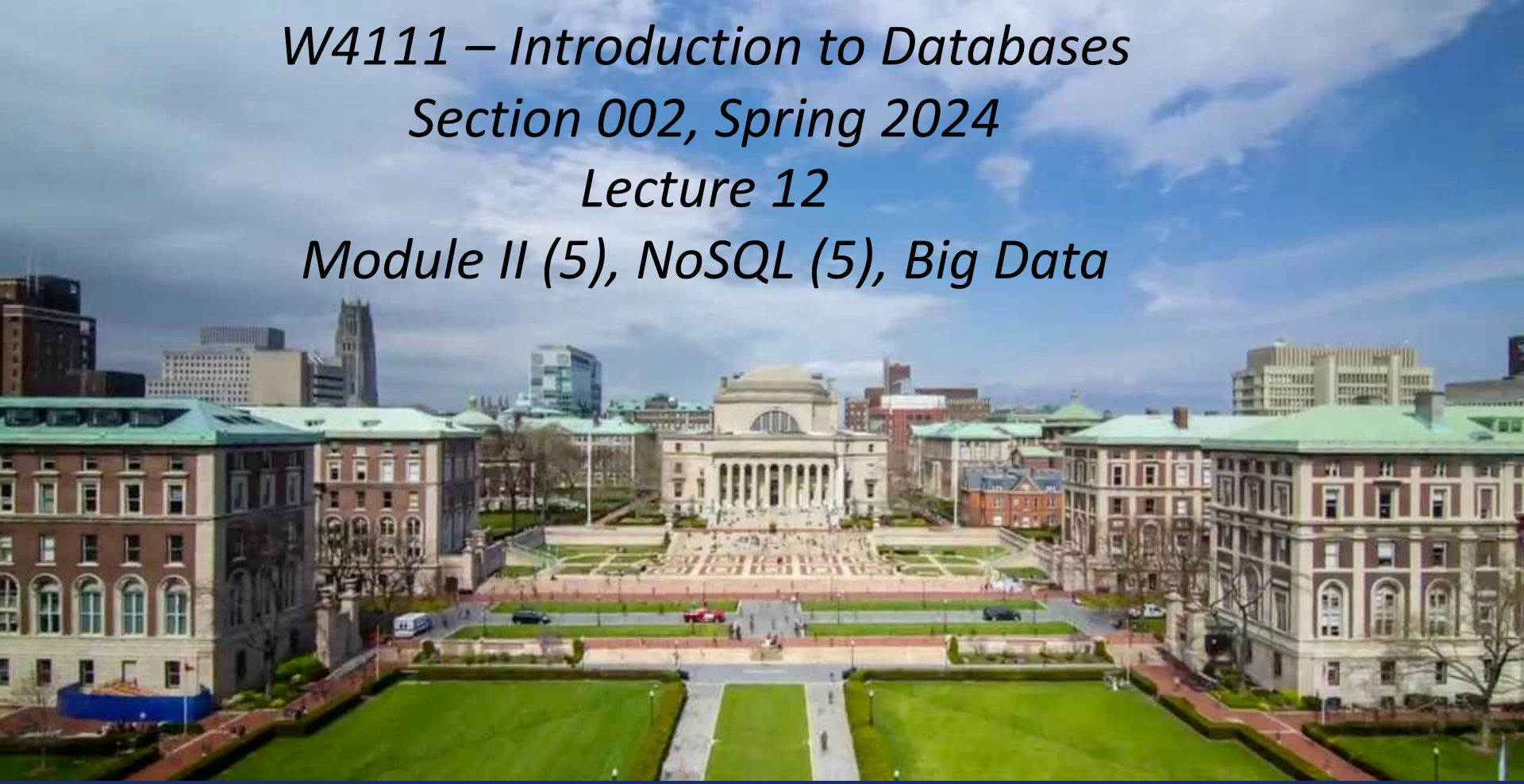
W4111 – Introduction to Databases
Section 002, Spring 2024
Lecture 12
Module II (5), NoSQL (5), Big Data



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W4111 – Introduction to Databases
Section 002, Spring 2024
Lecture 12
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We will start in a couple of minutes.

Reminder

Modules

Each section of W4111 is slightly different based on student interest and professor's focus. There is a common, core syllabus. Professors cover topics in different orders and grouping based on teaching style.

This section of W4111 has four modules:

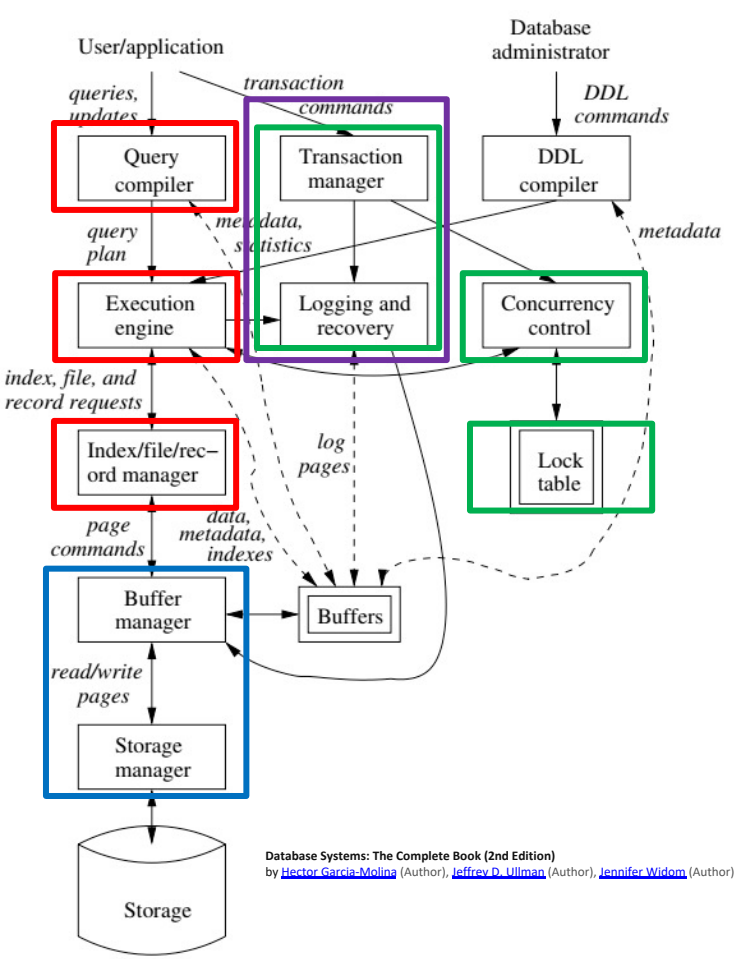
- **Foundational concepts (50% of semester):** This module covers concepts like data models, relational model, relational databases and applications, schema, normalization, … The module focuses on the relational model and relational databases. The concepts are critical and foundational for all types of databases and data centric applications.
- **Database management system architecture and implementation (10%):** This module covers the software architecture, algorithms and implementation techniques that allow databases management systems to deliver functions. Topics include memory hierarchy, storage systems, caching/buffer pools, indexes, query processing, query optimization, transaction processing, isolation and concurrency control.
- **NoSQL – "Not Only SQL" databases (20%):** This module provides motivation for "NoSQL" data models and databases, and covers examples and use cases. The module also includes cloud databases and databases-as-a-service.
- **Data Enabled Decision Support (20%):** This module covers data warehouses, data import and cleanse, OLAP, Pivot Tables, Star Schema, reporting and visualization, and provides and overview of analysis techniques, e.g. clustering, classification, analysis, mining.

Module II, Part 5

Reminder

Transactions

- Find things quickly.
- Load/Save quickly.
- Transactions
- Durability



Locking

Lock-Based Protocols

- A lock is a mechanism to control concurrent access to a data item
- Data items can be locked in two modes :
  1. **exclusive** *(X) mode*. Data item can be both read as well as written. X-lock is requested using **lock-X** instruction.
  2. **shared** *(S) mode*. Data item can only be read. S-lock is requested using **lock-S** instruction.
- Lock requests are made to concurrency-control manager. Transaction can proceed only after request is granted.

Lock-Based Protocols (Cont.)

- **Lock-compatibility matrix**

	S	X
S	true	false
X	false	false

- A transaction may be granted a lock on an item if the requested lock is compatible with locks already held on the item by other transactions
- Any number of transactions can hold shared locks on an item,
- But if any transaction holds an exclusive on the item no other transaction may hold any lock on the item.

Deadlock

- Consider the partial schedule

T_3	T_4
lock-X(B)	
read(B)	
$B := B - 50$	
write(B)	
	lock-S(A)
	read(A)
	lock-S(B)
lock-X(A)	

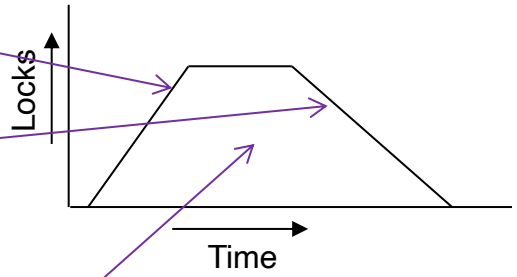
- Neither T_3 nor T_4 can make progress — executing **lock-S**(*B*) causes T_4 to wait for T_3 to release its lock on *B*, while executing **lock-X**(*A*) causes T_3 to wait for T_4 to release its lock on *A*.
- Such a situation is called a **deadlock**.
  - To handle a deadlock one of T_3 or T_4 must be rolled back and its locks released.

Deadlock (Cont.)

- The potential for deadlock exists in most locking protocols. Deadlocks are a necessary evil.
- **Starvation** is also possible if concurrency control manager is badly designed. For example:
  - A transaction may be waiting for an X-lock on an item, while a sequence of other transactions request and are granted an S-lock on the same item.
  - The same transaction is repeatedly rolled back due to deadlocks.
- Concurrency control manager can be designed to prevent starvation.

The Two-Phase Locking Protocol

- A protocol which ensures conflict-serializable schedules.
- Phase 1: **Growing Phase**
  - Transaction may obtain locks
  - Transaction may not release locks
- Phase 2: **Shrinking Phase**
  - Transaction may release locks
  - Transaction may not obtain locks
- The protocol assures serializability. It can be proved that the transactions can be serialized in the order of their **lock points** (i.e., the point where a transaction acquired its final lock).



The Two-Phase Locking Protocol (Cont.)

- Two-phase locking *does not* ensure freedom from deadlocks
- Extensions to basic two-phase locking needed to ensure recoverability of freedom from cascading roll-back
  - **Strict two-phase locking:** a transaction must hold all its exclusive locks till it commits/aborts.
    - Ensures recoverability and avoids cascading roll-backs
  - **Rigorous two-phase locking**: a transaction must hold *all* locks till commit/abort.
    - Transactions can be serialized in the order in which they commit.
- Most databases implement rigorous two-phase locking, *but refer to it as simply two-phase locking*

The Two-Phase Locking Protocol (Cont.)

- Two-phase locking is not a necessary condition for serializability
  - There are conflict serializable schedules that cannot be obtained if the two-phase locking protocol is used.
- In the absence of extra information (e.g., ordering of access to data), two-phase locking is necessary for conflict serializability *in the following sense*:
  - *Given a transaction T_i that does not follow two-phase locking, we can find a transaction T_j that uses two-phase locking, and a schedule for T_i and T_j that is not conflict serializable.*

T_1	T_2
lock-X(B)	
read(B)	
$B := B - 50$	
write(B)	
unlock(B)	
	lock-S(A)
	read(A)
	unlock(A)
	lock-S(B)
	read(B)
	unlock(B)
	display($A + B$)
lock-X(A)	
read(A)	
$A := A + 50$	
write(A)	
unlock(A)	

Locking Protocols

- Given a locking protocol (such as 2PL)
  - A schedule S is **legal** under a locking protocol if it can be generated by a set of transactions that follow the protocol
  - A protocol **ensures** serializability if all legal schedules under that protocol are serializable

Lock Conversions

- Two-phase locking protocol with lock conversions:
  - Growing Phase:
    - can acquire a lock-S on item
    - can acquire a lock-X on item
    - can **convert** a lock-S to a lock-X (**upgrade**)
  - Shrinking Phase:
    - can release a lock-S
    - can release a lock-X
    - can convert a lock-X to a lock-S (**downgrade**)
- This protocol ensures serializability

Automatic Acquisition of Locks

- A transaction T_i issues the standard read/write instruction, without explicit locking calls.
- The operation **read**(D) is processed as:

```
if Ti has a lock on D
then
    read(D)
else begin
    if necessary wait until no other
        transaction has a lock-X on D
    grant Ti a lock-S on D;
    read(D)
end
```

Automatic Acquisition of Locks (Cont.)

- The operation **write**(*D*) is processed as:

```
if Ti has a lock-X on D
  then
    write(D)
  else begin
      if necessary wait until no other trans. has any lock on D,
      if Ti has a lock-S on D
          then
              upgrade lock on D to lock-X
          else
              grant Ti a lock-X on D
          write(D)
    end;
```

- **All locks are released after commit or abort**

Implementation of Locking

- A **lock manager** can be implemented as a separate process
- Transactions can send lock and unlock requests as messages
- The lock manager replies to a lock request by sending a lock grant messages (or a message asking the transaction to roll back, in case of a deadlock)
  - The requesting transaction waits until its request is answered
- The lock manager maintains an in-memory data-structure called a **lock table** to record granted locks and pending requests

Deadlock Handling

- System is **deadlocked** if there is a set of transactions such that every transaction in the set is waiting for another transaction in the set.

T_3	T_4
lock-X(B)	
read(B)	
$B := B - 50$	
write(B)	
	lock-S(A)
	read(A)
	lock-S(B)
lock-X(A)	

Deadlock Handling

- ***Deadlock prevention*** protocols ensure that the system will *never* enter into a deadlock state. Some prevention strategies:
  - Require that each transaction locks all its data items before it begins execution (pre-declaration).
  - Impose partial ordering of all data items and require that a transaction can lock data items only in the order specified by the partial order (graph-based protocol).

More Deadlock Prevention Strategies

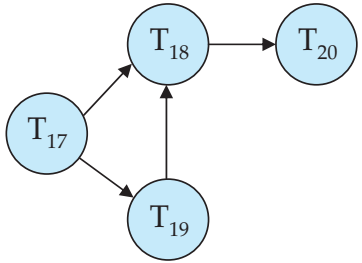
- **wait-die** scheme — non-preemptive
  - Older transaction may wait for younger one to release data item.
  - Younger transactions never wait for older ones; they are rolled back instead.
  - A transaction may die several times before acquiring a lock
- **wound-wait** scheme — preemptive
  - Older transaction *wounds* (forces rollback) of younger transaction instead of waiting for it.
  - Younger transactions may wait for older ones.
  - Fewer rollbacks than *wait-die* scheme.
- In both schemes, a rolled back transactions is restarted with its original timestamp.
  - Ensures that older transactions have precedence over newer ones, and starvation is thus avoided.

Deadlock prevention (Cont.)

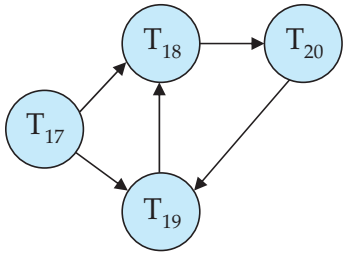
- **Timeout-Based Schemes**:
  - A transaction waits for a lock only for a specified amount of time. After that, the wait times out and the transaction is rolled back.
  - Ensures that deadlocks get resolved by timeout if they occur
  - Simple to implement
  - But may roll back transaction unnecessarily in absence of deadlock
    - Difficult to determine good value of the timeout interval.
  - Starvation is also possible

Deadlock Detection

- **Wait-for graph**
  - *Vertices:* transactions
  - *Edge from* $T_i \rightarrow T_j$. : if T_i is waiting for a lock held in conflicting mode by T_j
- The system is in a deadlock state if and only if the wait-for graph has a cycle.
- Invoke a deadlock-detection algorithm periodically to look for cycles.



Wait-for graph without a cycle



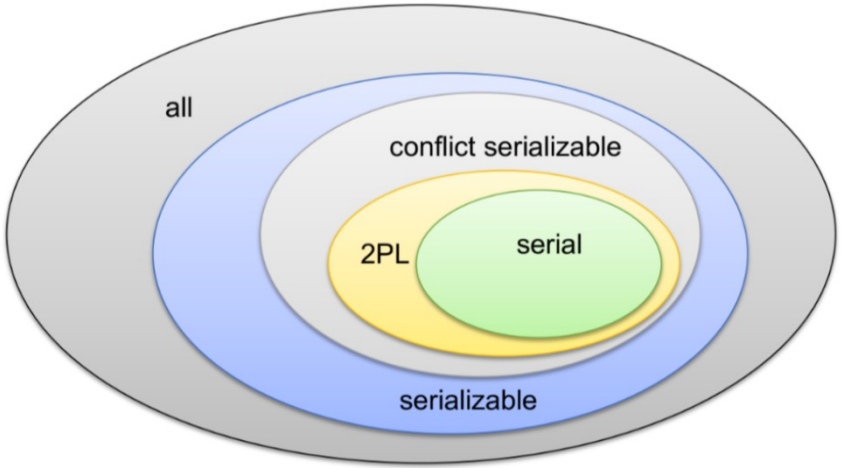
Wait-for graph with a cycle

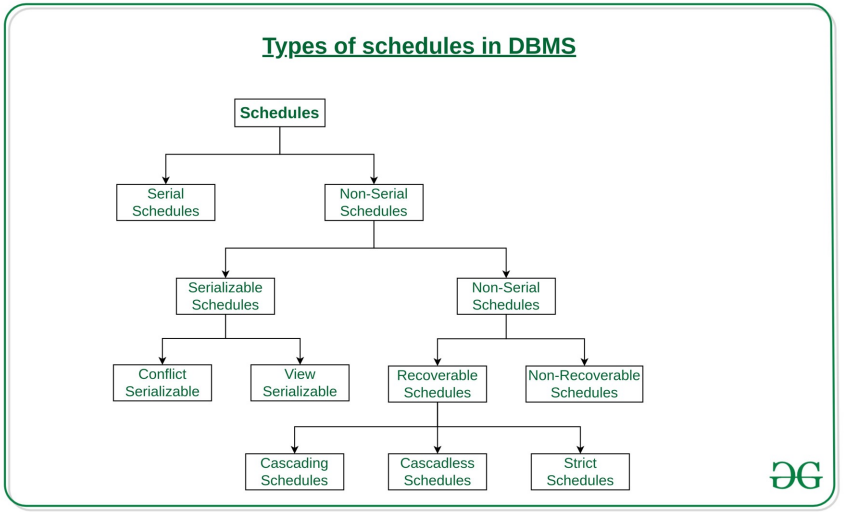
Deadlock Recovery

- When deadlock is detected :
  - Some transaction will have to rolled back (made a **victim**) to break deadlock cycle.
    - Select that transaction as victim that will incur minimum cost
  - Rollback -- determine how far to roll back transaction
    - **Total rollback**: Abort the transaction and then restart it.
    - **Partial rollback**: Roll back victim transaction only as far as necessary to release locks that another transaction in cycle is waiting for
- Starvation can happen (why?)
  - One solution: oldest transaction in the deadlock set is never chosen as victim

Schedules, Serializable

Schedules and Serializable





- We covered serial schedules, 2PL and serializable in the previous lecture.
- The types of schedules are much more complex.
- There are also forms of conflict management and lock types other than R/W.
- We will talk a little bit about them for awareness.
- These are academically interesting but do not come up in practice.

Serializability

- **Basic Assumption** – Each transaction preserves database consistency.
- Thus, serial execution of a set of transactions preserves database consistency.
- A (possibly concurrent) schedule is serializable if it is equivalent to a serial schedule. Different forms of schedule equivalence give rise to the notions of:
  1. **Conflict serializability**
  2. **View serializability**

Simplified view of transactions

- We ignore operations other than **read** and **write** instructions
- We assume that transactions may perform arbitrary computations on data in local buffers in between reads and writes.
- Our simplified schedules consist of only **read** and **write** instructions.

Conflicting Instructions

- Instructions I_i and I_j of transactions T_i and T_j respectively, **conflict** if and only if there exists some item Q accessed by both I_i and I_j, and at least one of these instructions wrote Q.
  1. I_i = **read**(Q), I_j = **read**(Q). I_i and I_j don't conflict.
  2. I_i = **read**(Q), I_j = **write**(Q). They conflict.
  3. I_i = **write**(Q), I_j = **read**(Q). They conflict
  4. I_i = **write**(Q), I_j = **write**(Q). They conflict
- Intuitively, a conflict between I_i and I_j forces a (logical) temporal order between them.
- If I_i and I_j are consecutive in a schedule and they do not conflict, their results would remain the same even if they had been interchanged in the schedule.

Conflict Serializability

- If a schedule *S* can be transformed into a schedule *S'* by a series of swaps of non-conflicting instructions, we say that *S* and *S'* are **conflict equivalent**.
- We say that a schedule *S* is **conflict serializable** if it is conflict equivalent to a serial schedule

Conflict Serializability (Cont.)

- Schedule 3 can be transformed into Schedule 6, a serial schedule where T_2 follows T_1, by series of swaps of non-conflicting instructions. Therefore Schedule 3 is conflict serializable.

T_1	T_2
read (A)	
write (A)	
	read (A)
	write (A)
read (B)	
write (B)	
	read (B)
	write (B)

Schedule 3

T_1	T_2
read (A)	
write (A)	
read (B)	
write (B)	
	read (A)
	write (A)
	read (B)
	write (B)

Schedule 6

Conflict Serializability (Cont.)

- Example of a schedule that is not conflict serializable:

T_3	T_4
read (Q)	
	write (Q)
write (Q)	

- We are unable to swap instructions in the above schedule to obtain either the serial schedule < T_3, T_4 >, or the serial schedule < T_4, T_3 >.

View Serializability

- Let S and S' be two schedules with the same set of transactions. S and S' are **view equivalent** if the following three conditions are met, for each data item Q,
  1. If in schedule S, transaction T_i reads the initial value of Q, then in schedule S' also transaction T_i must read the initial value of Q.
  2. If in schedule S transaction T_i executes **read**(Q), and that value was produced by transaction T_j (if any), then in schedule S' also transaction T_i must read the value of Q that was produced by the same **write**(Q) operation of transaction T_j .
  3. The transaction (if any) that performs the final **write**(Q) operation in schedule S must also perform the final **write**(Q) operation in schedule S'.
- As can be seen, view equivalence is also based purely on **reads** and **writes** alone.

View Serializability (Cont.)

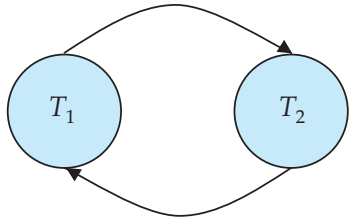
- A schedule S is **view serializable** if it is view equivalent to a serial schedule.
- Every conflict serializable schedule is also view serializable.
- Below is a schedule which is view-serializable but *not* conflict serializable.

T_{27}	T_{28}	T_{29}
read (Q)		
	write (Q)	
write (Q)		
		write (Q)

- What serial schedule is above equivalent to?
- Every view serializable schedule that is not conflict serializable has **blind writes**.

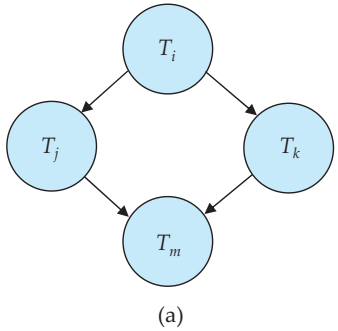
Testing for Serializability

- Consider some schedule of a set of transactions T_1, T_2, ..., T_n
- **Precedence graph** — a direct graph where the vertices are the transactions (names).
- We draw an arc from T_i to T_j if the two transaction conflict, and T_i accessed the data item on which the conflict arose earlier.
- We may label the arc by the item that was accessed.
- Example of a precedence graph

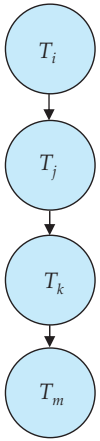


Test for Conflict Serializability

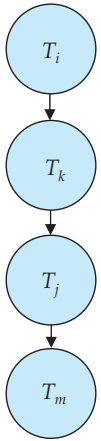
- A schedule is conflict serializable if and only if its precedence graph is acyclic.
- Cycle-detection algorithms exist which take order n^2 time, where n is the number of vertices in the graph.
  - (Better algorithms take order $n + e$ where e is the number of edges.)
- If precedence graph is acyclic, the serializability order can be obtained by a *topological sorting* of the graph.
  - This is a linear order consistent with the partial order of the graph.
  - For example, a serializability order for Schedule A would be
    $T_5 \rightarrow T_1 \rightarrow T_3 \rightarrow T_2 \rightarrow T_4$
    - Are there others?



(a)



(b)



(c)

Recoverable Schedules

Need to address the effect of transaction failures on concurrently running transactions.

- **Recoverable schedule** — if a transaction T_j reads a data item previously written by a transaction T_i, then the commit operation of T_i appears before the commit operation of T_j.
- The following schedule (Schedule 11) is not recoverable

T_8	T_9
read (A)	
write (A)	
	read (A)
	commit
read (B)	

- If T_8 should abort, T_9 would have read (and possibly shown to the user) an inconsistent database state. Hence, database must ensure that schedules are recoverable.

Cascading Rollbacks

- **Cascading rollback** – a single transaction failure leads to a series of transaction rollbacks. Consider the following schedule where none of the transactions has yet committed (so the schedule is recoverable)

T_{10}	T_{11}	T_{12}
read (A)		
read (B)		
write (A)		
	read (A)	
	write (A)	
		read (A)
abort		

If T_{10} fails, T_{11} and T_{12} must also be rolled back.

- Can lead to the undoing of a significant amount of work

Concurrency Control vs. Serializability Tests

- Concurrency-control protocols allow concurrent schedules, but ensure that the schedules are conflict/view serializable, and are recoverable and cascadeless .
- Concurrency control protocols (generally) do not examine the precedence graph as it is being created
  - Instead a protocol imposes a discipline that avoids non-serializable schedules.
  - We study such protocols in Chapter 16.
- Different concurrency control protocols provide different tradeoffs between the amount of concurrency they allow and the amount of overhead that they incur.
- Tests for serializability help us understand why a concurrency control protocol is correct.

Weak Levels of Consistency

- Some applications are willing to live with weak levels of consistency, allowing schedules that are not serializable
  - E.g., a read-only transaction that wants to get an approximate total balance of all accounts
  - E.g., database statistics computed for query optimization can be approximate (why?)
  - Such transactions need not be serializable with respect to other transactions
- Tradeoff accuracy for performance

Levels of Consistency in SQL-92

- **Serializable** — default
- **Repeatable read** — only committed records to be read.
  - Repeated reads of same record must return same value.
  - However, a transaction may not be serializable – it may find some records inserted by a transaction but not find others.
- **Read committed** — only committed records can be read.
  - Successive reads of record may return different (but committed) values.
- **Read uncommitted** — even uncommitted records may be read.

ACID, CAP, BASE

BASE

Eventually-consistent services are often classified as providing BASE (Basically Available, Soft state, Eventual consistency) semantics, in contrast to traditional ACID (Atomicity, Consistency, Isolation, Durability) guarantees. Rough definitions of each term in BASE:

- **Basically Available**: basic reading and writing operations are available as much as possible (using all nodes of a database cluster), but without any kind of consistency guarantees (the write may not persist after conflicts are reconciled, the read may not get the latest write)
- **Soft state**: without consistency guarantees, after some amount of time, we only have some probability of knowing the state, since it may not yet have converged
- **Eventually consistent**: If the system is functioning and we wait long enough after any given set of inputs, we will eventually be able to know what the state of the database is, and so any further reads will be consistent with our expectations

ACID – BASE (Simplistic Comparison)

ACID (relational)	BASE (NoSQL)
Strong consistency	Weak consistency
Isolation	Last write wins (Or other strategy)
Transaction	Program managed
Robust database	Simple database
Simple code (SQL)	Complex code
Available and consistent	Available and partition-tolerant
Scale-up (limited)	Scale-out (unlimited)
Shared (disk, mem, proc etc.)	Nothing shared (parallellizable)

CAP Theorem

- Consistency

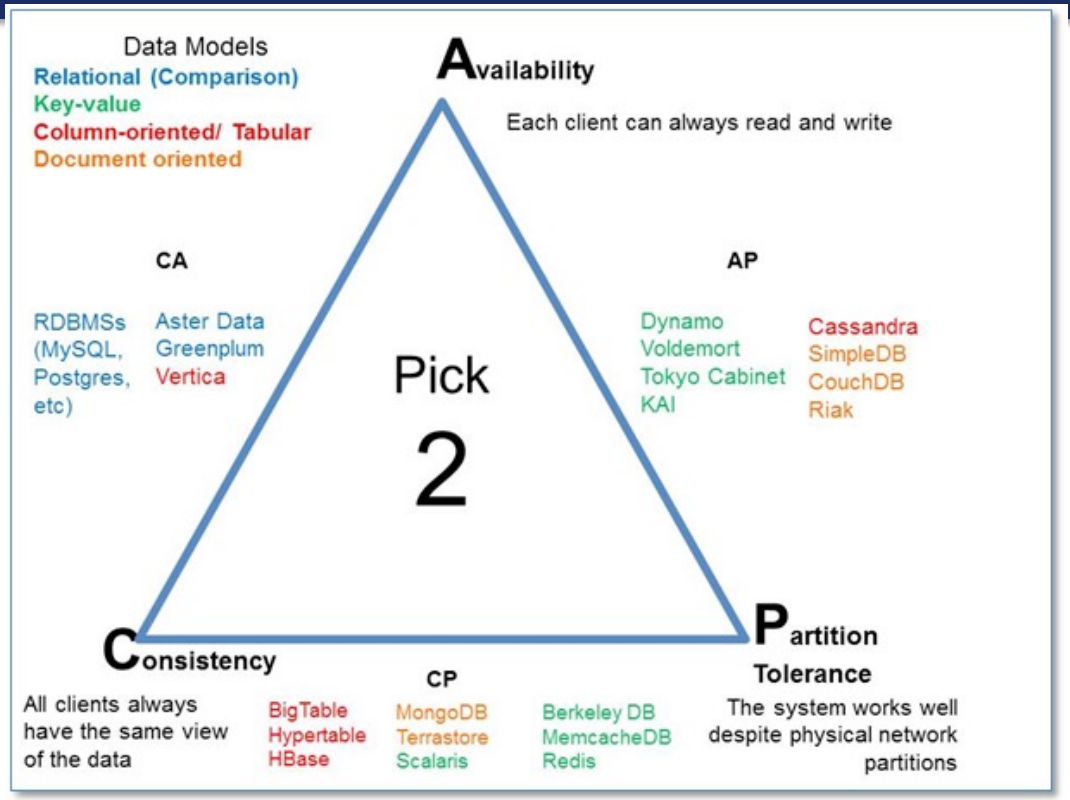
  Every read receives the most recent write or an error.

- Availability

  Every request receives a (non-error) response – without guarantee that it contains the most recent write.

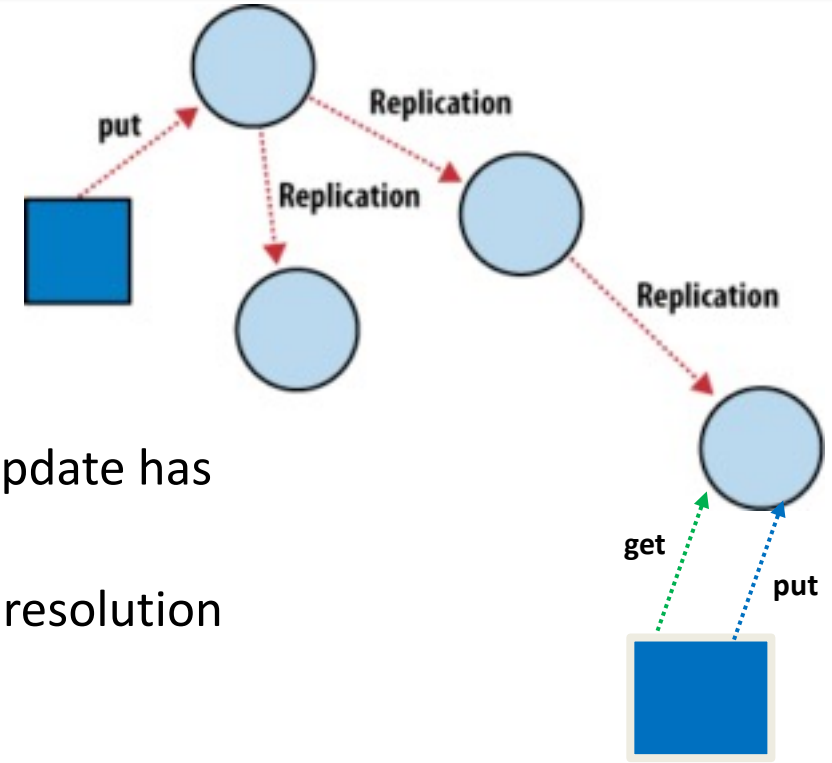
- Partition Tolerance

  The system continues to operate despite an arbitrary number of messages being dropped (or delayed) by the network between nodes



Eventual Consistency

- Availability and scalability via
  - Multiple, replicated data stores.
  - Read goes to “any” replica.
  - PUT/POST/DELETE
    - Goes to any replica
    - Change propagate asynchronously
- GET may not see the latest value if the update has not propagated to the replica.
- There are several algorithms for conflict resolution
  - Detect and handle in application.
  - Clock/change vectors/version numbers
  - … …



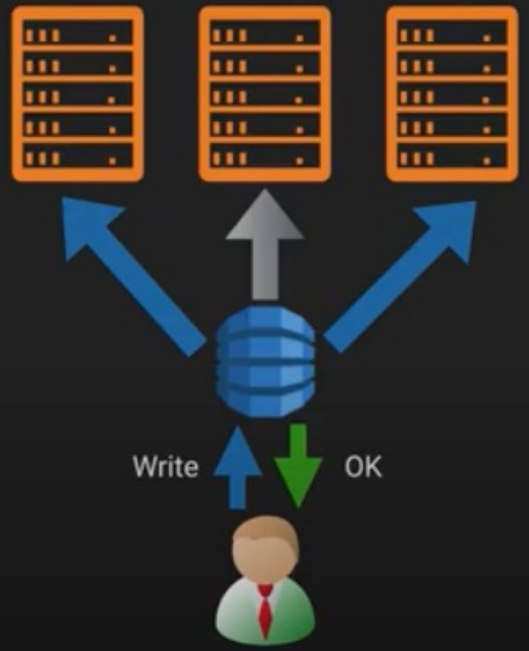
DynamoDB Model

DynamoDB Basics

DynamoDB Consistency Model

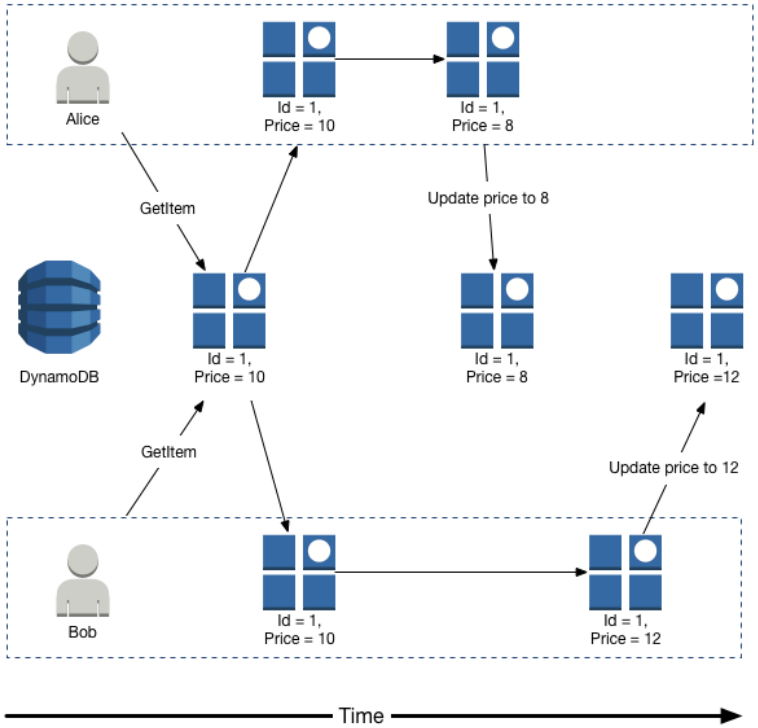
A CLOUD GURU

- **SSD** Storage
- Consistent, reliable **low latency** reads and writes
- Every data block is stored **three times**
- Data write requested
- **OK** (**200**) Received
- Background Full Sync occurs

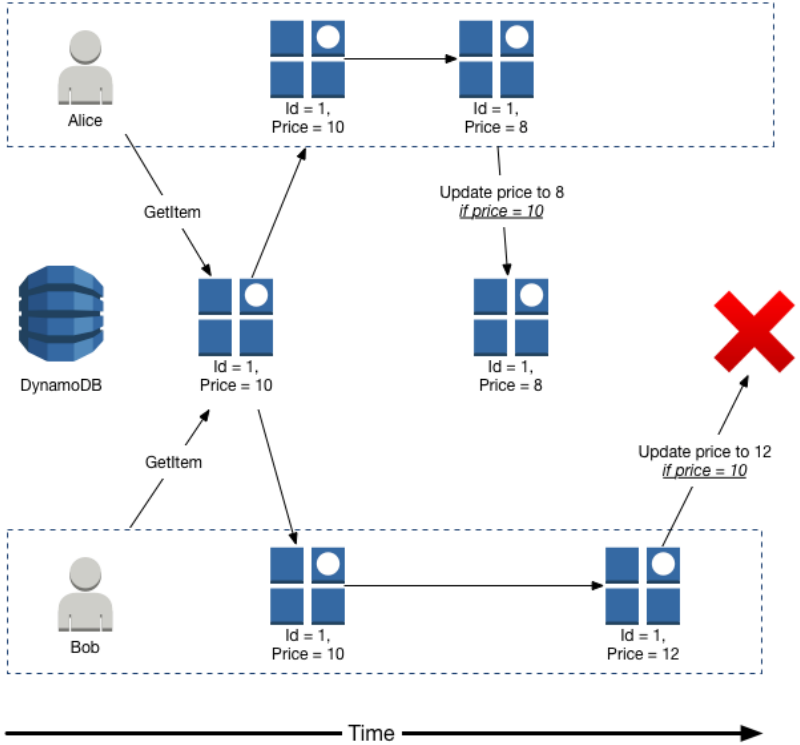


DynamoDB Conditional Writes

Write-Write Conflict: Lost Update



Write-Write Conflict: Fail and Retry



DynamoDB Update Expression

```python
def add_response(table_name, comment_id, commenter_email, response):
    table = dynamodb.Table(table_name)
    Key={
        "comment_id": comment_id
    }
    dt = time.time()
    dts = time.strftime('%Y-%m-%d %H:%M:%S', time.gmtime(dt))

    full_rsp = {
        "email": commenter_email,
        "datetime": dts,
        "response": response,
        "response_id": str(uuid.uuid4()),
        "version_id": str(uuid.uuid4())
    }
    UpdateExpression="SET responses = list_append(responses, :i)"
    ExpressionAttributeValues={
        ':i': [full_rsp]
    }
    ReturnValues="UPDATED_NEW"

    res = table.update_item(
        Key=Key,
        UpdateExpression=UpdateExpression,
        ExpressionAttributeValues=ExpressionAttributeValues,
        ReturnValues=ReturnValues
    )

    return res
```

- Increased concurrency is possible with more flexible operations.
- CRUD requires READ and then UPDATE
- Some datatypes and database support more flexible operations:
  - Add to list
  - Add/subtract from a number
  - etc.
- In many cases these operations do not conflict, and is more flexible than X-locks.

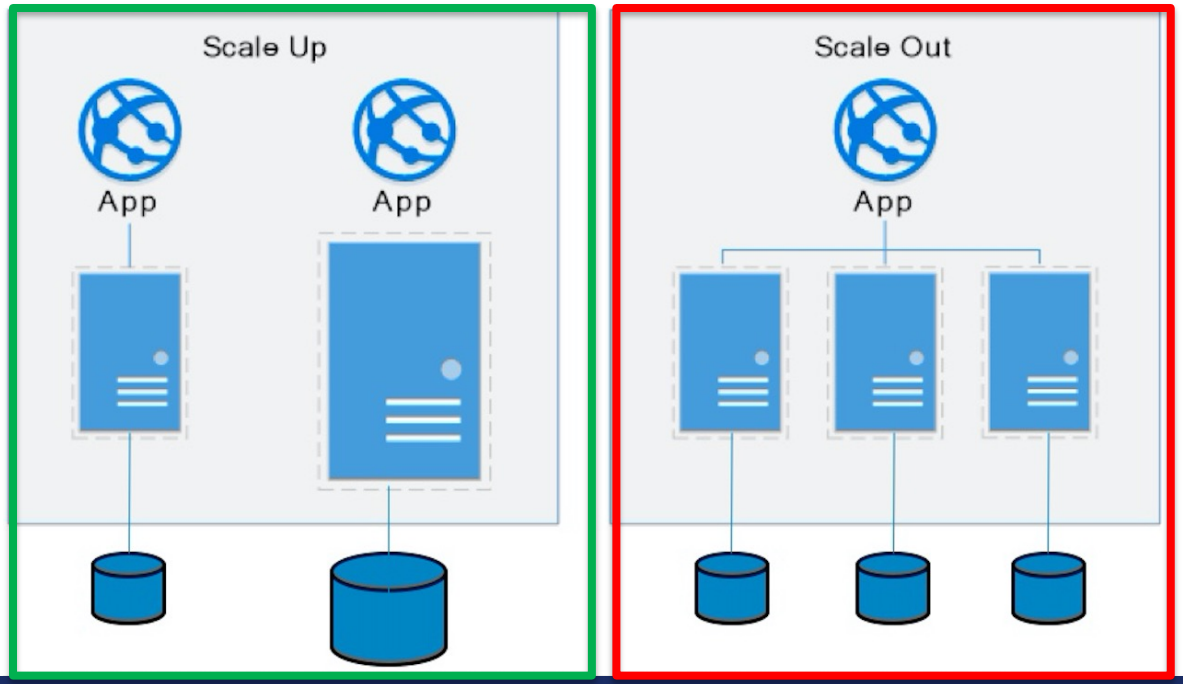
Scalability
Availability

Approaches to Scalability

Scalability is the property of a system to handle a growing amount of work by adding resources to the system.

Replace system with a bigger machine,
e.g. more memory, CPU, ...

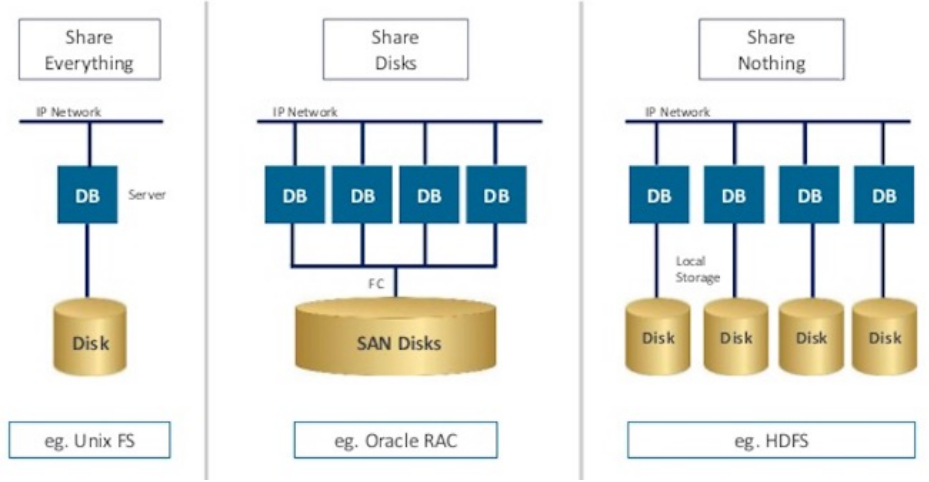
Add another system.



- Scale-up:
  - Less incremental.
  - More disruptive.
  - More expensive for extremely large systems.
  - Does not improve availability
- Scale-out:
  - Incremental cost.
  - Data replication enables availability.
  - Does not work well for functions like JOIN, referential integrity, ...

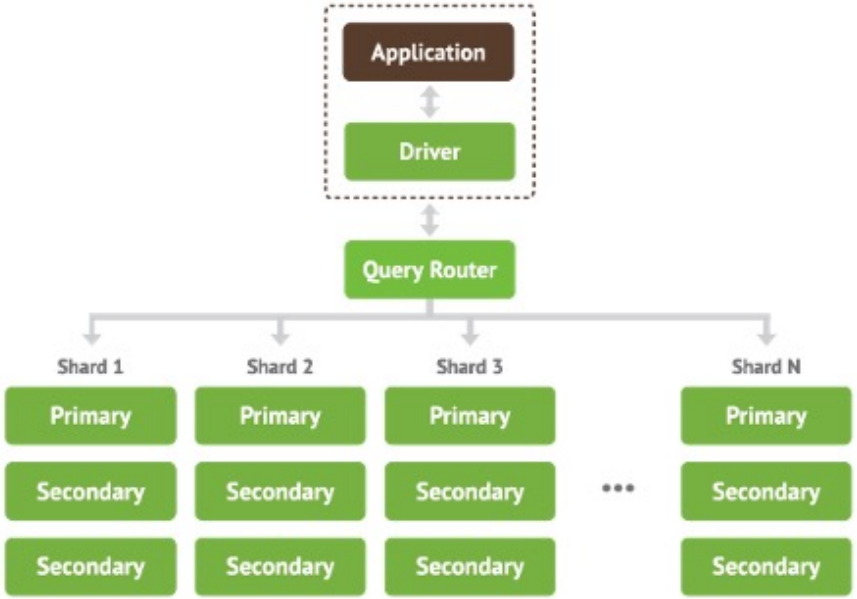
Disk Architecture for Scale-Out

- Share disks:
  - Is basically scale-up for data/disks. You can use NAS, SAN and RAID.
  - Isolation/Integrity requires distributed locking to control access from multiple database servers.
- Share nothing:
  - Is basically scale-out for disks.
  - Data is partitioned into *shards* based on a function f() applied to a key.
  - Can improve availability, at the code consistency, with data replication.
  - There is a router that sends requests to the proper shard based on the function.

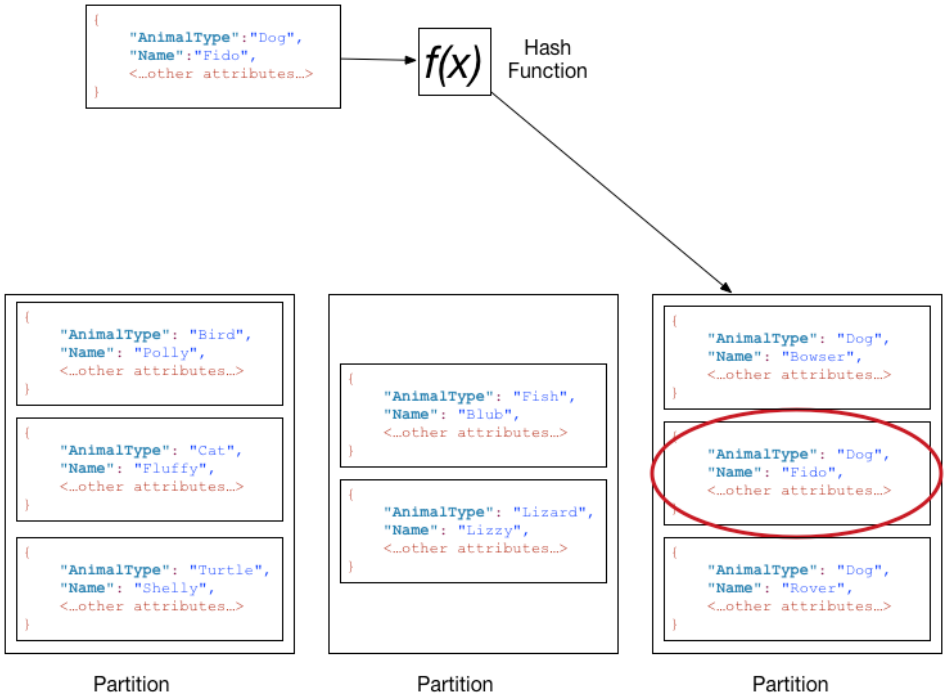


Shared Nothing, Scale-Out

MongoDB Sharding



DynamoDB Partitioning



Data Enablement
Decision Support

Overview

Overview

- **Data analytics**: the processing of data to infer patterns, correlations, or models for prediction
- Primarily used to make business decisions
  - Per individual customer
    - E.g., what product to suggest for purchase
  - Across all customers
    - E.g., what products to manufacture/stock, in what quantity
- Critical for businesses today

Overview (Cont.)

- Common steps in data analytics
  - Gather data from multiple sources into one location
    - Data warehouses also integrated data into common schema
    - Data often needs to be **extracted** from source formats, **transformed** to common schema, and **loaded** into the data warehouse
      - Can be done as **ETL (extract-transform-load)**, or **ELT (extract-load-transform)**
  - Generate aggregates and reports summarizing data
    - Dashboards showing graphical charts/reports
    - **Online analytical processing (OLAP) systems** allow interactive querying
    - Statistical analysis using tools such as R/SAS/SPSS
      - Including extensions for parallel processing of big data
  - Build **predictive models** and use the models for decision making

Overview (Cont.)

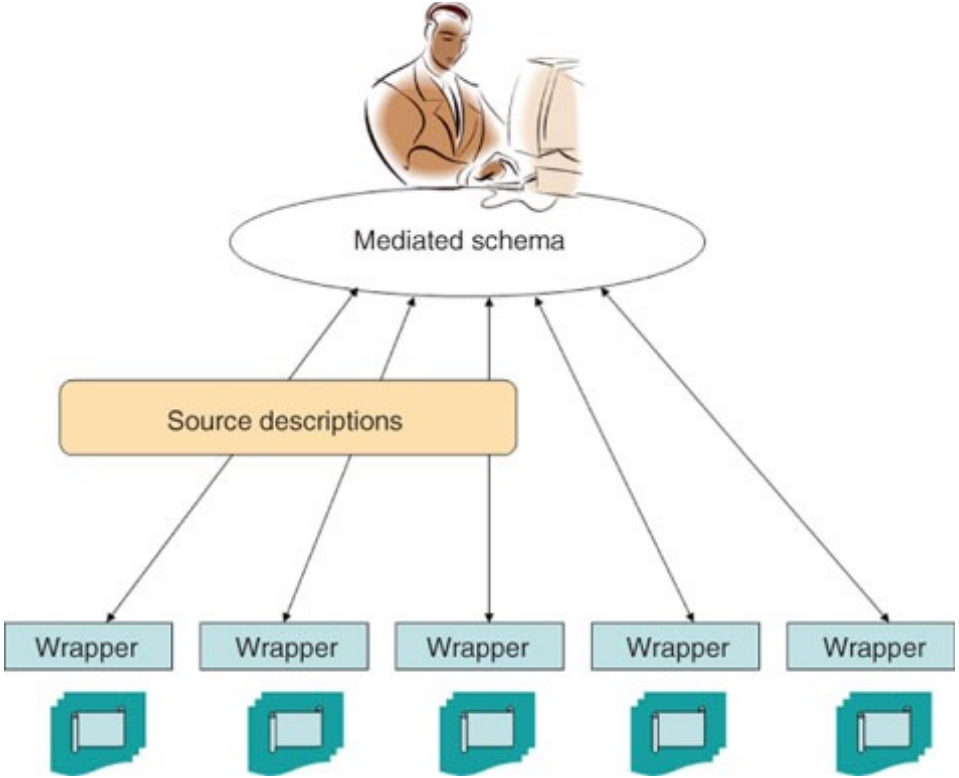
- Predictive models are widely used today
  - E.g., use customer profile features (e.g. income, age, gender, education, employment) and past history of a customer to predict likelihood of default on loan
    - and use prediction to make loan decision
  - E.g., use past history of sales (by season) to predict future sales
    - And use it to decide what/how much to produce/stock
    - And to target customers
- Other examples of business decisions:
  - What items to stock?
  - What insurance premium to change?
  - To whom to send advertisements?

Overview (Cont.)

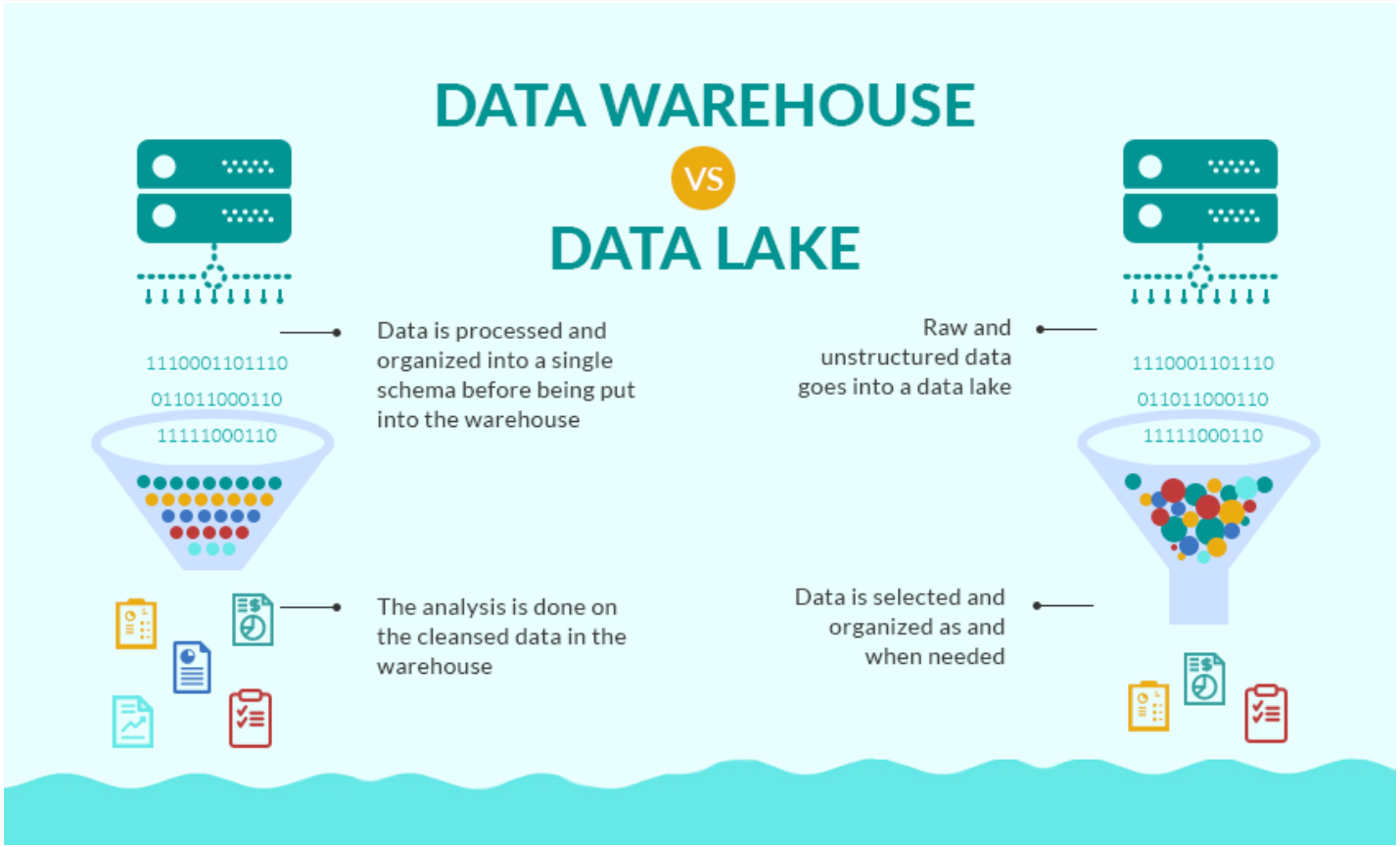
- **Machine learning** techniques are key to finding patterns in data and making predictions
- **Data mining** extends techniques developed by machine-learning communities to run them on very large datasets
- The term **business intelligence (BI)** is synonym for data analytics
- The term **decision support** focuses on reporting and aggregation

Enterprise Information Integration
ETL
Data Warehouse, Data Lake

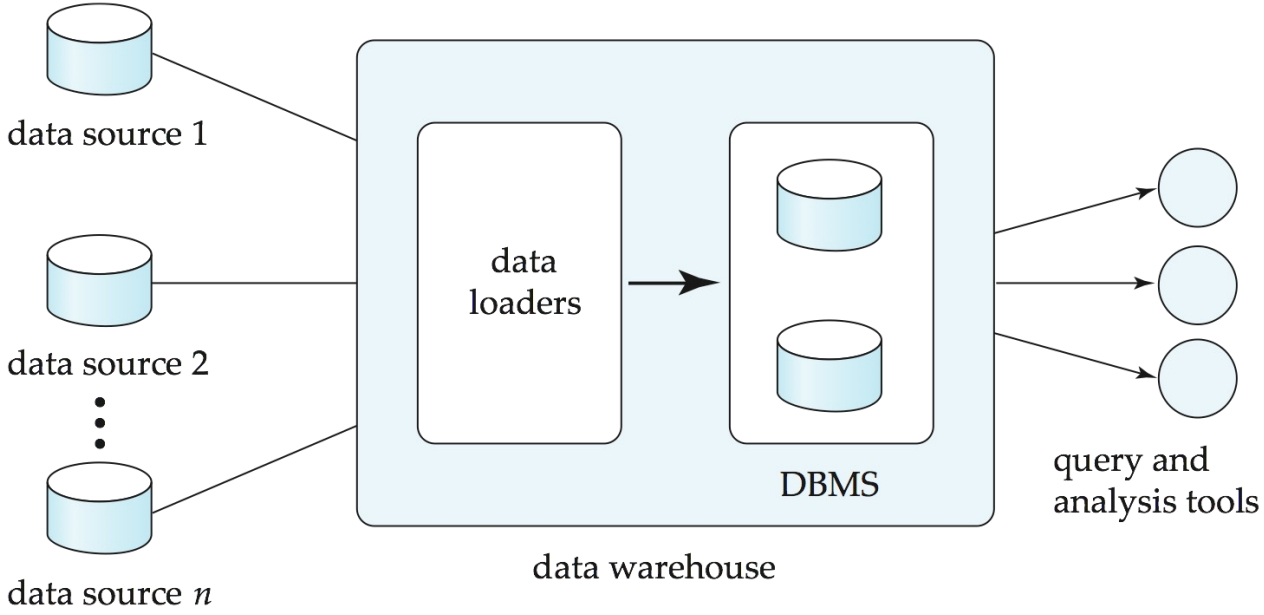
Enterprise Information Integration



Data Warehouse and Data Lake



Data Warehousing



Overview (Cont.)

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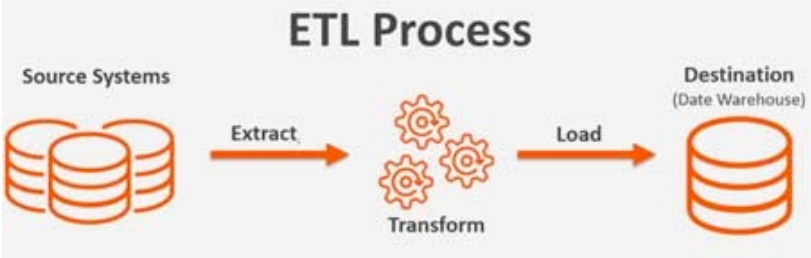
ETL Concepts

https://databricks.com/glossary/extract-transform-load



Extract

The first step of this process is extracting data from the target sources that could include an ERP, CRM, Streaming sources, and other enterprise systems as well as data from third-party sources. There are different ways to perform the extraction: **Three Data Extraction methods:**

1. Partial Extraction – The easiest way to obtain the data is if the if the source system notifies you when a record has been changed
2. Partial Extraction- with update notification - Not all systems can provide a notification in case an update has taken place; however, they can point those records that have been changed and provide an extract of such records.
3. Full extract – There are certain systems that cannot identify which data has been changed at all. In this case, a full extract is the only possibility to extract the data out of the system. This method requires having a copy of the last extract in the same format so you can identify the changes that have been made.

Transform

Next, the transform function converts the raw data that has been extracted from the source server. As it cannot be used in its original form in this stage it gets cleansed, mapped and transformed, often to a specific data schema, so it will meet operational needs. This process entails several transformation types that ensure the quality and integrity of data; below are the most common as well as advanced transformation types that prepare data for analysis:

- Basic transformations:
- Cleaning
- Format revision
- Data threshold validation checks
- Restructuring
- Deduplication
- Advanced transformations:
- Filtering
- Merging
- Splitting
- Derivation
- Summarization
- Integration
- Aggregation
- Complex data validation

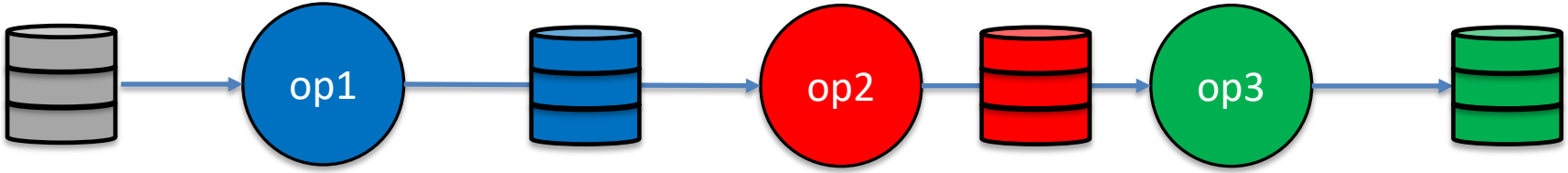
Load

Finally, the load function s is the process of writing converted data from a staging area to a target database, which may or may not have previously existed. Depending on the requirements of the application, this process may be either quite simple or intricate.

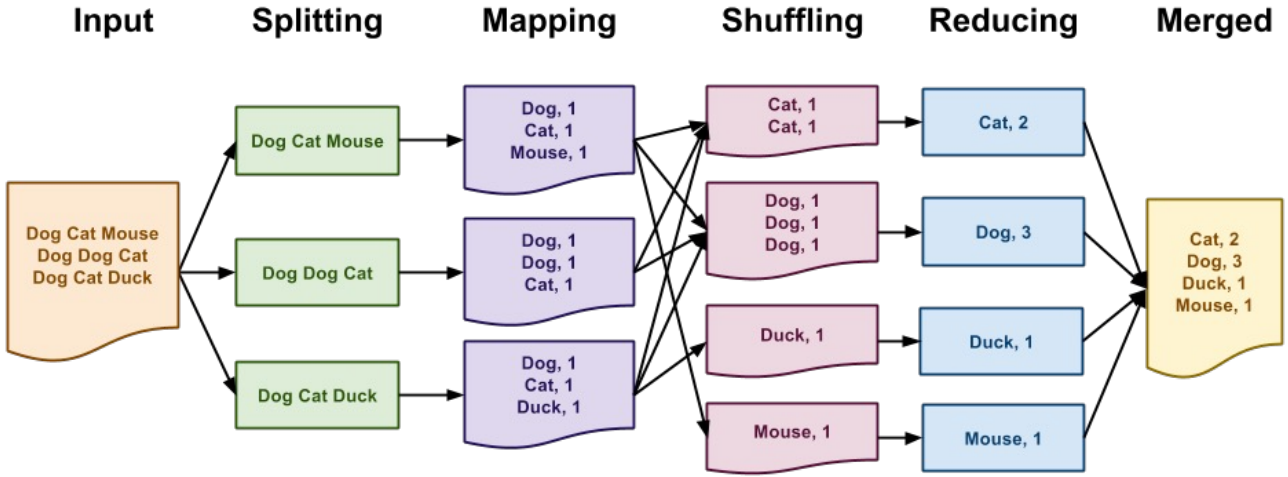
Mapreduce
Spark

MapReduce

MapReduce is a data flow program with relatively simple operators on the data set.



With each operator implemented in parallel on multiple nodes for performance.



What is we want more complex “operators?”

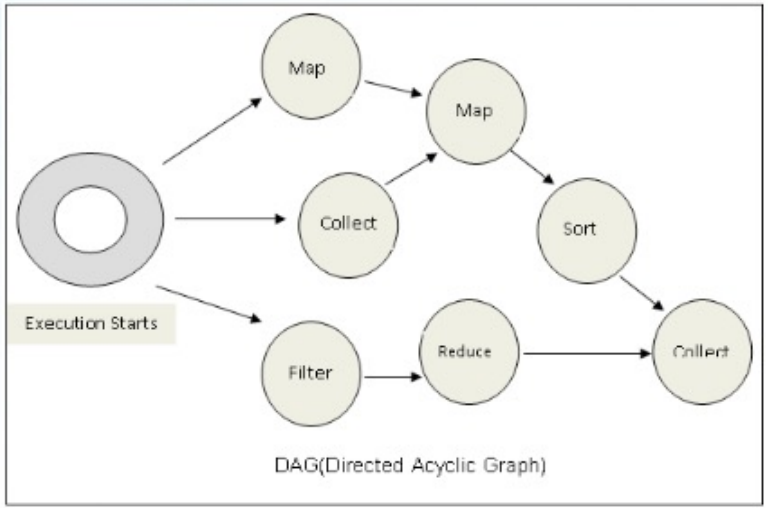
Algebraic Operations

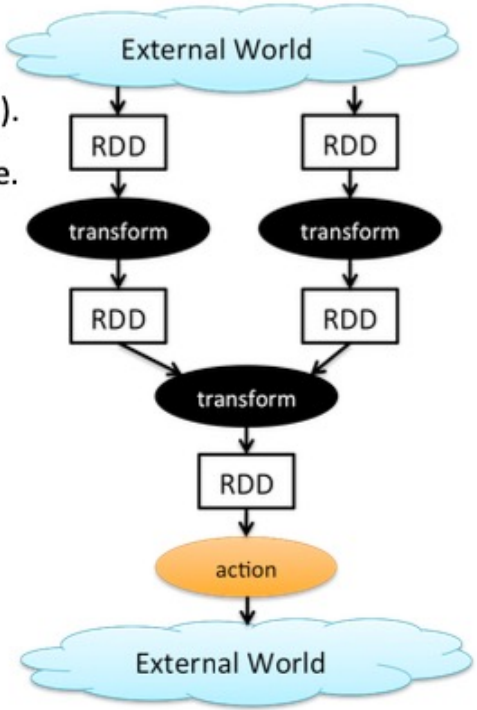
- Current generation execution engines
  - natively support algebraic operations such as joins, aggregation, etc. natively.
  - Allow users to create their own algebraic operators
  - Support trees of algebraic operators that can be executed on multiple nodes in parallel
- E.g. Apache Tez, Spark
  - Tex provides low level API; Hive on Tez compiles SQL to Tez
  - Spark provides more user-friendly API

- In the relational model,
  - The are relations.
  - A fixed set of operators that produce relations from relations (closed).
  - Are declarative languages and compute the execution graph/plan.
- The Spark/... ... engines:
  - Enable programmers to develop and add new operators.
  - Operators convert reliable distributed datasets/data frames to new RDDs/data frames.
  - Data engineer explicitly defines the execution graph (data flow).

Spark

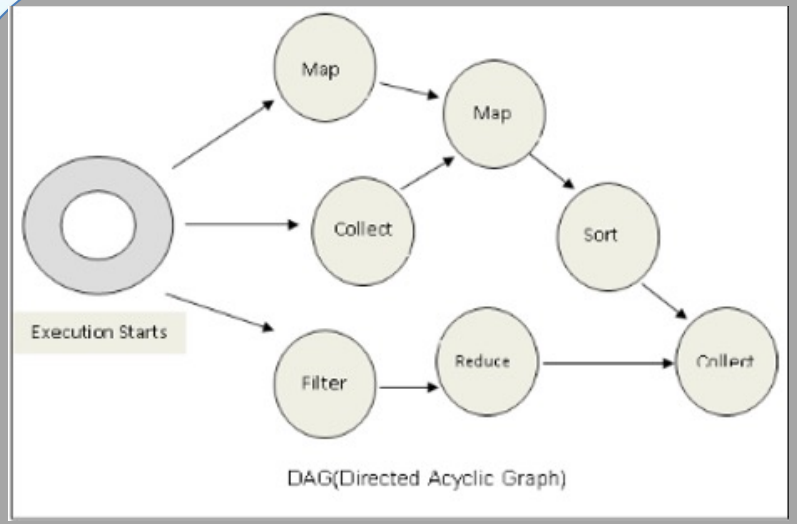
- All jobs in spark comprise a series of operators and run on a set of data.
- All the operators in a job are used to construct a DAG (Directed Acyclic Graph).
- The DAG is optimized by rearranging and combining operators where possible.

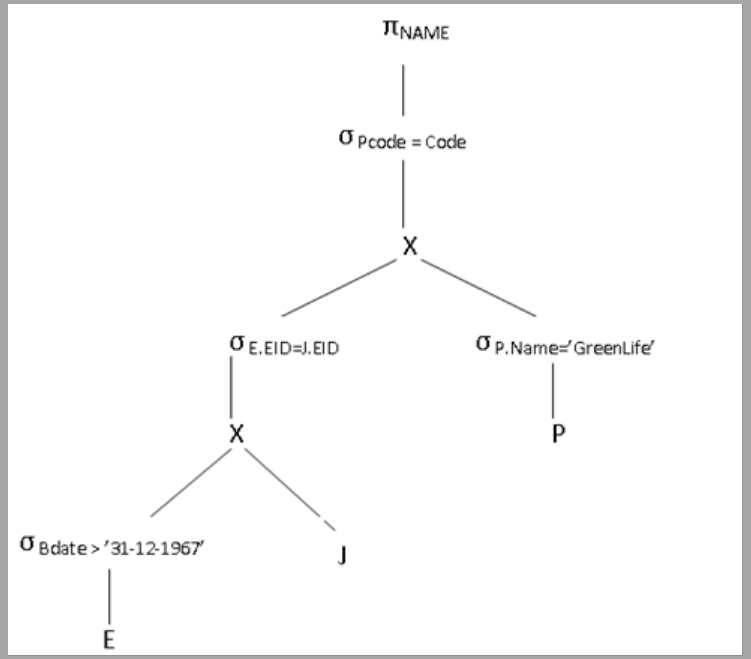




www.edureka.co/apache-spark-scala-training

Spark





Conceptually similar to query evaluation graph, but ...

- You explicitly define the graph.
- You can develop your own operators.

www.edureka.co/apache-spark-scala-training

Algebraic Operations in Spark

- **Resilient Distributed Dataset** (**RDD**) abstraction
  - Collection of records that can be stored across multiple machines
- RDDs can be created by applying algebraic operations on other RDDs
- RDDs can be lazily computed when needed
- Spark programs can be written in Java/Scala/R
  - Our examples are in Java
- Spark makes use of Java 8 Lambda expressions; the code

  s - > Arrays.asList(s.split(" ")).iterator()

  defines unnamed function that takes argument s and executes the expression Arrays.asList(s.split(" ")).iterator() on the argument
- Lambda functions are particularly convenient as arguments to map, reduce and other functions

Spark/PySpark

DataFrame

edureka!

- Inspired by DataFrames in R and Python (Pandas).
- DataFrames API is designed to make big data processing on tabular data easier.
- DataFrame is a distributed collection of data organized into named columns.
- Provides operations to filter, group, or compute aggregates, and can be used with Spark SQL.
- Can be constructed from structured data files, existing RDDs, tables in Hive, or external databases.

DataFrame features

edureka!

- Ability to scale from KBs to PBs
- Support for a wide array of data formats and storage systems
- State-of-the-art optimization and code generation through the spark SQL catalyst optimizer
- Seamless integration with all big data tooling and infrastructure via spark
- APIs for Python, Java, Scala, and R

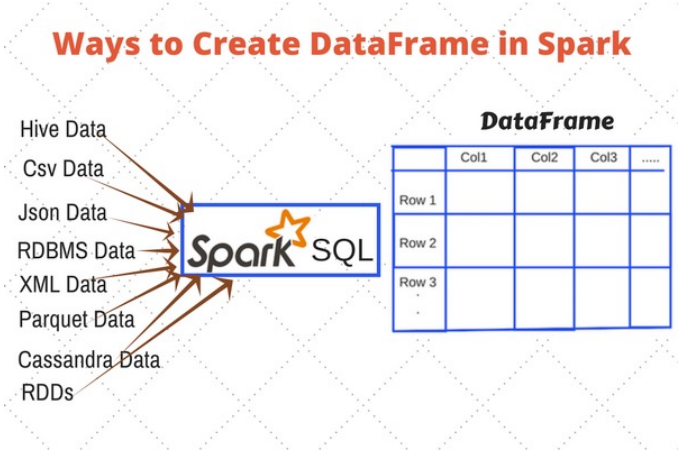
1. DataFrame in PySpark: Overview

In Apache Spark, a DataFrame is a distributed collection of rows under named columns. In simple terms, it is same as a table in relational database or an Excel sheet with Column headers. It also shares some common characteristics with RDD:

- **Immutable in nature** : We can create DataFrame / RDD once but can't change it. And we can transform a DataFrame / RDD after applying transformations.
- **Lazy Evaluations:** Which means that a task is not executed until an action is performed.
- **Distributed:** RDD and DataFrame both are distributed in nature.

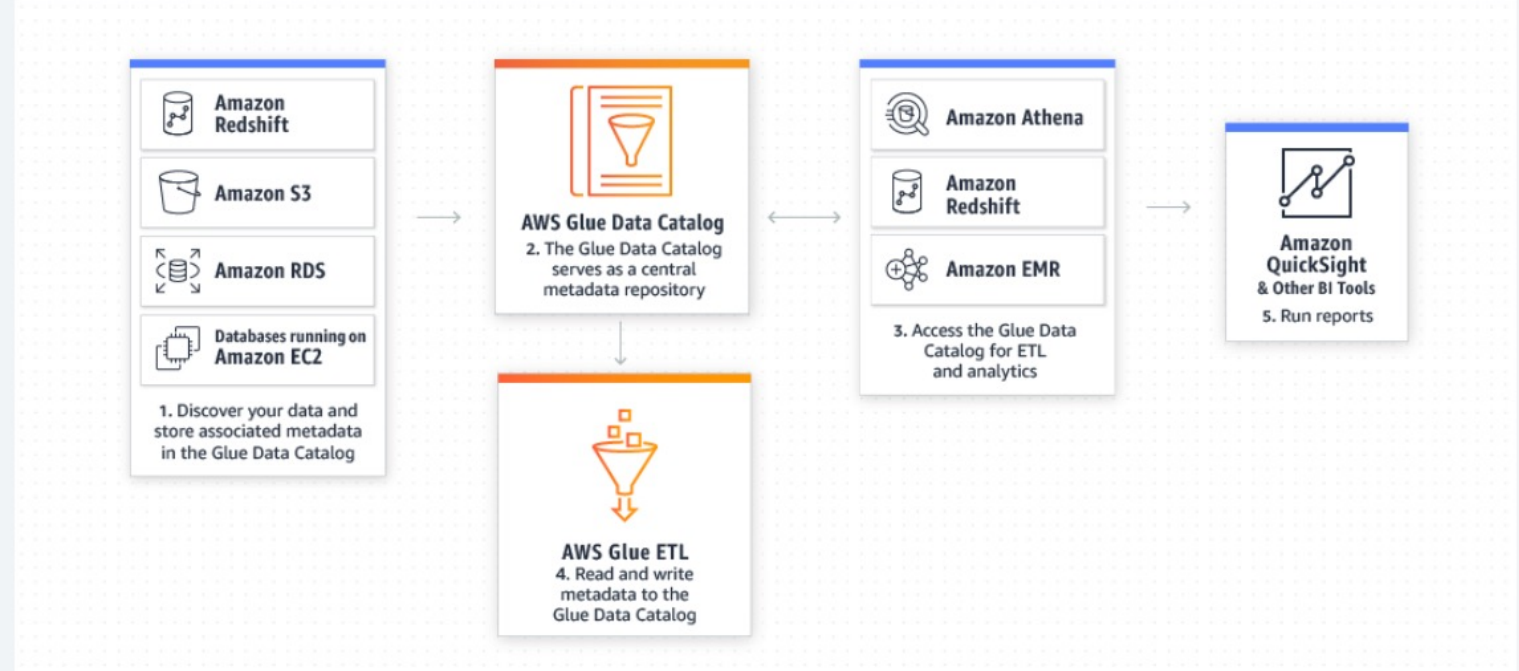
My first exposure to DataFrames was when I learnt about Pandas. Today, it is difficult for me to run my data science workflow with out Pandas DataFrames. So, when I saw similar functionality in Apache Spark, I was excited about the possibilities it opens up!

https://www.analyticsvidhya.com/blog/2016/10/spark-dataframe-and-operations/



AWS Glue Supports Spark

AWS Glue is a serverless data preparation service that makes it easy for data engineers, extract, transform, and load (ETL) developers, data analysts, and data scientists to extract, clean, enrich, normalize, and load data.



Crawlers/Classifiers

Automatic schema discovery

AWS Glue crawlers connect to your source or target data store, progresses through a prioritized list of classifiers to determine the schema for your data, and then creates metadata in your AWS Glue Data Catalog. The metadata is stored in tables in your data catalog and used in the authoring process of your ETL jobs. You can run crawlers on a schedule, on-demand, or trigger them based on an event to ensure that your metadata is up-to-date.

Built-In Classifiers in AWS Glue

AWS Glue provides built-in classifiers for various formats, including JSON, CSV, web logs, and many database systems.

If AWS Glue doesn't find a custom classifier that fits the input data format with 100 percent certainty, it invokes the built-in classifiers in the order shown in the following table. The built-in classifiers return a result to indicate whether the format matches (`certainty=1.0`) or does not match (`certainty=0.0`). The first classifier that has `certainty=1.0` provides the classification string and schema for a metadata table in your Data Catalog.

Classifier type	Classification string	Notes
		in the document. For information about creating a custom XML classifier to specify rows in the document, see Writing XML Custom Classifiers.
Amazon Ion	`ion`	Reads the beginning of the file to determine format.
Combined Apache log	`combined_apache`	Determines log formats through a grok pattern.
Apache log	`apache`	Determines log formats through a grok pattern.
Linux kernel log	`linux_kernel`	Determines log formats through a grok pattern.
Microsoft log	`microsoft_log`	Determines log formats through a grok pattern.
Ruby log	`ruby_logger`	Reads the beginning of the file to determine format.
Squid 3.x log	`squid`	Reads the beginning of the file to determine format.
Redis monitor log	`redismonlog`	Reads the beginning of the file to determine format.
Redis log	`redislog`	Reads the beginning of the file to determine format.

When Do I Use a Classifier?

You use classifiers when you crawl a data store to define metadata tables in the AWS Glue Data Catalog. You can set up your crawler with an ordered set of classifiers. When the crawler invokes a classifier, the classifier determines whether the data is recognized. If the classifier can't recognize the data or is not 100 percent certain, the crawler invokes the next classifier in the list to determine whether it can recognize the data.

Built-In Transforms

ApplyMapping

Maps source columns and data types from a `DynamicFrame` to target columns and data types in a returned `DynamicFrame`. You specify the mapping argument, which is a list of tuples that contain source column, source type, target column, and target type.

DropFields

Removes a field from a `DynamicFrame`. The output `DynamicFrame` contains fewer fields than the input. You specify which fields to remove using the `paths` argument. The `paths` argument points to a field in the schema tree structure using dot notation. For example, to remove field B, which is a child of field A in the tree, type `A.B` for the path.

DropNullFields

Removes null fields from a `DynamicFrame`. The output `DynamicFrame` does not contain fields of the null type in the schema.

Filter

Selects records from a `DynamicFrame` and returns a filtered `DynamicFrame`. You specify a function, such as a Lambda function, which determines whether a record is output (function returns true) or not (function returns false).

Join

Equijoin of two `DynamicFrames`. You specify the key fields in the schema of each frame to compare for equality. The output `DynamicFrame` contains rows where keys match.

Map

Applies a function to the records of a `DynamicFrame` and returns a transformed `DynamicFrame`. The supplied function is applied to each input record and transforms it to an output record. The map transform can add fields, delete fields, and perform lookups using an external API operation. If there is an exception, processing continues, and the record is marked as an error.

MapToCollection

Applies a transform to each `DynamicFrame` in a `DynamicFrameCollection`.

Built-In Transforms

Relationalize

Converts a `DynamicFrame` to a relational (rows and columns) form. Based on the data's schema, this transform flattens nested structures and creates `DynamicFrames` from arrays structures. The output is a collection of `DynamicFrames` that can result in data written to multiple tables.

RenameField

Renames a field in a `DynamicFrame`. The output is a `DynamicFrame` with the specified field renamed. You provide the new name and the path in the schema to the field to be renamed.

ResolveChoice

Use `ResolveChoice` to specify how a column should be handled when it contains values of multiple types. You can choose to either cast the column to a single data type, discard one or more of the types, or retain all types in either separate columns or a structure. You can select a different resolution policy for each column or specify a global policy that is applied to all columns.

SelectFields

Selects fields from a `DynamicFrame` to keep. The output is a `DynamicFrame` with only the selected fields. You provide the paths in the schema to the fields to keep.

SelectFromCollection

Selects one `DynamicFrame` from a collection of `DynamicFrames`. The output is the selected `DynamicFrame`. You provide an index to the `DynamicFrame` to select.

Spigot

Writes sample data from a `DynamicFrame`. Output is a JSON file in Amazon S3. You specify the Amazon S3 location and how to sample the `DynamicFrame`. Sampling can be a specified number of records from the beginning of the file or a probability factor used to pick records to write.

SplitFields

Splits fields into two `DynamicFrames`. Output is a collection of `DynamicFrames`: one with selected fields, and one with the remaining fields. You provide the paths in the schema to the selected fields.

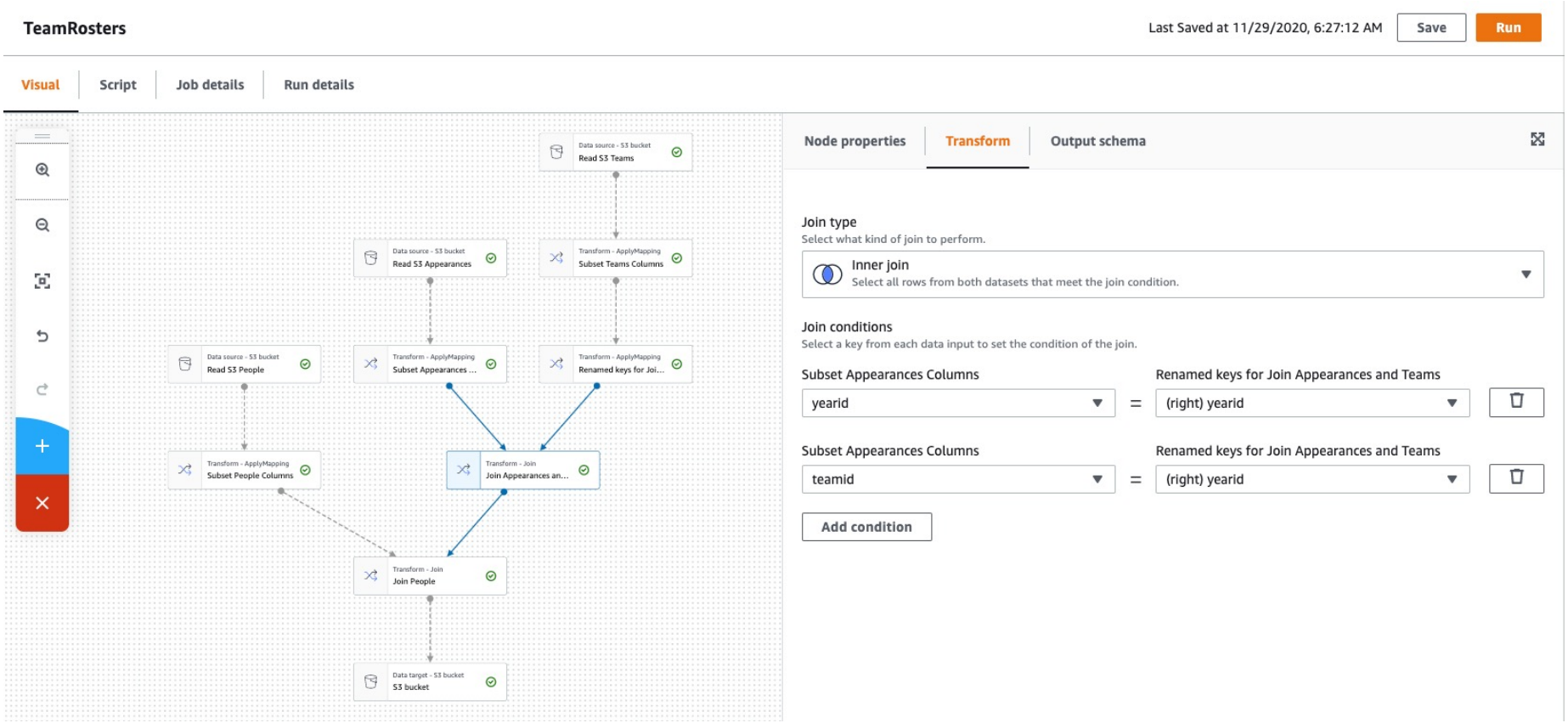
SplitRows

Splits rows in a `DynamicFrame` based on a predicate. The output is a collection of two `DynamicFrames`: one with selected rows, and one with the remaining rows. You provide the comparison based on fields in the schema. For example, `A > 4`.

Unbox

Unboxes a string field from a `DynamicFrame`. The output is a `DynamicFrame` with the selected string field reformatted. The string field can be parsed and replaced with several fields. You provide a path in the schema for the string field to reformat and its current format type. For example, you might have a CSV file that has one field that is in JSON format `{"a": 3, "b": "foo", "c": 1.2}`. This transform can reformat the JSON into three fields: an `int`, a `string`, and a `double`.

Visual Tools (There are similar tools for SQL, ETL, … …)



Conceptual Example

- Consider the IMDB dataset. We should convert (other conversion needed)

nconst	name	dateOfBirth	dateOfDeath	primaryProfession	knownFor
nm0000003	Brigitte Bardot	1934		actress,soundtrack,music_department	tt0057345,tt0059956,tt0054452,tt0049189
nm0000004	John Belushi	1949	1982	actor,soundtrack,writer	tt0077975,tt0072562,tt0080455,tt0078723
nm0000005	Ingmar Bergman	1918	2007	writer,director,actor	tt0050986,tt0083922,tt0060827,tt0050976
nm0000006	Ingrid Bergman	1915	1982	actress,soundtrack,producer	tt0038787,tt0036855,tt0034583,tt0038109
nm0000007	Humphrey Bogart	1899	1957	actor,soundtrack,producer	tt0043265,tt0040897,tt0034583,tt0037382
nm0000008	Marlon Brando	1924	2004	actor,soundtrack,director	tt0078788,tt0070849,tt0047296,tt0068646
nm0000009	Richard Burton	1925	1984	actor,soundtrack,producer	tt0087803,tt0061184,tt0059749,tt0057877
nm0000010	James Cagney	1899	1986	actor,soundtrack,director	tt0042041,tt0035575,tt0029870,tt0031867

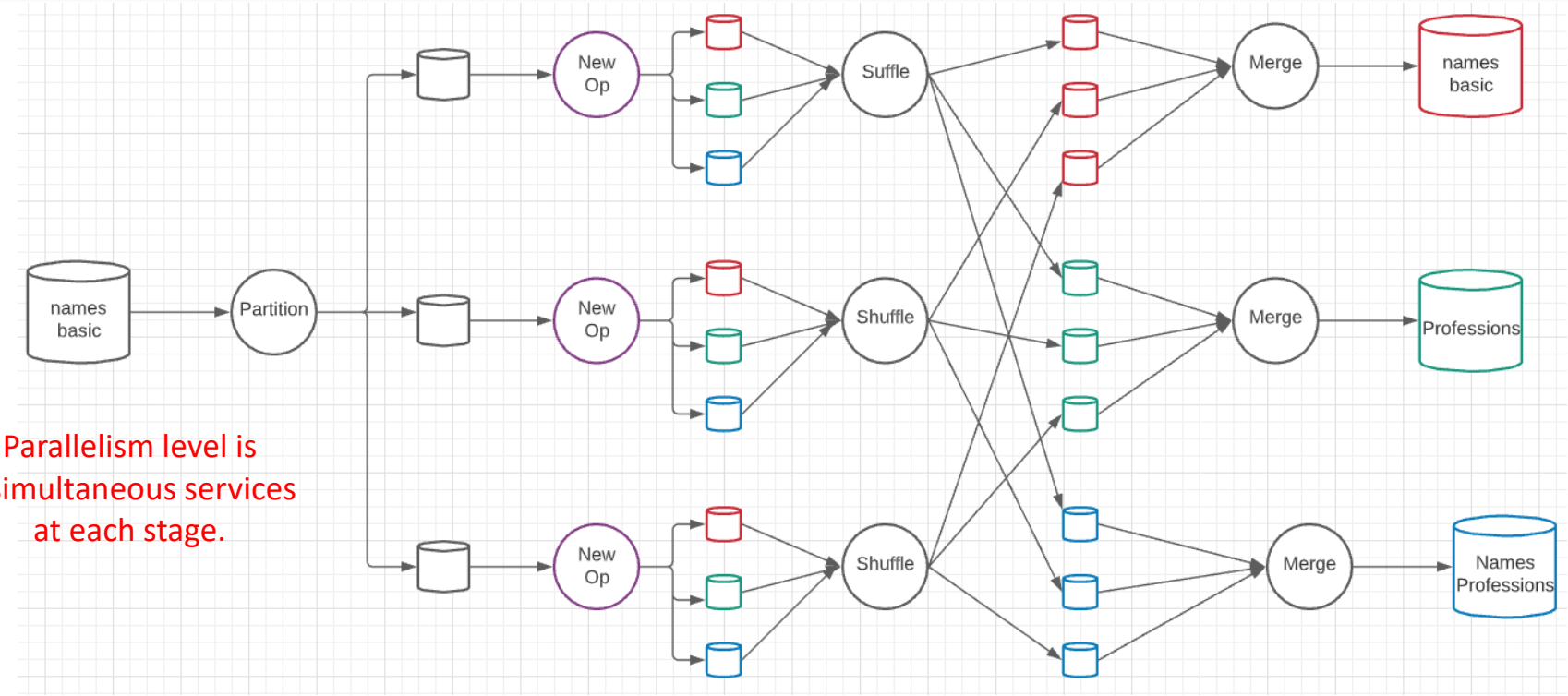
- To

nm0000001	Fred Astaire	1899	1987
nm0000002	Lauren Bacall	1924	2014
nm0000003	Brigitte Bardot	1934	
nm0000004	John Belushi	1949	1982
nm0000005	Ingmar Bergman	1918	2007
nm0000006	Ingrid Bergman	1915	1982
nm0000007	Humphrey Bogart	1899	1957
nm0000008	Marlon Brando	1924	2004
nm0000009	Richard Burton	1925	1984
nm0000010	James Cagney	1899	1986

nconst	profession_id
nm0000001	1
nm0000001	2
nm0000001	3
nm0000002	3
nm0000002	4
nm0000003	3
nm0000003	4
nm0000003	5
nm0000004	1
nm0000004	3

Profession	Profession_id
actor	1
miscellaneous	2
soundtrack	3
actress	4
music_department	5
writer	6
director	7
producer	8
make_up_department	9
composer	10
assistant_director	11

A New Algebraic Operator



Parallelism level is 3 simultaneous services at each stage.

- Input is a dataset and column ID
- Output is three datasets: dataset with column removed, table of distinct column values, associative entity.

OLAP

Data Analysis and OLAP

- **Online Analytical Processing (OLAP)**
  - Interactive analysis of data, allowing data to be summarized and viewed in different ways in an online fashion (with negligible delay)
- We use the following relation to illustrate OLAP concepts
  - *sales* (*item_name*, *color*, *clothes_size*, *quantity*)

  This is a simplified version of the *sales* fact table joined with the dimension tables, and many attributes removed (and some renamed)

Example sales relation

item_name	*color*	*clothes_size*	*quantity*
dress	dark	small	2
dress	dark	medium	6
dress	dark	large	12
dress	pastel	small	4
dress	pastel	medium	3
dress	pastel	large	3
dress	white	small	2
dress	white	medium	3
dress	white	large	0
pants	dark	small	14
pants	dark	medium	6
pants	dark	large	0
pants	pastel	small	1
pants	pastel	medium	0
pants	pastel	large	1
pants	white	small	3
pants	white	medium	0
pants	white	large	2
shirt	dark	small	2
shirt	dark	medium	6
shirt	dark	large	6
shirt	pastel	small	4
shirt	pastel	medium	1
shirt	pastel	large	2
shirt	white	small	17
shirt	white	medium	1
shirt	white	large	10
skirt	dark	small	2
skirt	dark	medium	5
…	…	…	…
…	…	…	…

Cross Tabulation of *sales* by *item_name* and *color*

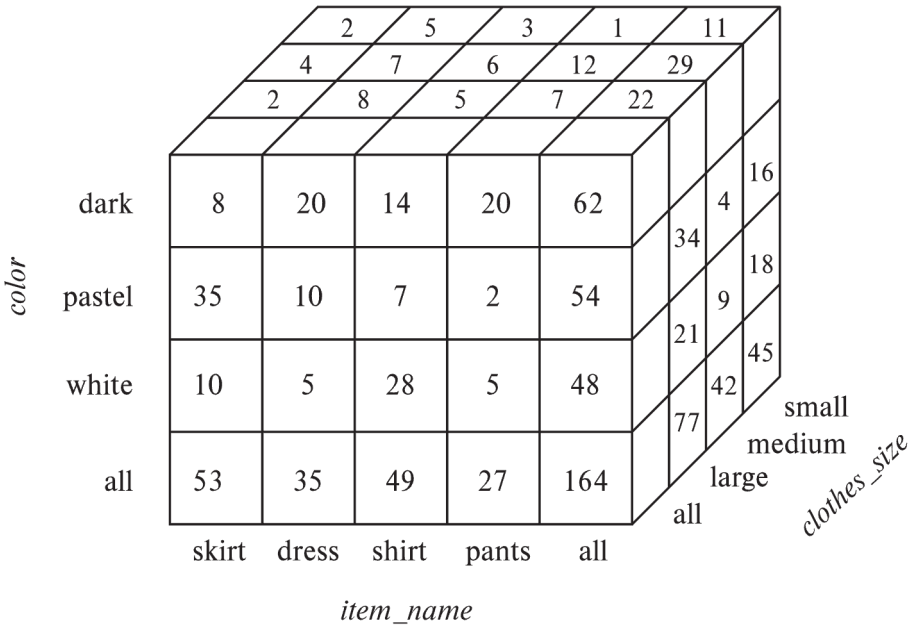
clothes_size **all**

item_name	*color* dark	pastel	white	total
skirt	8	35	10	53
dress	20	10	5	35
shirt	14	7	28	49
pants	20	2	5	27
total	62	54	48	164

- The table above is an example of a **cross-tabulation** (**cross-tab**), also referred to as a **pivot-table**.
  - Values for one of the dimension attributes form the row headers
  - Values for another dimension attribute form the column headers
  - Other dimension attributes are listed on top
  - Values in individual cells are (aggregates of) the values of the dimension attributes that specify the cell.

Data Cube

- A **data cube** is a multidimensional generalization of a cross-tab
- Can have n dimensions; we show 3 below
- Cross-tabs can be used as views on a data cube



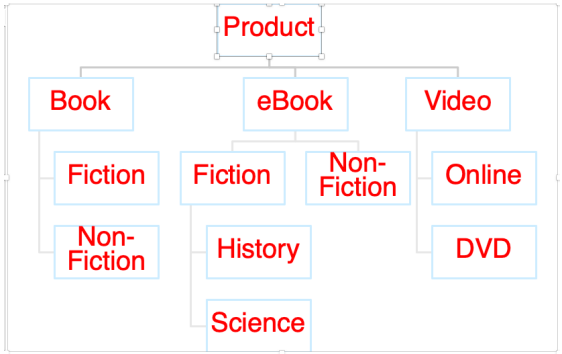
Online Analytical Processing Operations

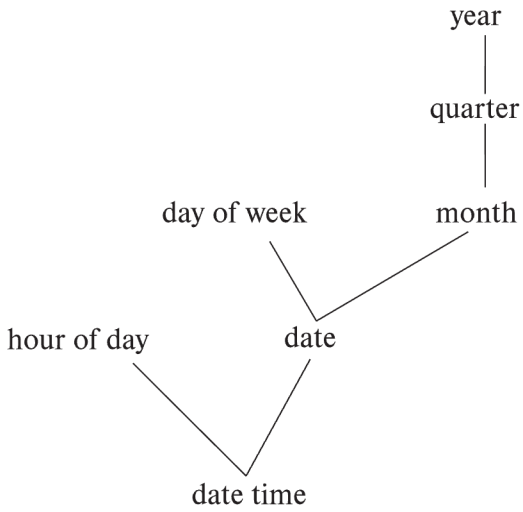
- **Pivoting:** changing the dimensions used in a cross-tab
  - E.g., moving colors to column names
- **Slicing:** creating a cross-tab for fixed values only
  - E.g., fixing color to white and size to small
  - Sometimes called **dicing**, particularly when values for multiple dimensions are fixed.
- **Rollup:** moving from finer-granularity data to a coarser granularity
  - E.g., aggregating away an attribute
  - E.g., moving from aggregates by day to aggregates by month or year
- **Drill down:** The opposite operation - that of moving from coarser-granularity data to finer-granularity data

Hierarchies on Dimensions

- **Hierarchy** on dimension attributes: lets dimensions be viewed at different levels of detail
- E.g., the dimension *datetime* can be used to aggregate by hour of day, date, day of week, month, quarter or year

Another dimension could be ...
Product category.

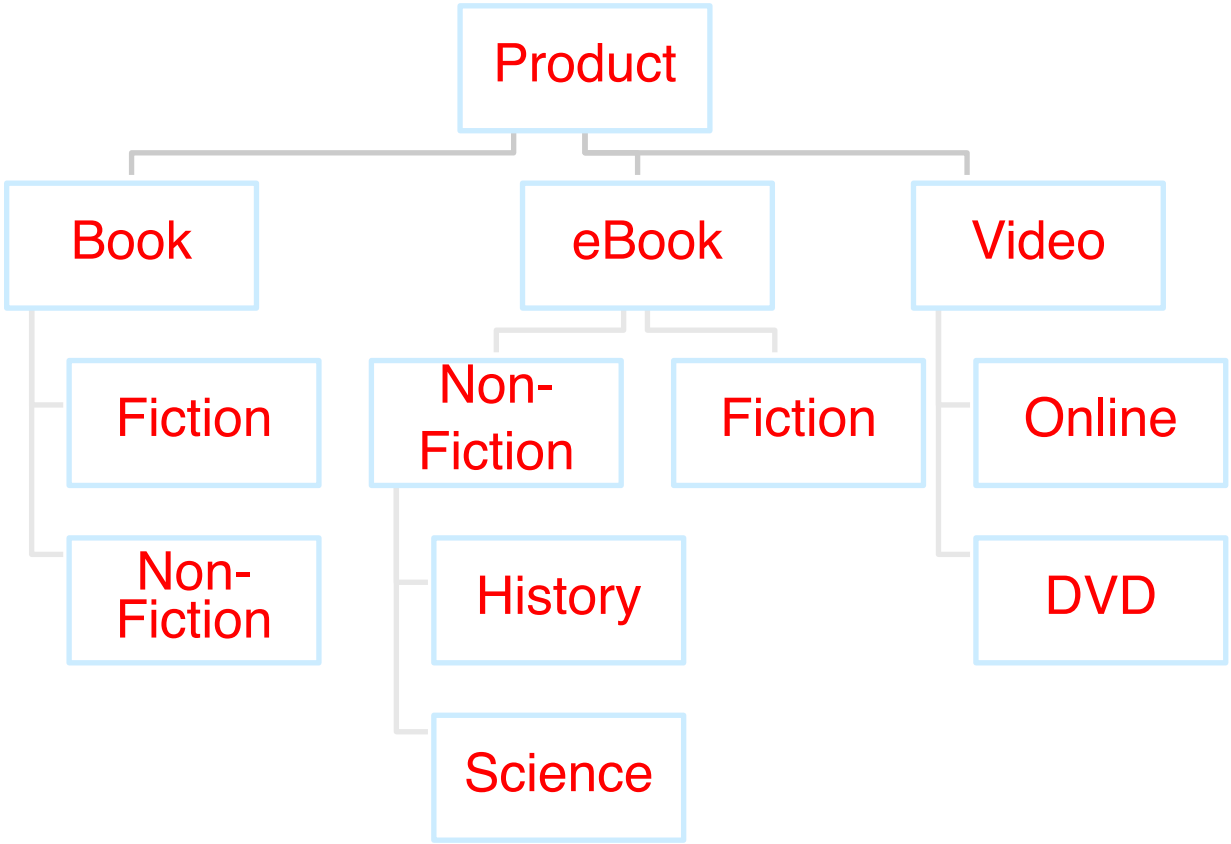




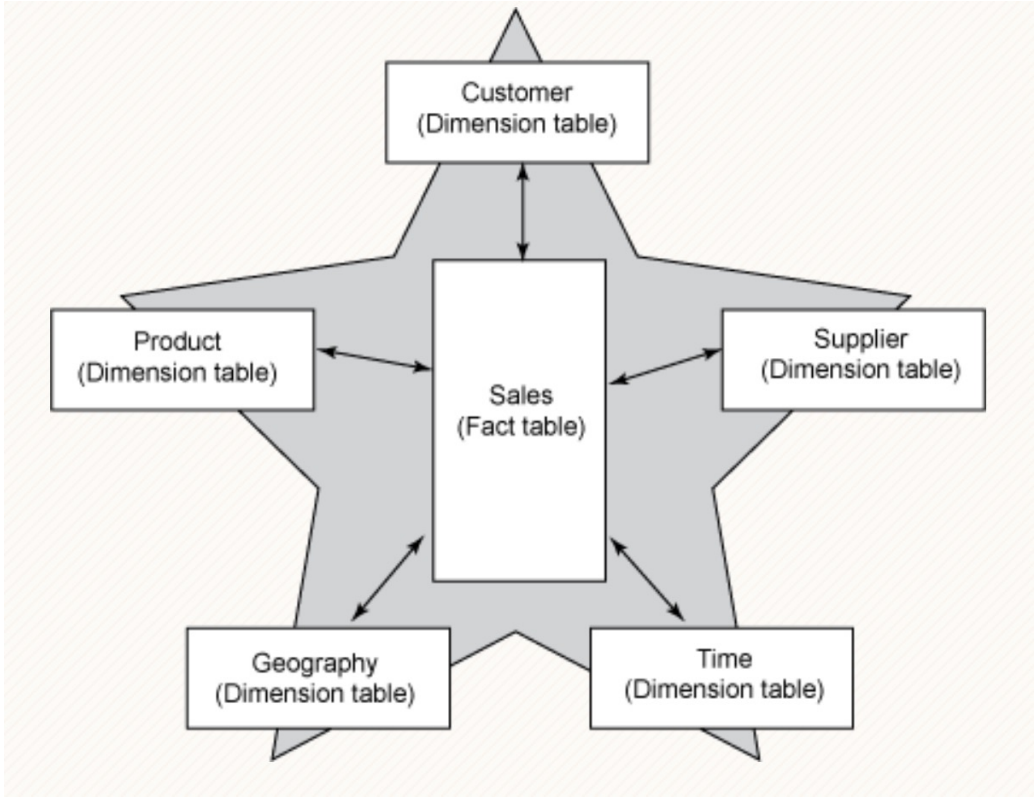
(a) time hierarchy

(b) location hierarchy

Another Dimension Example – Product Categories



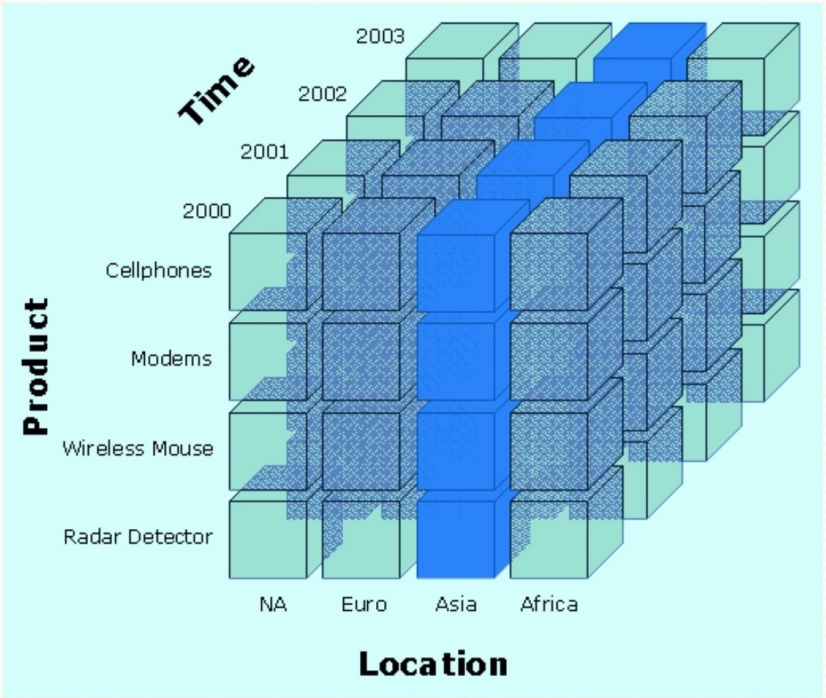
Facts and Dimensions



Slice

Slice:

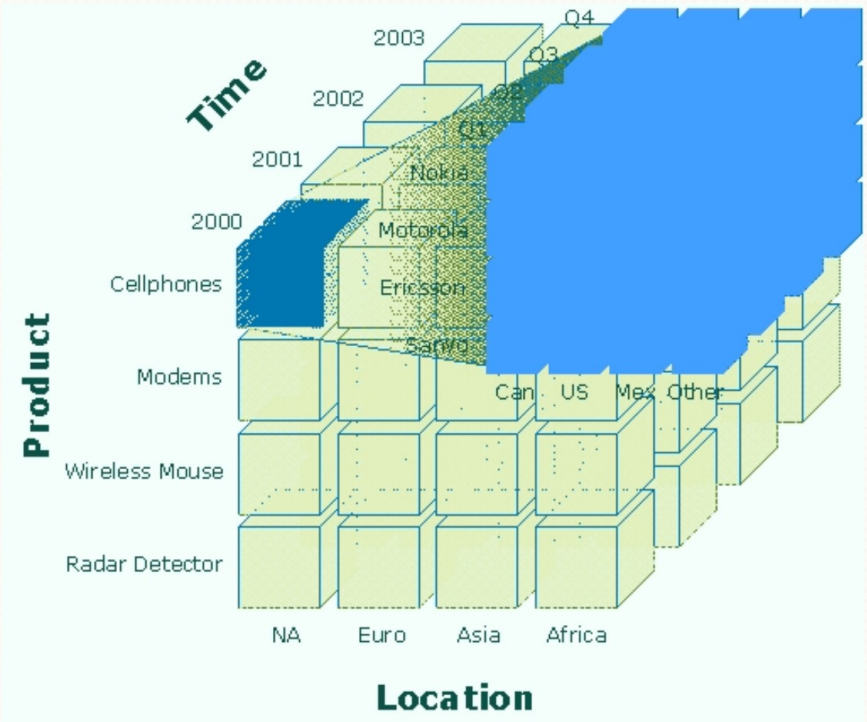
A slice is a subset of a multi-dimensional array corresponding to a single value for one or more members of the dimensions not in the subset.



Dice

Dice:

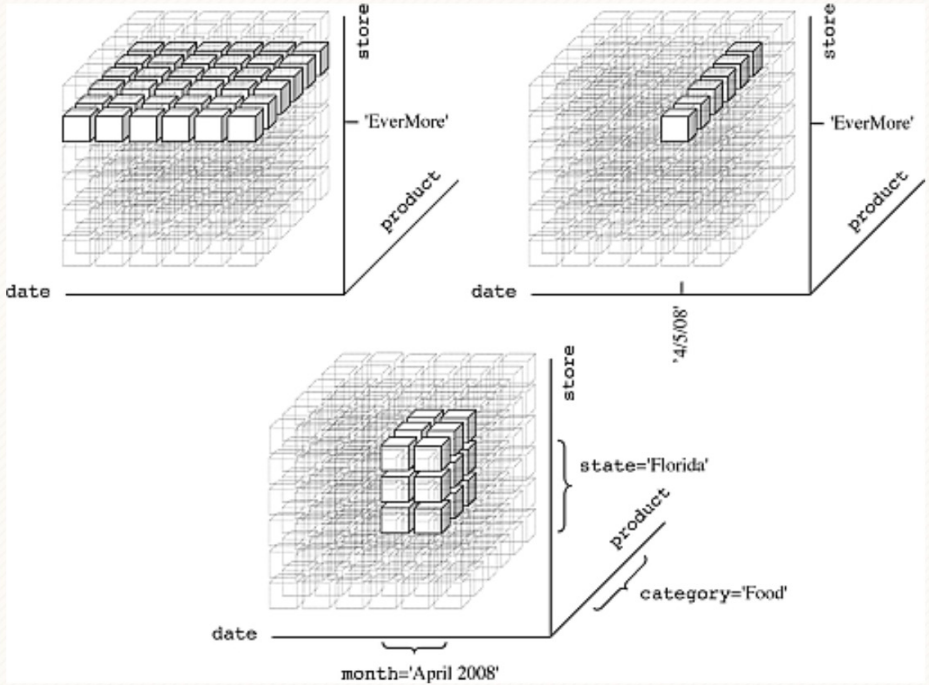
The dice operation is a slice on more than two dimensions of a data cube (or more than two consecutive slices).



Drilling

Drill Down/Up:

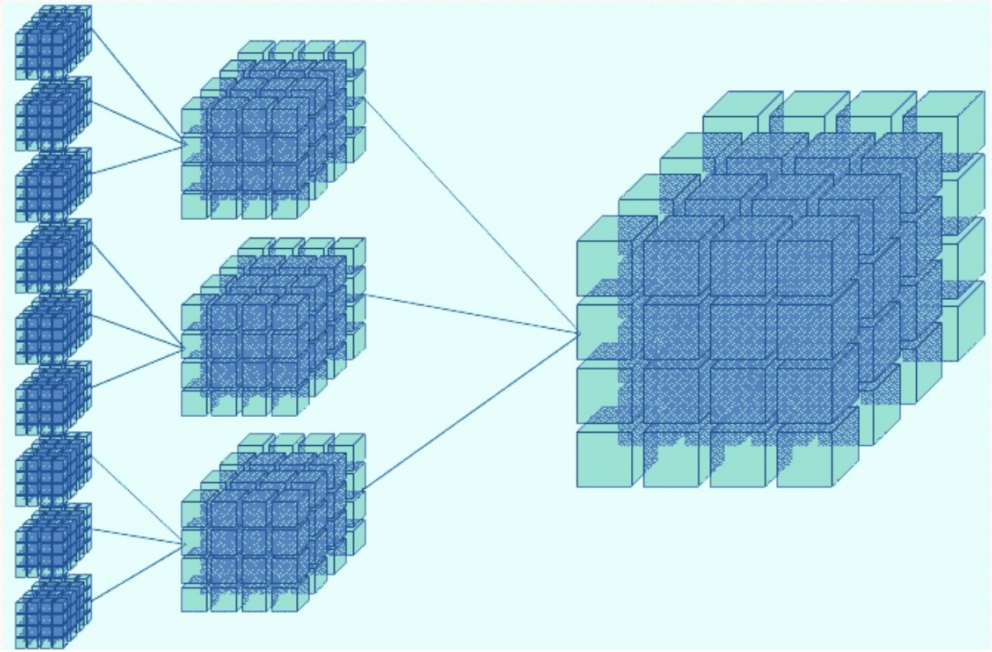
Drilling down or up is a specific analytical technique whereby the user navigates among levels of data ranging from the most summarized (up) to the most detailed (down).



Roll-up

Roll-up:

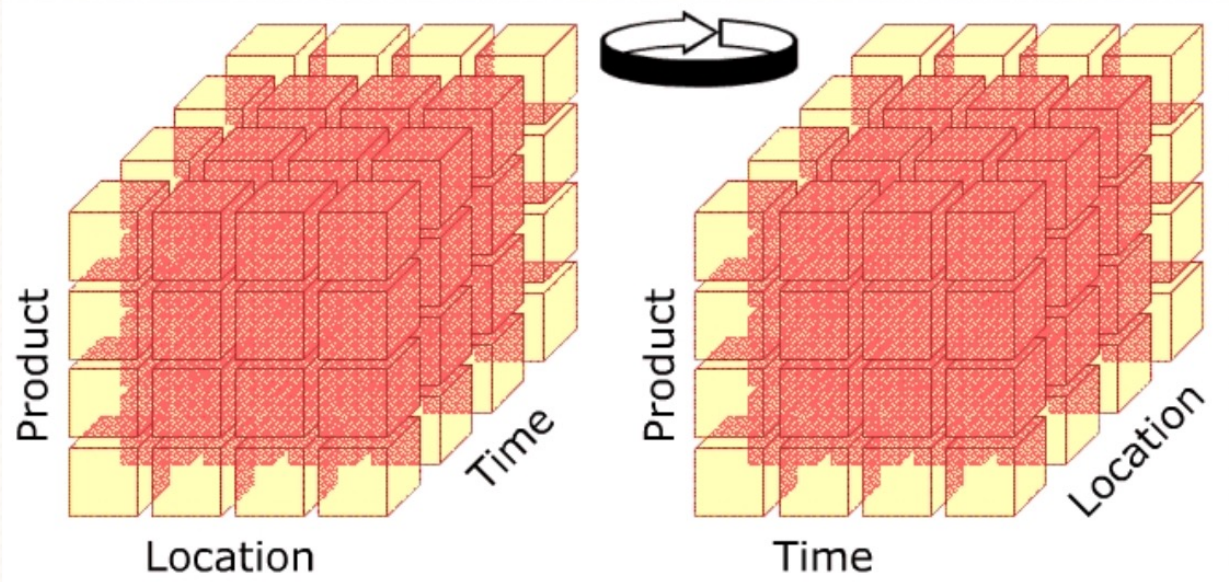
(Aggregate, Consolidate) A roll-up involves computing all of the data relationships for one or more dimensions. To do this, a computational relationship or formula might be defined.



Pivot

Pivot:

This operation is also called rotate operation. It rotates the data in order to provide an alternative presentation of data – the report or page display takes a different dimensional orientation.



Cross Tabulation With Hierarchy

- Cross-tabs can be easily extended to deal with hierarchies
- Can drill down or roll up on a hierarchy
- E.g. hierarchy: *item_name* → *category*

clothes_size: **all**

category	*item_name*	*color*				
		dark	pastel	white	total	
womenswear	skirt	8	8	10	53	
	dress	20	20	5	35	
	subtotal	28	28	15		88
menswear	pants	14	14	28	49	
	shirt	20	20	5	27	
	subtotal	34	34	33		76
total		62	62	48		164

Relational Representation of Cross-tabs

- Cross-tabs can be represented as relations
- We use the value **all** to represent aggregates.
- The SQL standard actually uses *null* values in place of **all**
  - Works with any data type
  - But can cause confusion with regular null values.

item_name	*color*	*clothes_size*	*quantity*
skirt	dark	**all**	8
skirt	pastel	**all**	35
skirt	white	**all**	10
skirt	**all**	**all**	53
dress	dark	**all**	20
dress	pastel	**all**	10
dress	white	**all**	5
dress	**all**	**all**	35
shirt	dark	**all**	14
shirt	pastel	**all**	7
shirt	white	**all**	28
shirt	**all**	**all**	49
pants	dark	**all**	20
pants	pastel	**all**	2
pants	white	**all**	5
pants	**all**	**all**	27
all	dark	**all**	62
all	pastel	**all**	54
all	white	**all**	48
all	**all**	**all**	164