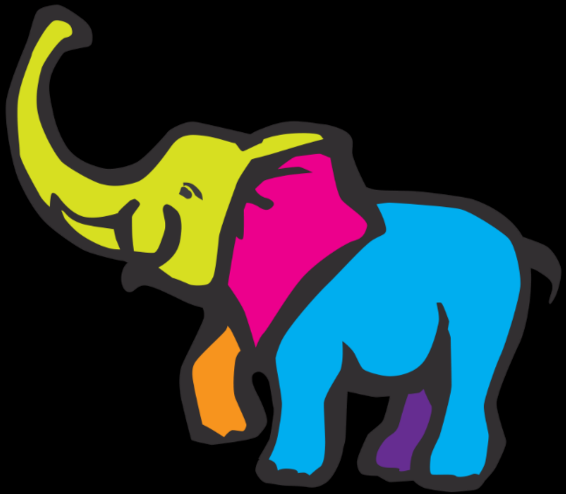
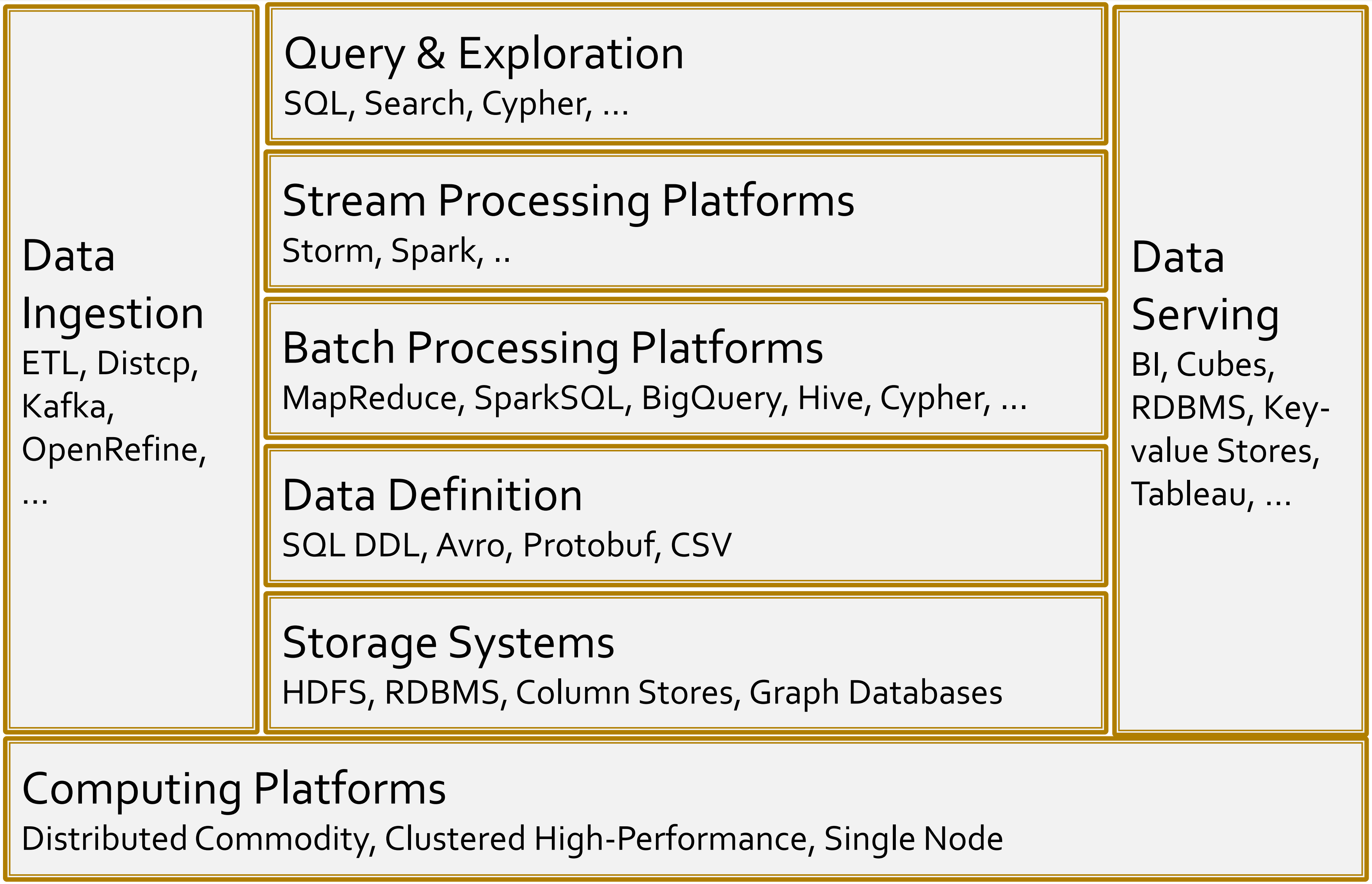
EECS4415:
Big Data Systems



Computing Platforms, Storage Systems, Data Definition

Big Data Technology & Analytics



Data Ingestion
ETL, Distcp, Kafka, OpenRefine, …

Query & Exploration
SQL, Search, Cypher, …

Stream Processing Platforms
Storm, Spark, ..

Batch Processing Platforms
MapReduce, SparkSQL, BigQuery, Hive, Cypher, …

Data Definition
SQL DDL, Avro, Protobuf, CSV

Storage Systems
HDFS, RDBMS, Column Stores, Graph Databases

Data Serving
BI, Cubes, RDBMS, Key-value Stores, Tableau, …

Computing Platforms
Distributed Commodity, Clustered High-Performance, Single Node

Big Data Technology & Analytics

Data Ingestion

ETL, Distcp, Kafka, OpenRefine, …

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SQL, Search, Cypher, …

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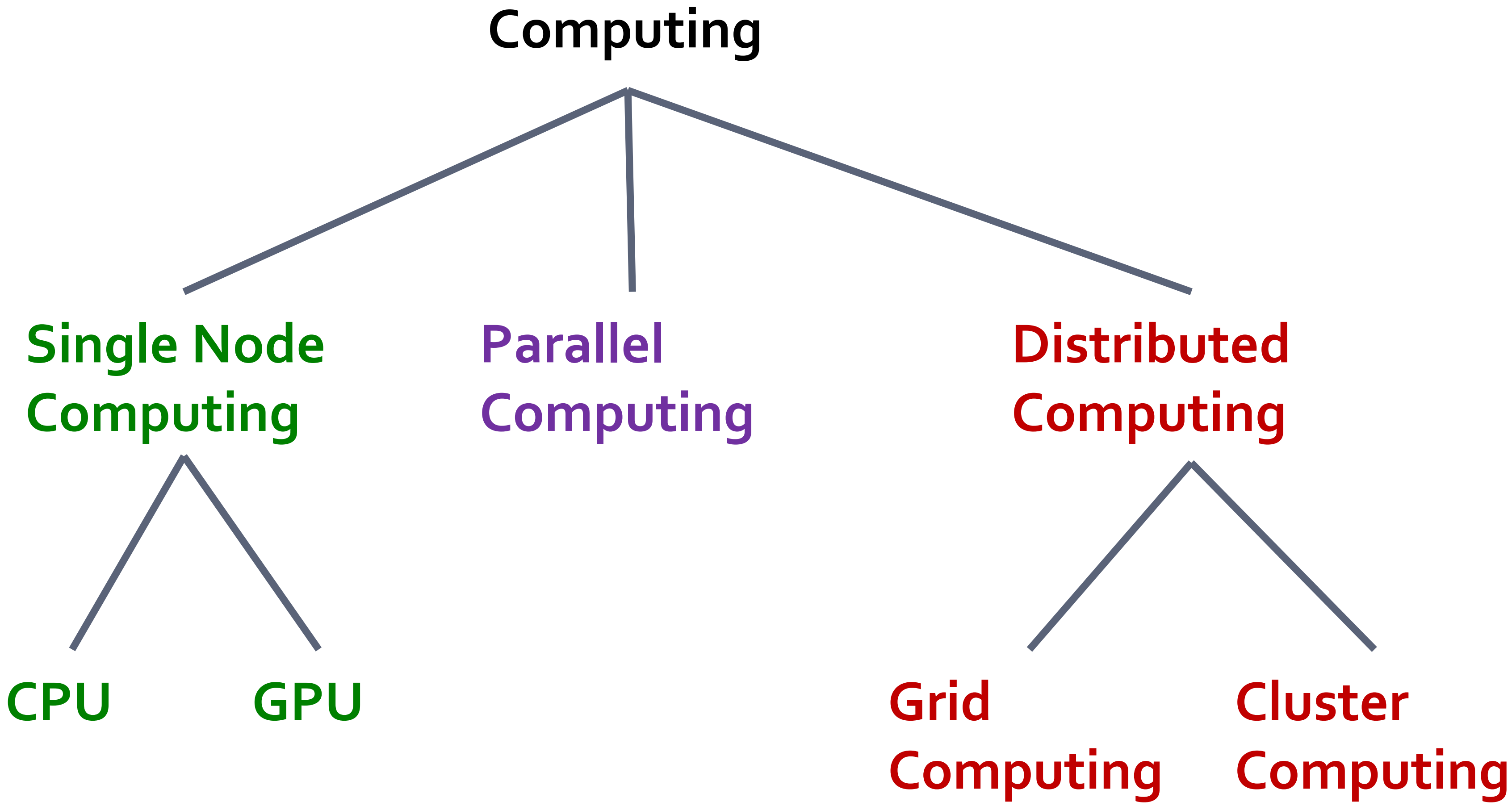
Computing Platforms

Distributed Commodity, Clustered High-Performance, Single Node

Computing Platforms

Computing Platforms



Computing

Single Node Computing

Parallel Computing

Distributed Computing

CPU

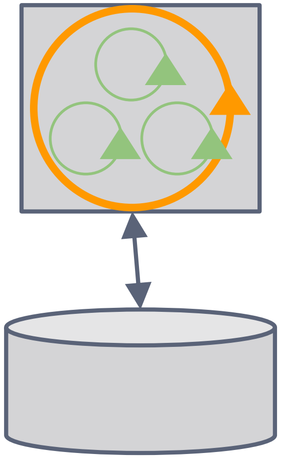
GPU

Grid Computing

Cluster Computing

Single Node Computing

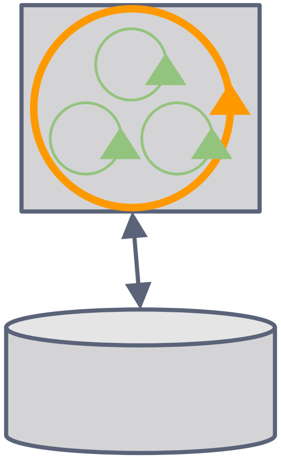
- A single node (usually multiple cores)
- Attached to a data store (Disc, SSD, …)
- One process with potentially multiple threads



Single Node Example

R: All processing is done on one computer

BidMat: All processing is done on one computer with specialized HW

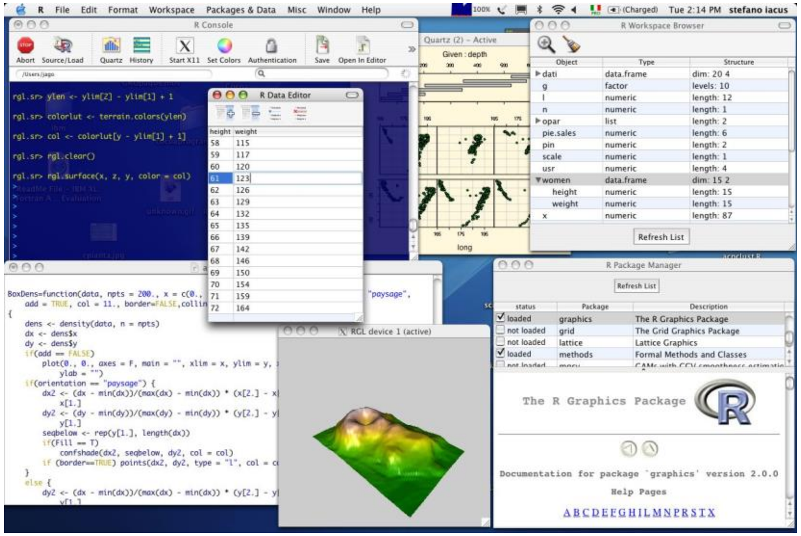


R

Single Node

In memory

Retrieve/Stores from Disc



```
rgl.sr> ylen <- ylim[2] - ylim[1] + 1

rgl.sr> colorlut <- terrain.colors(ylen)

rgl.sr> col <- colorlut[y - ylim[1] + 1]

rgl.sr> rgl.clear()

rgl.sr> rgl.surface(x, z, y, color = col)
>
>
>
```

```
BoxDens=function(data, npts = 200., x = c(0.,
    add = TRUE, col = 11., border=FALSE,collin
{
    dens <- density(data, n = npts)
    dx <- dens$x
    dy <- dens$y
    if(add == FALSE)
        plot(0., 0., axes = F, main = "", xlim = x, ylim = y,
            ylab = "")
    if(orientation == "paysage") {
        dx2 <- (dx - min(dx))/(max(dx) - min(dx)) * (x[2.] - x
            x[1.]
        dy2 <- (dy - min(dy))/(max(dy) - min(dy)) * (y[2.] - y
            y[1.]
        seqbelow <- rep(y[1.], length(dx))
        if(Fill == T)
            confshade(dx2, seqbelow, dy2, col = col)
        if (border==TRUE) points(dx2, dy2, type = "l", col = c
    }
    else {
        dy2 <- (dx - min(dx))/(max(dx) - min(dx)) * (y[2.] - y
```

height	weight
58	115
59	117
60	120
61	123
62	126
63	129
64	132
65	135
66	139
67	142
68	146
69	150
70	154
71	159
72	164

Object	Type	Structure
▶ dati	data.frame	dim: 20 4
g	factor	levels: 10
l	numeric	length: 12
n	numeric	length: 1
▶ opar	list	length: 2
pie.sales	numeric	length: 6
pin	numeric	length: 2
scale	numeric	length: 1
usr	numeric	length: 4
▼ women	data.frame	dim: 15 2
height	numeric	length: 15
weight	numeric	length: 15
x	numeric	length: 87

status	Package	Description
☑ loaded	graphics	The R Graphics Package
☐ not loaded	grid	The Grid Graphics Package
☐ not loaded	lattice	Lattice Graphics
☑ loaded	methods	Formal Methods and Classes

The R Graphics Package

Documentation for package `graphics' version 2.0.0

Help Pages

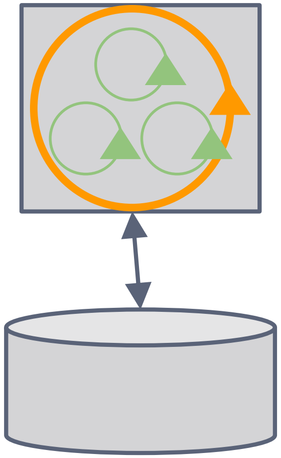
A B C D E F G H I L M N P R S T X

Pros

- Simple to program and debug

Cons

- Can only scale-up
- Does not deal with large data sets



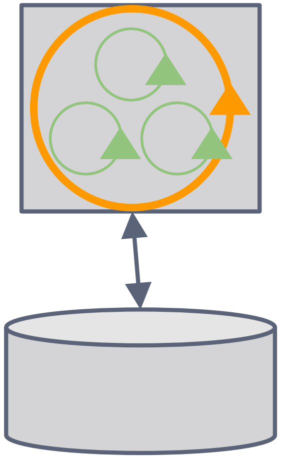
BidMat/BidMach

Single Node solution for large scale exploratory analysis

Specialized HW and SW for efficient Matrix operations

Elements:

- Data engine software for optimized operations
- HW design pattern for balancing Storage, CPU and GPU computing
- Optimized machine learning package
- Advanced communication patterns



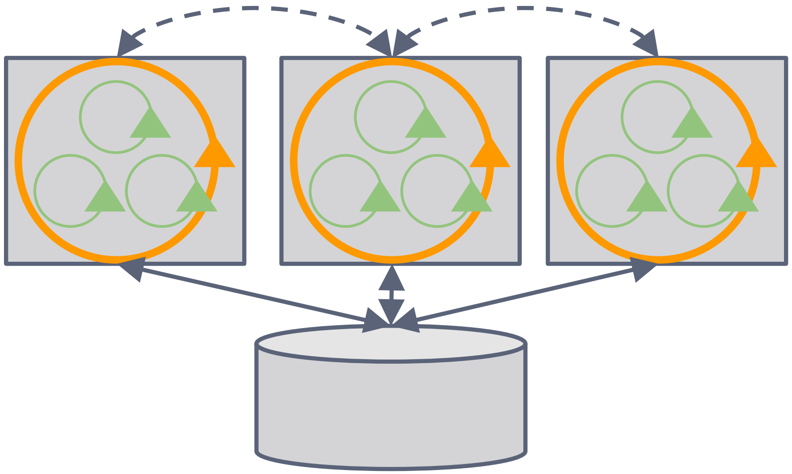
Parallel Computing

Common Data Store

Many Processors

Parallel execution of tasks

Processor communication



R Snow: Parallel R

R is a single thread computing application

R Snow enable multi threading/distribution

Pros

- Distributed/parallel
- Commonly known tool and model

Cons

- Each node requires access to all data

Distributed Computing

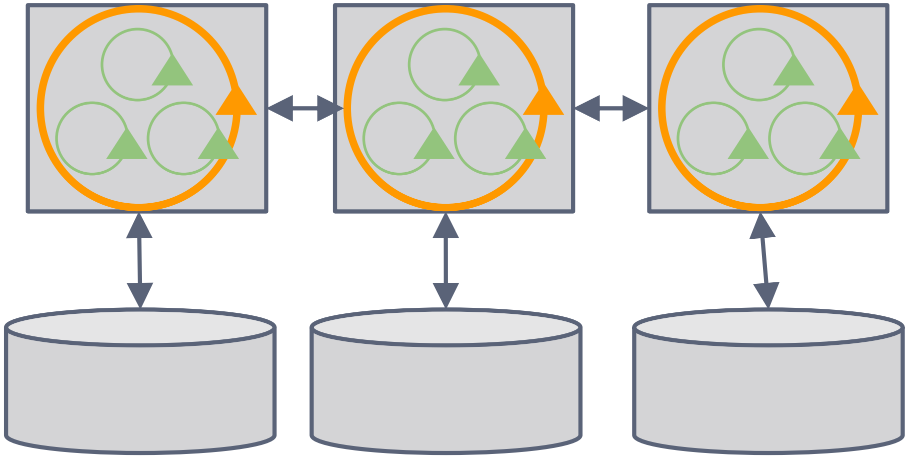
Connected processors collaborate to achieve a common goal

Requires:

- Message passing
- Coordination
- Scheduling
- Tolerate failures on individual nodes

Cluster Computing

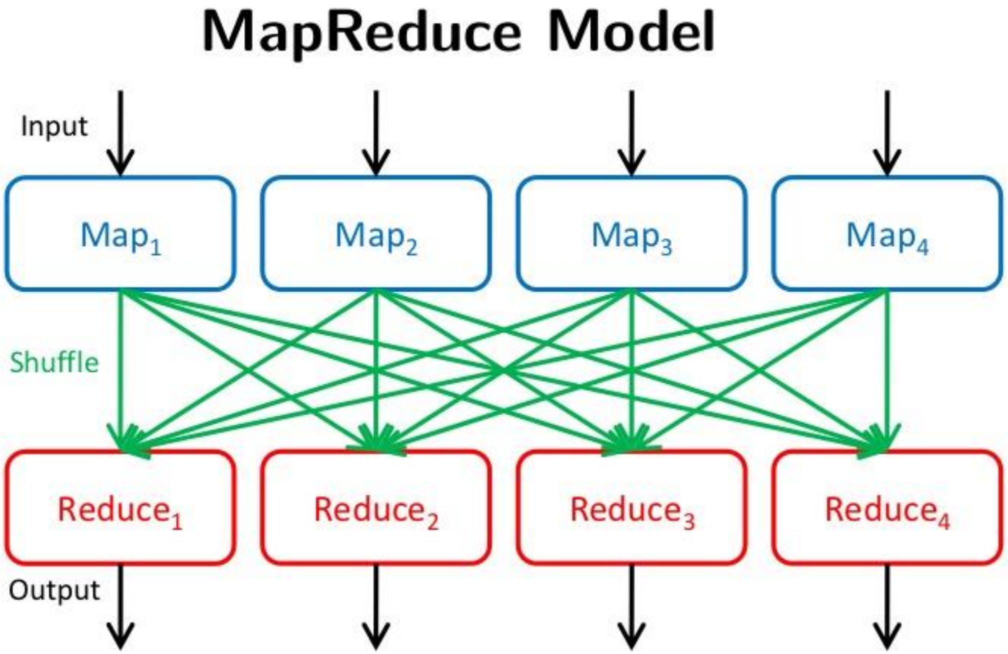
- Uniform nodes
- Data shards in a distributed storage



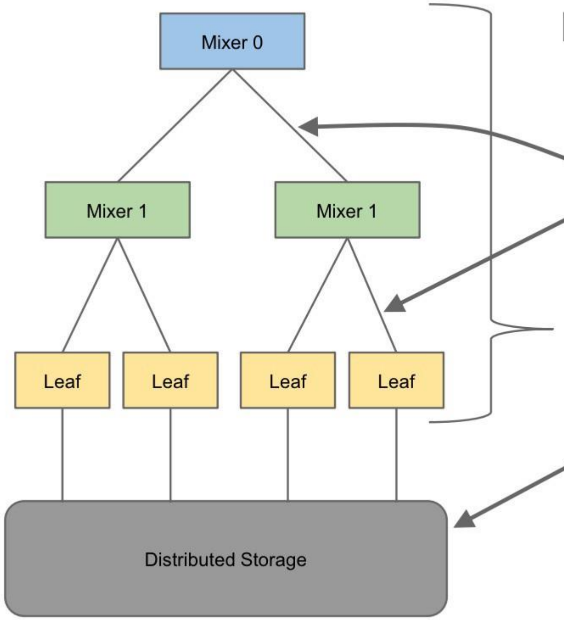
Cluster Computing Example

- Hadoop
- BigQuery
- Pregel
- Spark
- …

Hadoop/Map-Reduce



Dremel/BigQuery – General Model

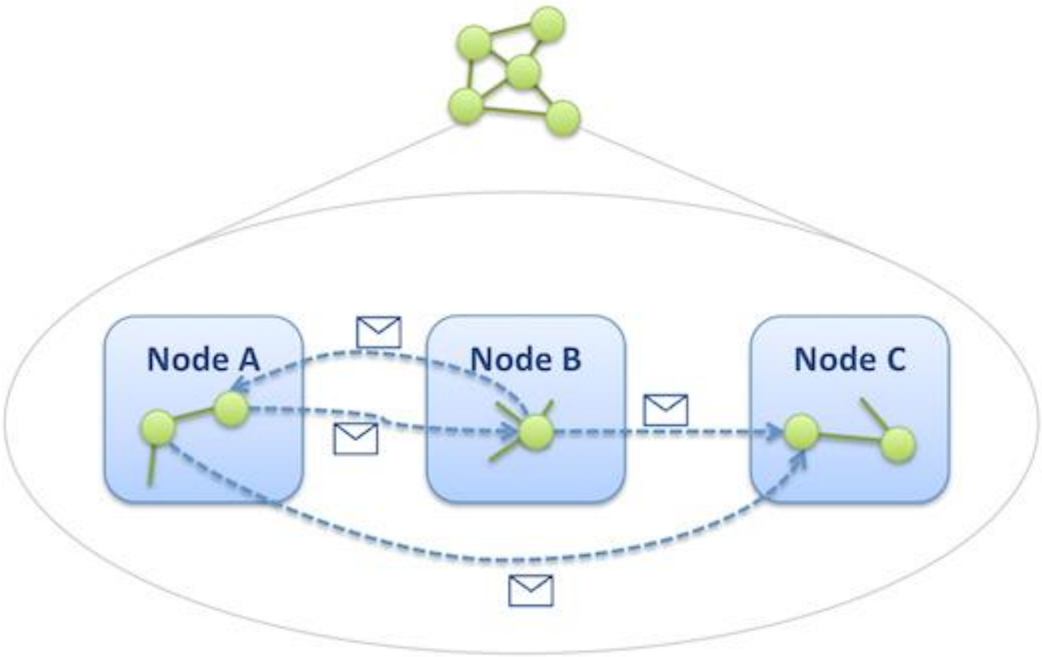


Dremel Architecture

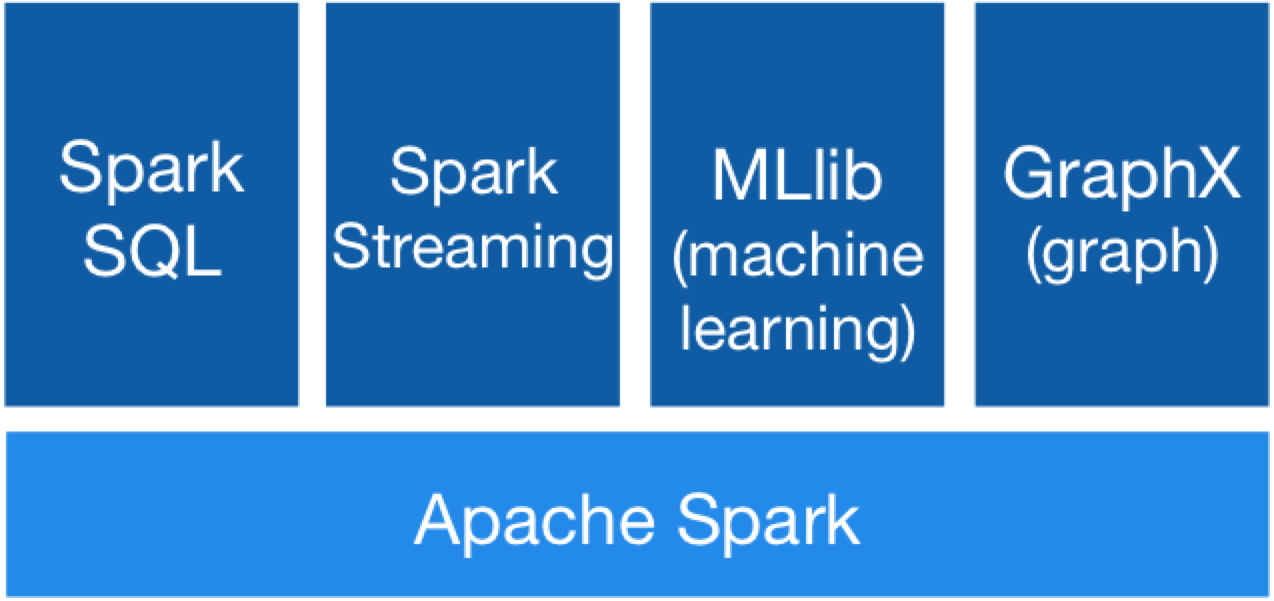
- Partial Reduction
- Diskless data flow
- Long lived shared serving tree
- Columnar Storage

Distributed Graph Computing

- Each node does computation
- Each node can be distributed
- Information is passed between nodes
- Execution is coordinated amongst nodes



Spark - General Model



Spark SQL

Spark Streaming

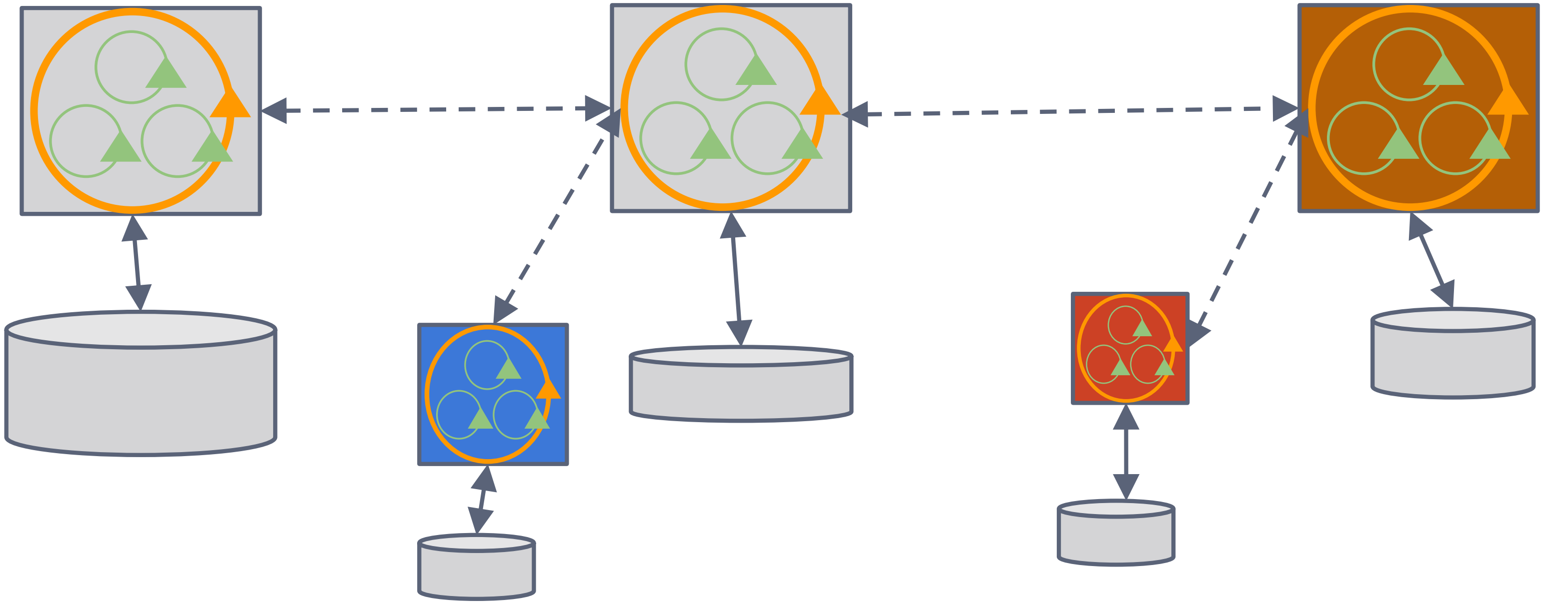
MLlib (machine learning)

GraphX (graph)

Apache Spark

Grid Computing

- Distributed Nodes
- Heterogeneous and Physically Separate Nodes



Grid Computing Example

- SETI@home (SETI Institute)
- Large Hadron Collider Computing Grid (CERN)
- NFCR Centre for Comp. Drug Discovery (Oxford Univ)
- Globus Toolkit (Globus Alliance)
- …

Data Storage:
Data Warehouse vs Data Lakes

Data Warehouse vs Data Lake

Data Warehouse

- Data Transformed to defined schema
- Loaded when usage identified
- Allows for quick response of defined queries

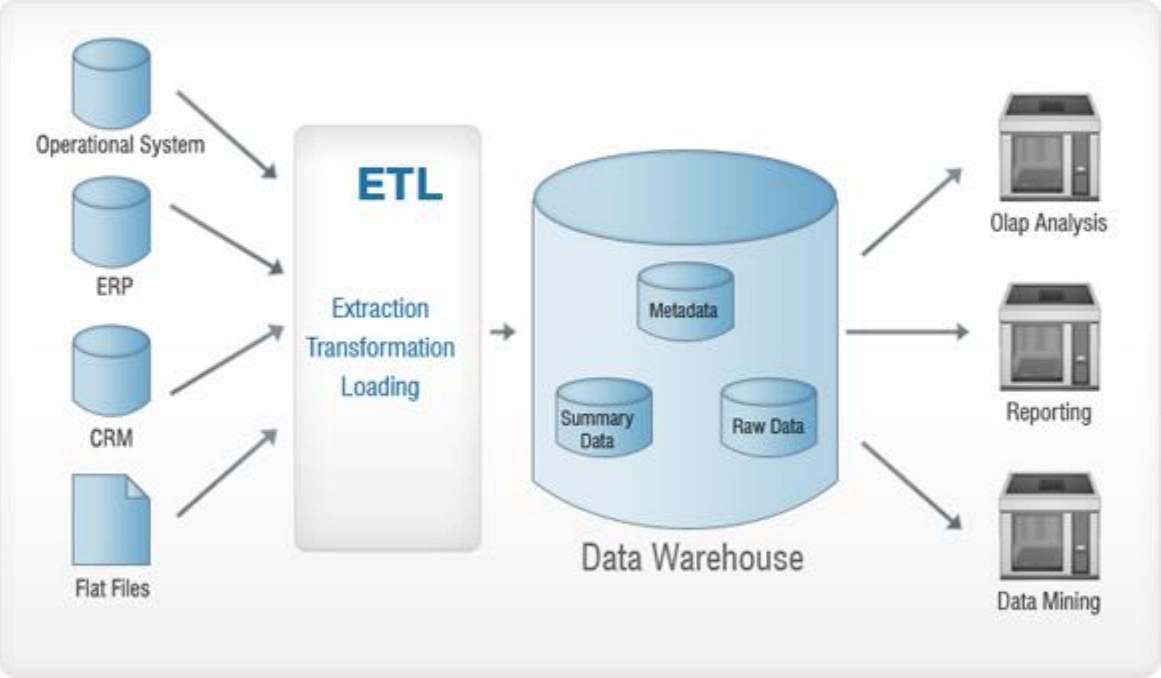
Data Lake

- Many data sources
- Retain all data
- Allows for exploration
- Apply transform as needed
- Apply schema as needed

Data Warehouse

Key points:

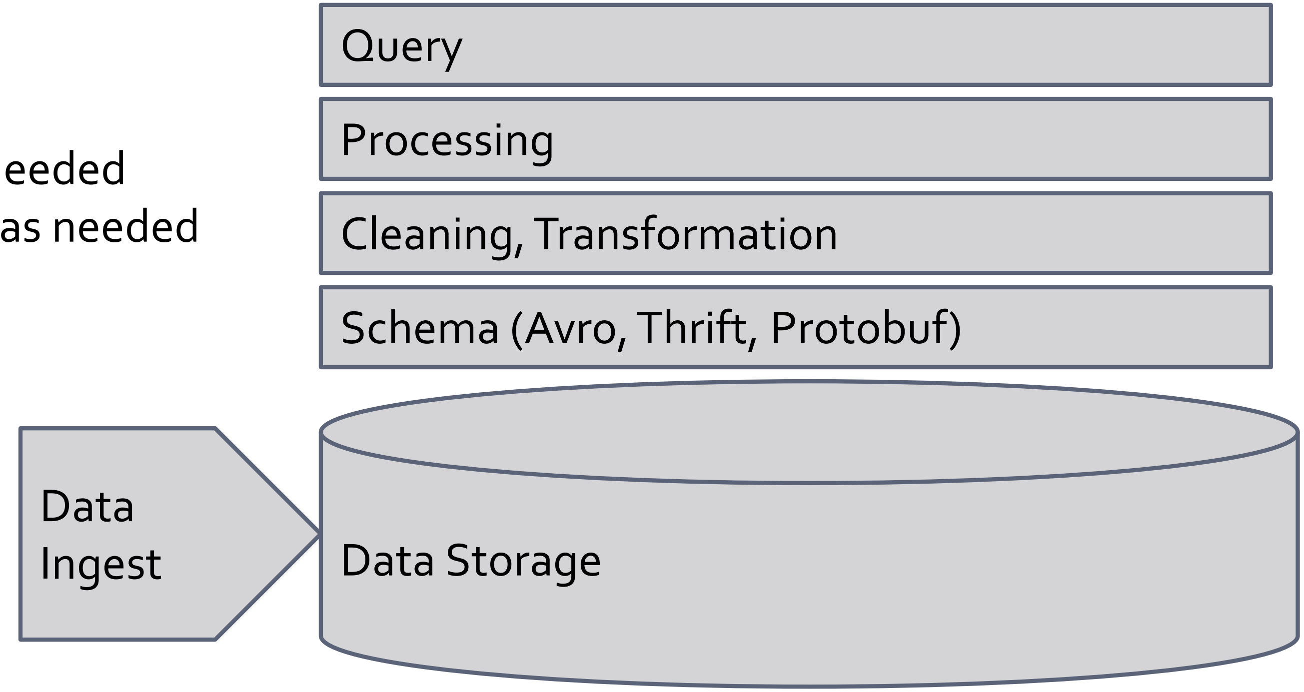
- Extract needed data
- Map to schema
- Prepare for defined use cases



Data Lake

Key points:

- Store all data
- Transform as needed
- Apply schema as needed



Query

Processing

Cleaning, Transformation

Schema (Avro, Thrift, Protobuf)

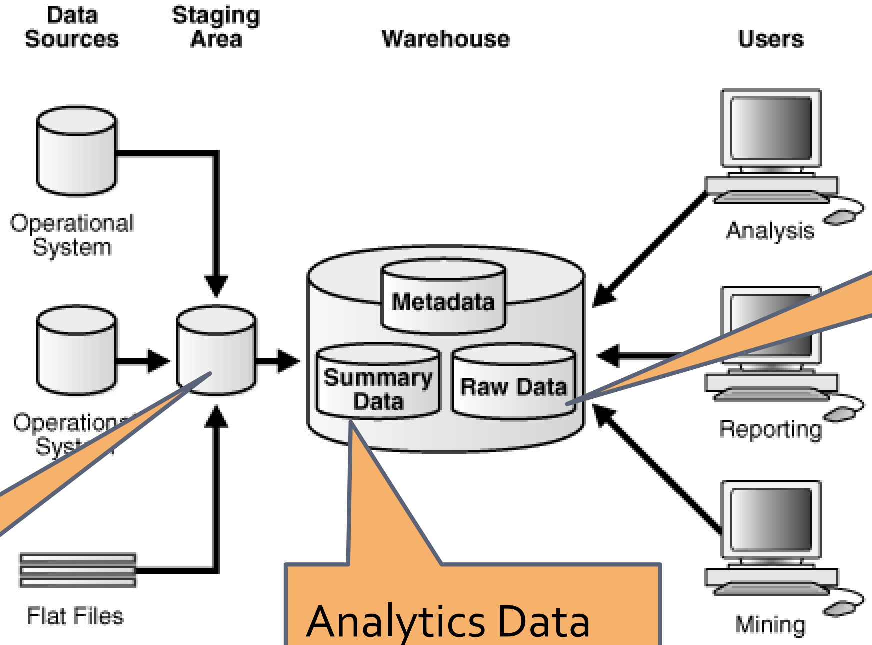
Data Ingest

Data Storage

Data Characteristics

- Understanding of data models and schemas in traditional BW
- Understanding of data models and schemas proposed for big data systems

Traditional Business Warehouse



New transactions and facts

Analytics Data

Transaction data and Fact based data model

OLTP vs OLAP

Online Transaction Processing (OLTP)

systems and approach that facilitate and manage **transaction-oriented applications**, typically for data entry and retrieval transaction processing

Online Analytics Processing (OLAP)

systems and approach to answering **multi-dimensional analytical queries** quickly

OLTP vs OLAP

OLTP

CRUD Transactions (Create, Read, Update, and Delete)

Frequent Updates

Example query:

```
UPDATE Employees
SET Salary='100,000'
WHERE EmployeeName='Alfred Nobel';
SELECT Salary FROM Employees
WHERE Salary ='Alfred Nobel';
```

OLAP

Aggregations

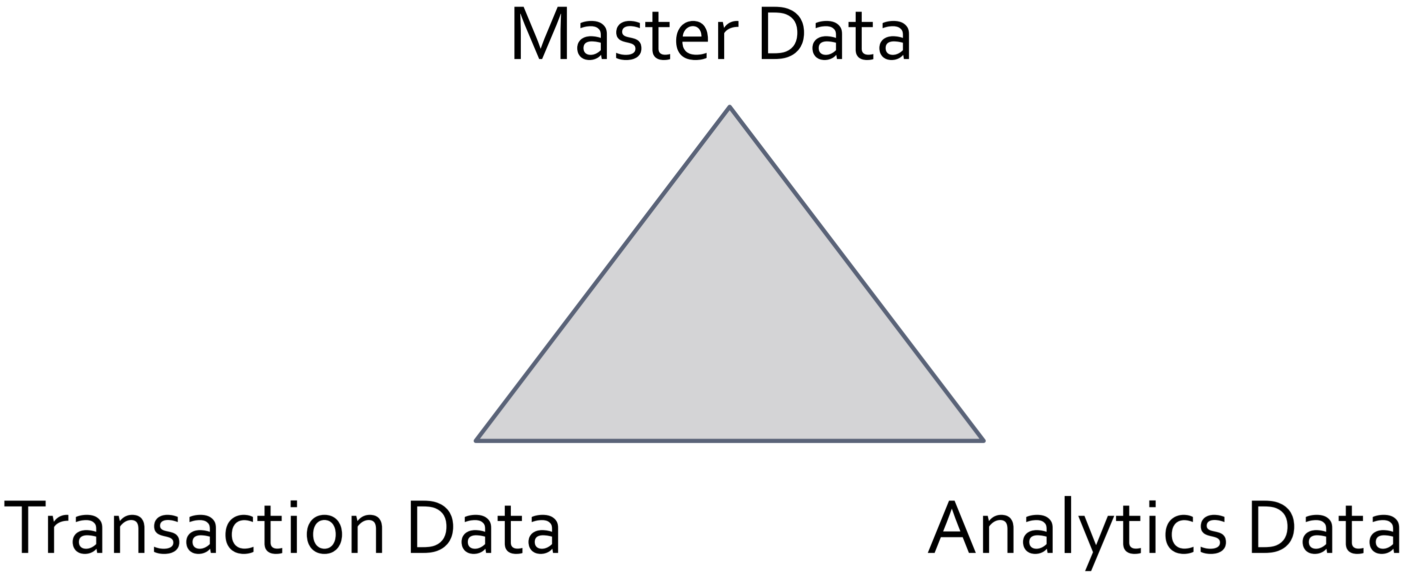
Drill-downs,

Roll-ups

Example query:

```
select o.customerid, o.orderid,
   o.orderdate, p.price, sum
   (p.price) over (partition by
   o.customerid order by o.orderdate)
   running_total
```

The Data



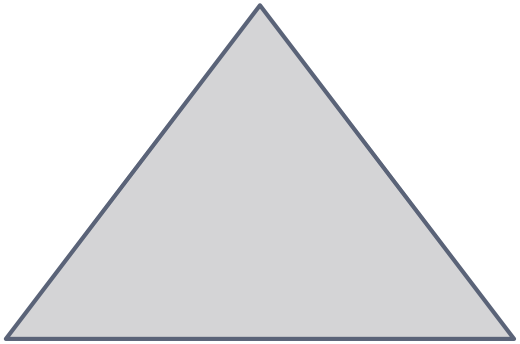
Master Data

Transaction Data

Analytics Data

Master Data: The source of truth in your system, cannot withstand corruption
Transaction Data: Keeps relationships (e.g., who bought what)
Analytics Data: Aggregated/processed transaction data

Data Warehouse Model



Master Data
(Dimension Tables)

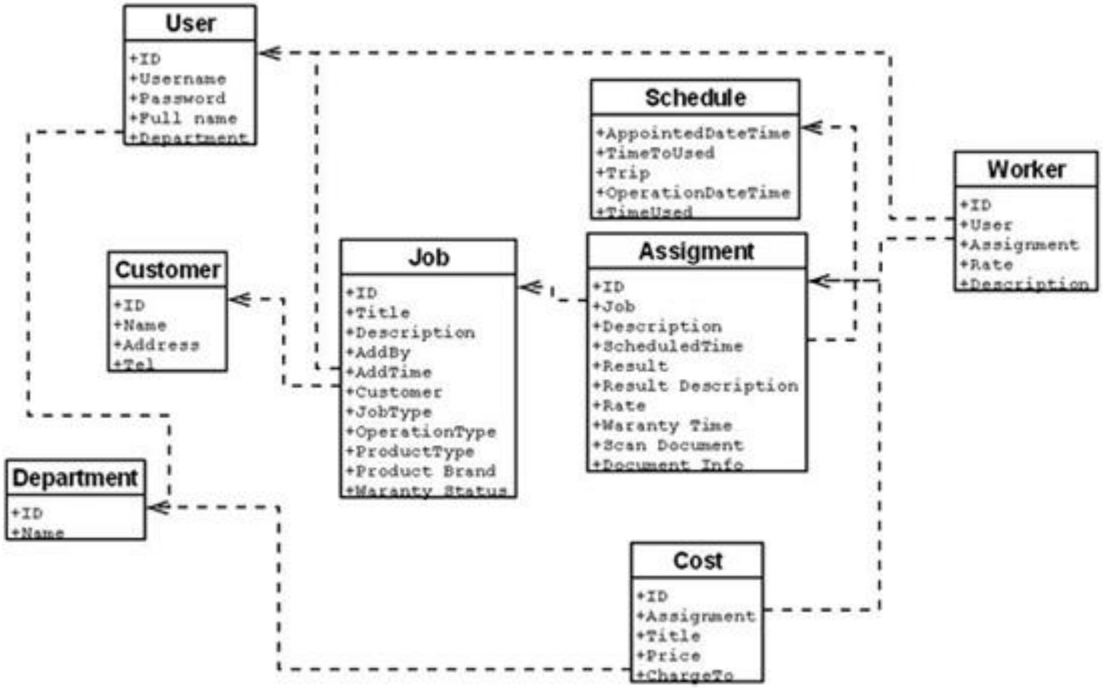
Transaction Data
(Fact table)

Analytics Data
(Cuboid)

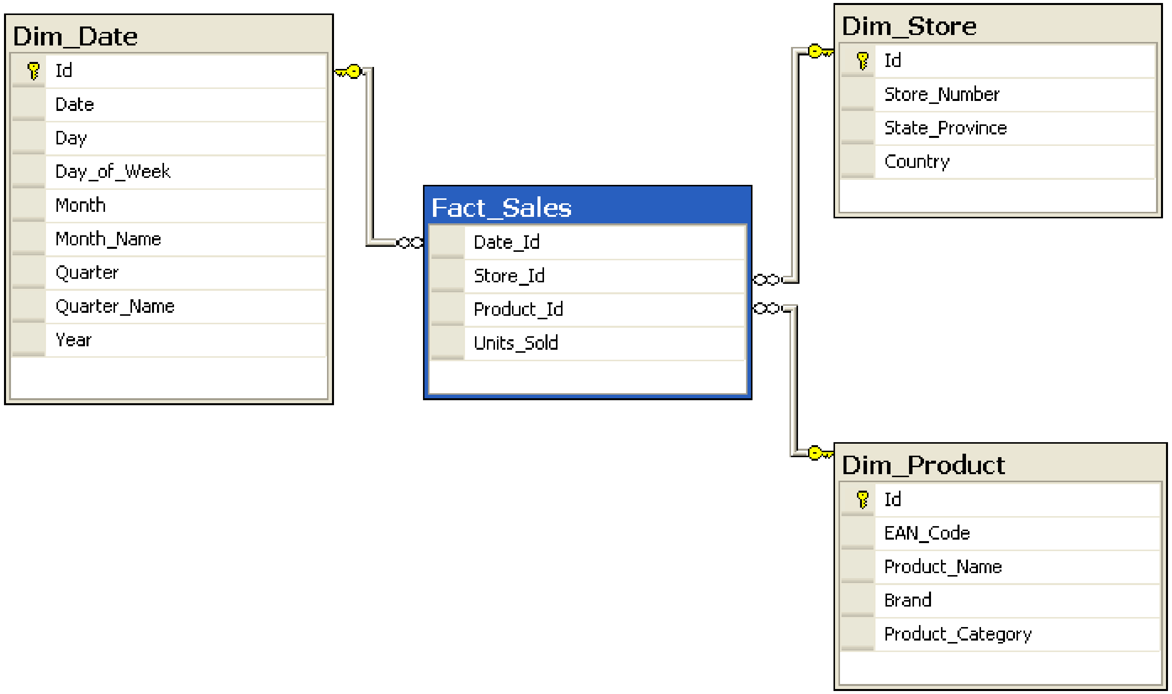
Master Data (Dimensions)

Captures concepts and relationships that participate in transactions

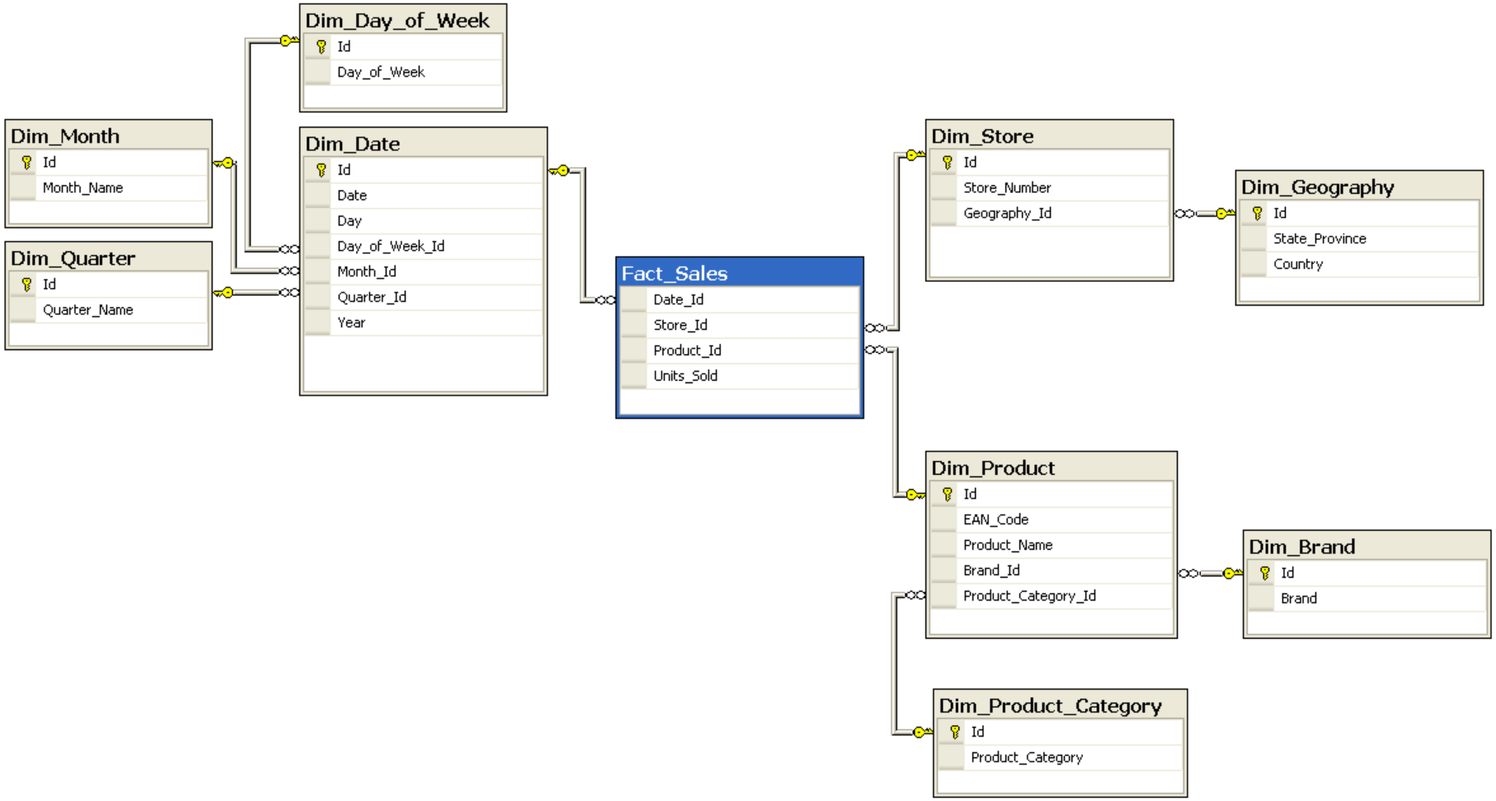
object, relationship, object attributes



Star Schema


Dim_Date
Id
Date
Day
Day_of_Week
Month
Month_Name
Quarter
Quarter_Name
Year
Fact_Sales
Date_Id
Store_Id
Product_Id
Units_Sold
Dim_Store
Id
Store_Number
State_Province
Country
Dim_Product
Id
EAN_Code
Product_Name
Brand
Product_Category

Snow flake Schema



Transaction Data (Fact Table)

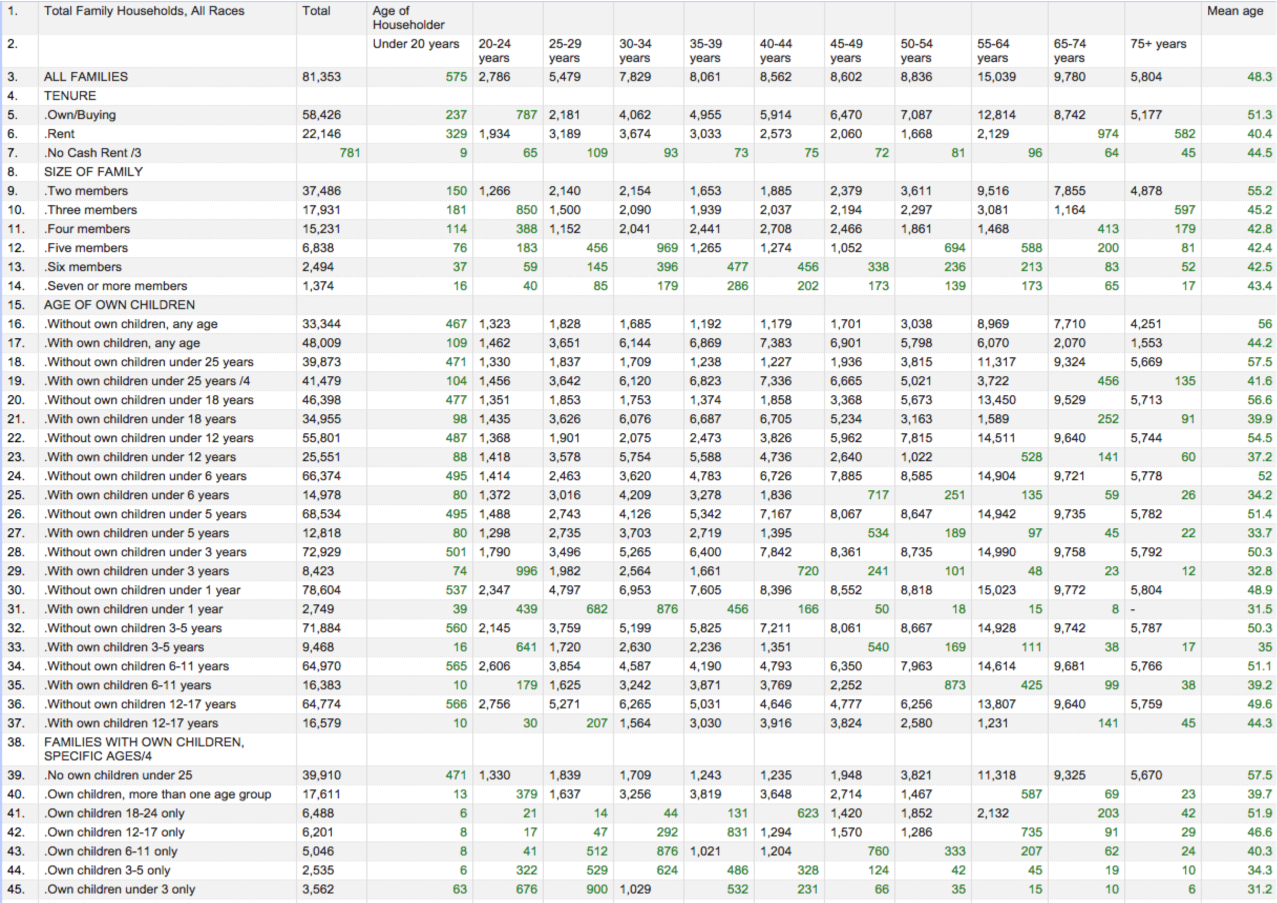
Each Record Captures a Transaction
(id, object, amount, time, ...)

Complaint ID	Product	Sub-product	Issue	Sub-issue	State	ZIP code	Submitted via	Date received	Date sent to con	Company	Company respo	Timely respons
1354490	Debt collection		Cont'd attempts collect debt not owed	Debt is not mine	OH	44077	Web	04/30/2015	04/30/2015	Expert Global Solutions, Inc.	In progress	Yes
1355160	Student loan	Non-federal student loan	Dealing with my lender or servicer		NJ	8807	Web	04/30/2015	04/30/2015	Transworld Systems Inc.	In progress	Yes
1355730	Credit reporting		Incorrect information on credit report	Account status	IL	60618	Web	04/30/2015	04/30/2015	FNIS (Fidelity National Information Services, Inc.)	Closed with explanation	Yes
1355607	Debt collection	Other (phone, health club, etc.)	Disclosure verification of debt	Right to dispute notice not received	WA	98133	Web	04/30/2015	04/30/2015	Stellar Recovery Inc.	Closed with explanation	Yes
1354249	Bank account or service	Checking account	Problems caused by my funds being low		AL	35127	Web	04/30/2015	04/30/2015	Wells Fargo	Closed with explanation	Yes
1354326	Bank account or service	Checking account	Account opening, closing, or management		TX	78575	Web	04/30/2015	04/30/2015	Ally Financial Inc.	In progress	Yes
1351925	Bank account or service	Checking account	Account opening, closing, or management		FL	34677	Web	04/29/2015	04/29/2015	HSBC	Closed with explanation	Yes
1352573	Debt collection	Medical	Cont'd attempts collect debt not owed	Debt was paid	NV	89143	Web	04/29/2015	04/29/2015	Nevada Credico, Inc.	Closed with explanation	Yes
1354227	Debt collection	Medical	False statements or representation	Indicated committed crime not paying	FL	32792	Web	04/29/2015	04/30/2015	Transworld Systems Inc.	In progress	Yes
1354200	Debt collection	Credit card	False statements or representation	Indicated committed crime not paying	AZ	85304	Web	04/29/2015	04/30/2015	Patenaude & Felix APC	Closed with explanation	Yes
1352929	Debt collection	Other (phone, health club, etc.)	Cont'd attempts collect debt not owed	Debt is not mine	NC	27534	Web	04/29/2015	04/29/2015	M&S Recovery Solutions	Closed with explanation	Yes
1354191	Bank account or service	Checking account	Problems caused by my funds being low		CA	90044	Web	04/29/2015	04/30/2015	Wells Fargo	Closed with explanation	Yes
1354115	Debt collection	Medical	Cont'd attempts collect debt not owed	Debt is not mine	TX	77449	Web	04/29/2015	04/29/2015	Commonwealth Financial Systems, Inc.	Closed with explanation	Yes
1353502	Consumer loan	Vehicle loan	Problems when you are unable to pay		TX	75287	Web	04/29/2015	04/29/2015	Ally Financial Inc.	In progress	Yes
1353732	Mortgage	Conventional fixed mortgage	Loan servicing, payments, escrow account		GA	35114	Web	04/29/2015	04/29/2015	United Security Financial Corp	Closed with non-monetary relief	Yes
1353334	Bank account or service	Checking account	Account opening, closing, or management		ID	83705	Web	04/29/2015	04/29/2015	Wells Fargo	Closed with explanation	Yes
1353247	Money transfers	Domestic (US) money transfer	Fraud or scam		AR	72712	Web	04/29/2015	04/29/2015	MoneyGram	In progress	Yes
1352727	Mortgage	Conventional adjustable mortgage (ARM)	Loan modification,collection,foreclosure		FL	32808	Web	04/29/2015	04/29/2015	Bayview Loan Servicing, LLC	In progress	Yes

Analytics Data

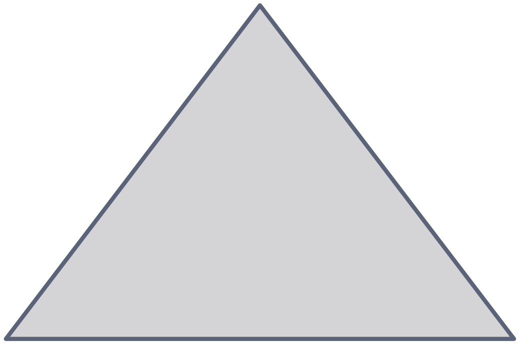
Roll-ups, drill downs, summaries

summary, average, grouping



1.	Total Family Households, All Races	Total	Age of Householder										Mean age
2.			Under 20 years	20-24 years	25-29 years	30-34 years	35-39 years	40-44 years	45-49 years	50-54 years	55-64 years	65-74 years	75+ years	
3.	ALL FAMILIES	81,353	575	2,786	5,479	7,829	8,061	8,562	8,602	8,836	15,039	9,780	5,804	48.3
4.	TENURE													
5.	.Own/Buying	58,426	237	787	2,181	4,062	4,955	5,914	6,470	7,087	12,814	8,742	5,177	51.3
6.	.Rent	22,146	329	1,934	3,189	3,674	3,033	2,573	2,060	1,668	2,129	974	582	40.4
7.	.No Cash Rent /3	781	9	65	109	93	73	75	72	81	96	64	45	44.5
8.	SIZE OF FAMILY													
9.	.Two members	37,486	150	1,266	2,140	2,154	1,653	1,885	2,379	3,611	9,516	7,855	4,878	55.2
10.	.Three members	17,931	181	850	1,500	2,090	1,939	2,037	2,194	2,297	3,081	1,164	597	45.2
11.	.Four members	15,231	114	388	1,152	2,041	2,441	2,708	2,466	1,861	1,468	413	179	42.8
12.	.Five members	6,838	76	183	456	969	1,265	1,274	1,052	694	588	200	81	42.4
13.	.Six members	2,494	37	59	145	396	477	456	338	236	213	83	52	42.5
14.	.Seven or more members	1,374	16	40	85	179	286	202	173	139	173	65	17	43.4
15.	AGE OF OWN CHILDREN													
16.	.Without own children, any age	33,344	467	1,323	1,828	1,685	1,192	1,179	1,701	3,038	8,969	7,710	4,251	56
17.	.With own children, any age	48,009	109	1,462	3,651	6,144	6,869	7,383	6,901	5,798	6,070	2,070	1,553	44.2
18.	.Without own children under 25 years	39,873	471	1,330	1,837	1,709	1,238	1,227	1,936	3,815	11,317	9,324	5,669	57.5
19.	.With own children under 25 years /4	41,479	104	1,456	3,642	6,120	6,823	7,336	6,665	5,021	3,722	456	135	41.6
20.	.Without own children under 18 years	46,398	477	1,351	1,853	1,753	1,374	1,858	3,368	5,673	13,450	9,529	5,713	56.6
21.	.With own children under 18 years	34,955	98	1,435	3,626	6,076	6,687	6,705	5,234	3,163	1,589	252	91	39.9
22.	.Without own children under 12 years	55,801	487	1,368	1,901	2,075	2,473	3,826	5,962	7,815	14,511	9,640	5,744	54.5
23.	.With own children under 12 years	25,551	88	1,418	3,578	5,754	5,588	4,736	2,640	1,022	528	141	60	37.2
24.	.Without own children under 6 years	66,374	495	1,414	2,463	3,620	4,783	6,726	7,885	8,585	14,904	9,721	5,778	52
25.	.With own children under 6 years	14,978	80	1,372	3,016	4,209	3,278	1,836	717	251	135	59	26	34.2
26.	.Without own children under 5 years	68,534	495	1,488	2,743	4,126	5,342	7,167	8,067	8,647	14,942	9,735	5,782	51.4
27.	.With own children under 5 years	12,818	80	1,298	2,735	3,703	2,719	1,395	534	189	97	45	22	33.7
28.	.Without own children under 3 years	72,929	501	1,790	3,496	5,265	6,400	7,842	8,361	8,735	14,990	9,758	5,792	50.3
29.	.With own children under 3 years	8,423	74	996	1,982	2,564	1,661	720	241	101	48	23	12	32.8
30.	.Without own children under 1 year	78,604	537	2,347	4,797	6,953	7,605	8,396	8,552	8,818	15,023	9,772	5,804	48.9
31.	.With own children under 1 year	2,749	39	439	682	876	456	166	50	18	15	8	-	31.5
32.	.Without own children 3-5 years	71,884	560	2,145	3,759	5,199	5,825	7,211	8,061	8,667	14,928	9,742	5,787	50.3
33.	.With own children 3-5 years	9,468	16	641	1,720	2,630	2,236	1,351	540	169	111	38	17	35
34.	.Without own children 6-11 years	64,970	565	2,606	3,854	4,587	4,190	4,793	6,350	7,963	14,614	9,681	5,766	51.1
35.	.With own children 6-11 years	16,383	10	179	1,625	3,242	3,871	3,769	2,252	873	425	99	38	39.2
36.	.Without own children 12-17 years	64,774	566	2,756	5,271	6,265	5,031	4,646	4,777	6,256	13,807	9,640	5,759	49.6
37.	.With own children 12-17 years	16,579	10	30	207	1,564	3,030	3,916	3,824	2,580	1,231	141	45	44.3
38.	FAMILIES WITH OWN CHILDREN, SPECIFIC AGES/4													
39.	.No own children under 25	39,910	471	1,330	1,839	1,709	1,243	1,235	1,948	3,821	11,318	9,325	5,670	57.5
40.	.Own children, more than one age group	17,611	13	379	1,637	3,256	3,819	3,648	2,714	1,467	587	69	23	39.7
41.	.Own children 18-24 only	6,488	6	21	14	44	131	623	1,420	1,852	2,132	203	42	51.9
42.	.Own children 12-17 only	6,201	8	17	47	292	831	1,294	1,570	1,286	735	91	29	46.6
43.	.Own children 6-11 only	5,046	8	41	512	876	1,021	1,204	760	333	207	62	24	40.3
44.	.Own children 3-5 only	2,535	6	322	529	624	486	328	124	42	45	19	10	34.3
45.	.Own children under 3 only	3,562	63	676	900	1,029	532	231	66	35	15	10	6	31.2

Big Data Architecture Model

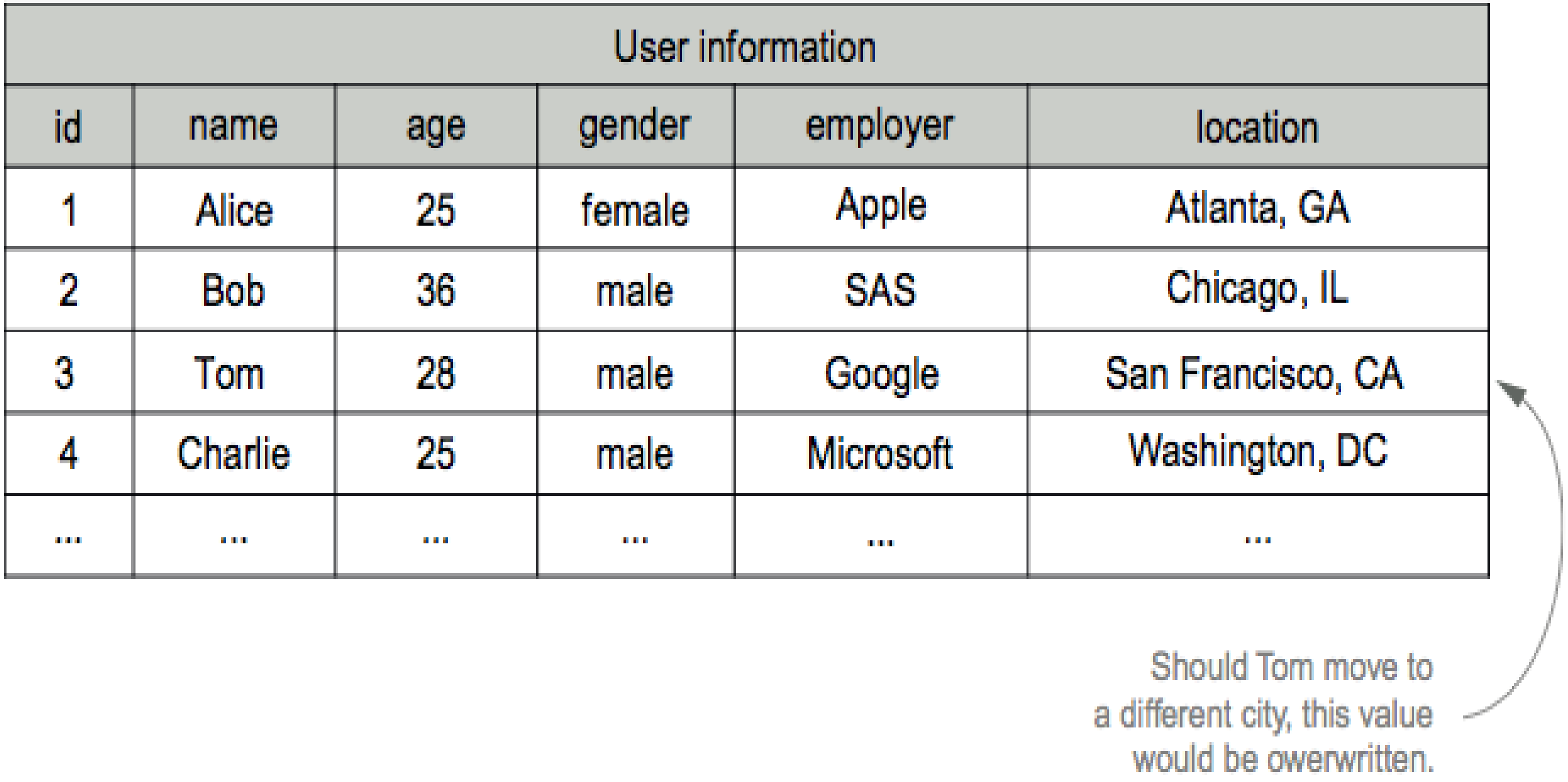


Master Data
(fact based, Immutable, Dimensions)

Transaction Data
(Log items)

Analytics Data
(Aggregates, Roll-ups)

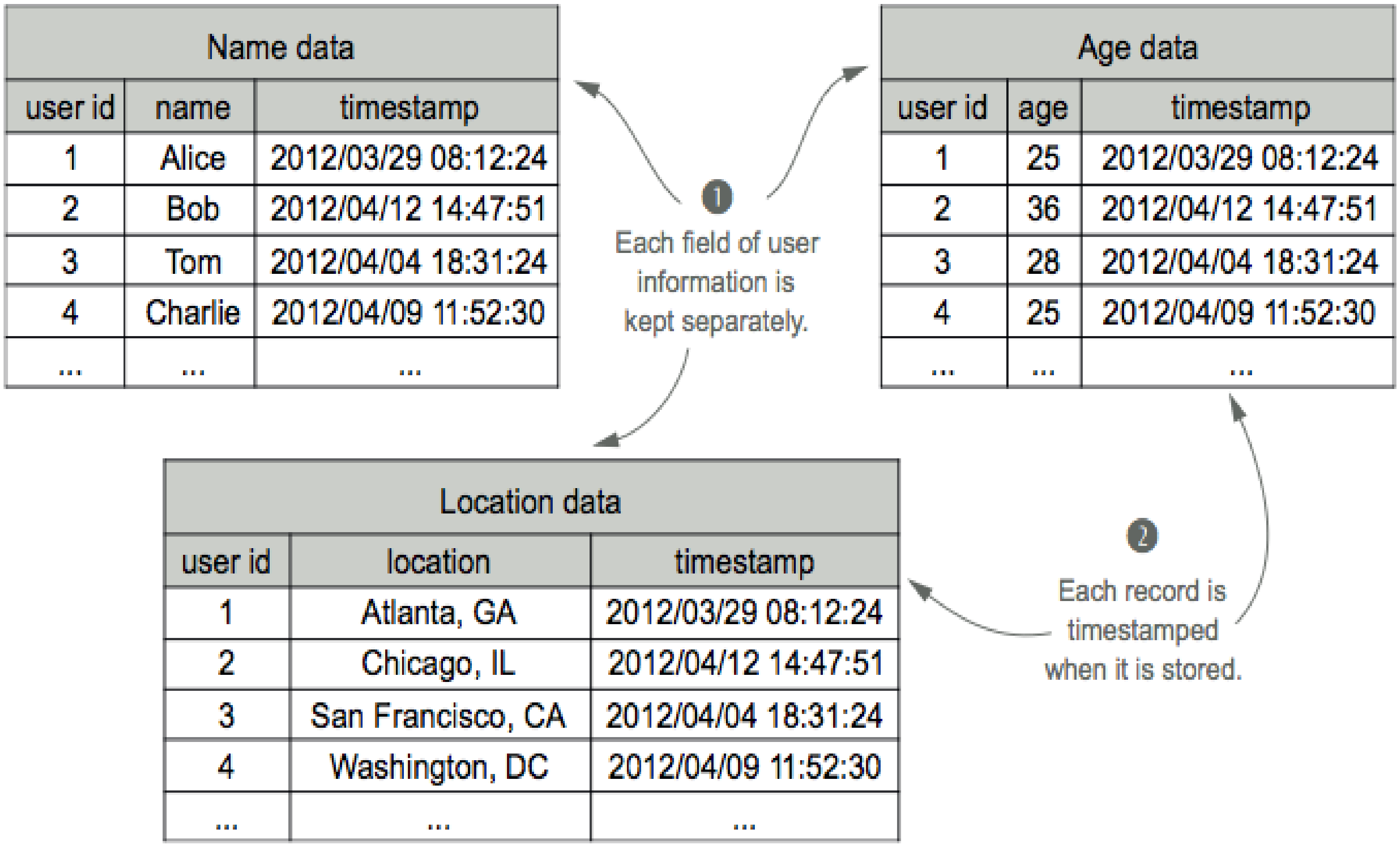
Mutable table



User information					
id	name	age	gender	employer	location
1	Alice	25	female	Apple	Atlanta, GA
2	Bob	36	male	SAS	Chicago, IL
3	Tom	28	male	Google	San Francisco, CA
4	Charlie	25	male	Microsoft	Washington, DC
...	...	...	...	...	...

Should Tom move to
a different city, this value
would be owerwritten.

Fact Based, Immutable



Name data

user id	name	timestamp
1	Alice	2012/03/29 08:12:24
2	Bob	2012/04/12 14:47:51
3	Tom	2012/04/04 18:31:24
4	Charlie	2012/04/09 11:52:30
...	...	...

Age data

user id	age	timestamp
1	25	2012/03/29 08:12:24
2	36	2012/04/12 14:47:51
3	28	2012/04/04 18:31:24
4	25	2012/04/09 11:52:30
...	...	...

Location data

user id	location	timestamp
1	Atlanta, GA	2012/03/29 08:12:24
2	Chicago, IL	2012/04/12 14:47:51
3	San Francisco, CA	2012/04/04 18:31:24
4	Washington, DC	2012/04/09 11:52:30
...	...	...

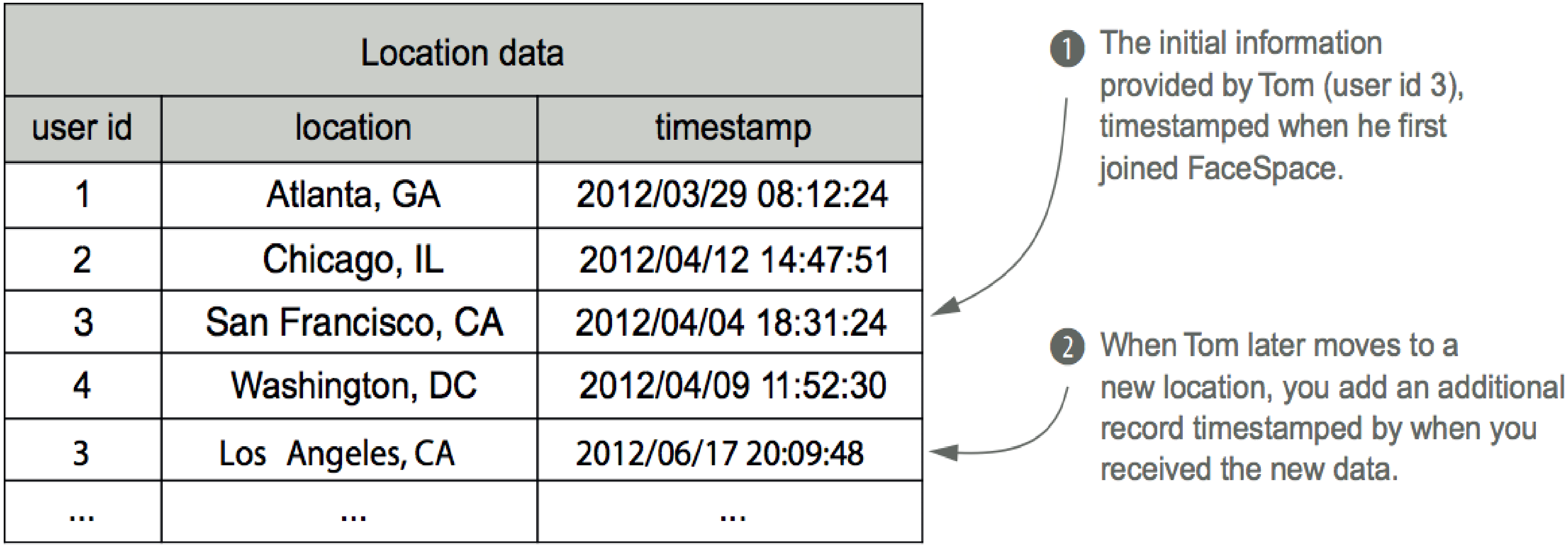
❶ Each field of user information is kept separately.

❷ Each record is timestamped when it is stored.

In the fact-based model, you deconstruct the data into fundamental units called ***facts***

Benefits of a fact based model

- Supports queries about any time in history
- Enables complex queries (that a predefined schema might have have ignored)



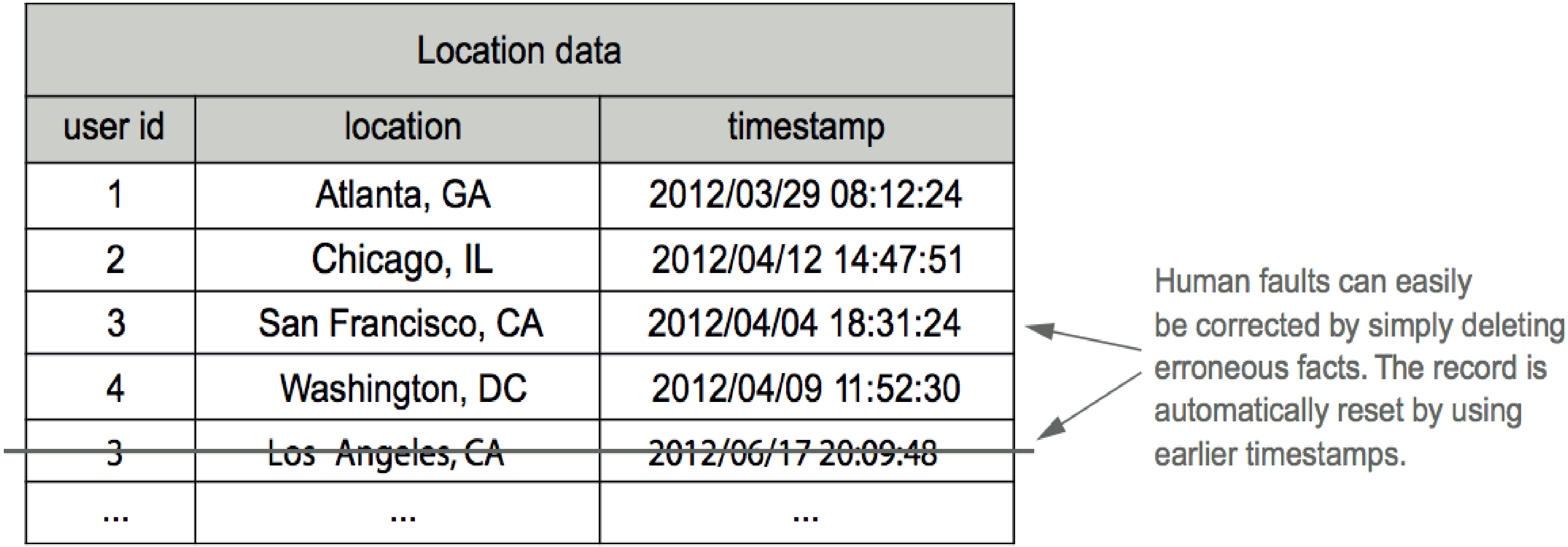
Location data		
user id	location	timestamp
1	Atlanta, GA	2012/03/29 08:12:24
2	Chicago, IL	2012/04/12 14:47:51
3	San Francisco, CA	2012/04/04 18:31:24
4	Washington, DC	2012/04/09 11:52:30
3	Los Angeles, CA	2012/06/17 20:09:48
...	...	...

① The initial information provided by Tom (user id 3), timestamped when he first joined FaceSpace.

② When Tom later moves to a new location, you add an additional record timestamped by when you received the new data.

Benefits of a fact based model

More easily correctable (remove erroneous facts)



Location data		
user id	location	timestamp
1	Atlanta, GA	2012/03/29 08:12:24
2	Chicago, IL	2012/04/12 14:47:51
3	San Francisco, CA	2012/04/04 18:31:24
4	Washington, DC	2012/04/09 11:52:30
~~3~~	~~Los Angeles, CA~~	~~2012/06/17 20:09:48~~
...	...	...

Human faults can easily be corrected by simply deleting erroneous facts. The record is automatically reset by using earlier timestamps.

Storage Systems

DBMS: Relational and Columnar

Two kinds of ***database management systems***

- **Relational Databases**
  - Presents via Declarative Query Languages
  - Organize underlying storage **row-wise**
    - Sometimes column-wise
- **Columnar Databases**
  - Presents via API and Declarative Query Languages
  - Organize underlying storage **column-wise**

How Do Relational DBs Work?

Logical Schema

<RowID>	EmployeeID	FirstName	LastName	Dept	Salary
001	12	John	Smith	Marketing	90
002	24	Sue	Richards	Engine	130
003	35	Maggie	Smith	DataSci	120
004	44	Bobby	Jones	DataSci	120

- Records stored as **tables**
    - Schema validated **on-write**
    - Typically **indexed**
- Records may be persisted
    - Row-wise
    - Column-wise
- Additional structures can be applied to enhance access
    - Secondary Indices
    - Materialized Views
    - Stored Procedures

Physical Schema

```
001:12,John,Smith,Marketing,90\n
002:24,Sue,Richards,Engine,130\n
003:35,Maggie,Smith,DataSci,120\n
004:44,Bobby,Jones,DataSci,120\n
```

Row-Oriented

- Very fast to insert rows
- Very fast to retrieve **whole** rows
- Slower to retrieve whole columns

How Do Columnar DBs Work?

Logical Schema

<RowID>	EmployeeID	FirstName	LastName	Dept	Salary
001	12	John	Smith	Marketing	90
002	24	Sue	Richards	Engine	130
003	35	Maggie	Smith	DataSci	120
004	44	Bobby	Jones	DataSci	120

- Records stored as **tables**
- Largely for analytical workloads
    - Read-mostly
    - Bulk-insertion
- Additional access structures
- **Presumption**
    - More likely to read all values of a column than all values of a row
    - Optimize storage for fast column retrieval

Physical Schema

12:001;24:002;35:003;44:004\n
John:001;Sue:002;Maggie:003;Bobby:004\n
Smith:001,003;Richards:002;Jones:004\m
Marketing:001;Engine:002;**DataSci:003,004**\n
90:001;130:002;**120:003,004**\n

Column-Oriented

- Very fast to retrieve columns
- May save space for sparse data
- Slow to insert, slow for row reads

When are They Useful?

Relational

- Most common data storage and retrieval system
- Many drivers, declarative language (SQL)
- Good for fast inserts
- Good for (some) fast reads
- Good for sharing data among applications
- Limited schema-on-read support
- Can be costly or difficult to scale

Columnar

- Optimized for analytical workloads
- Maintains relational data model
- Good for analytical operations
- Good for horizontal scaling
- Bad for fast writes
- Bad for fast row-wise reads

NoSQL and HDFS

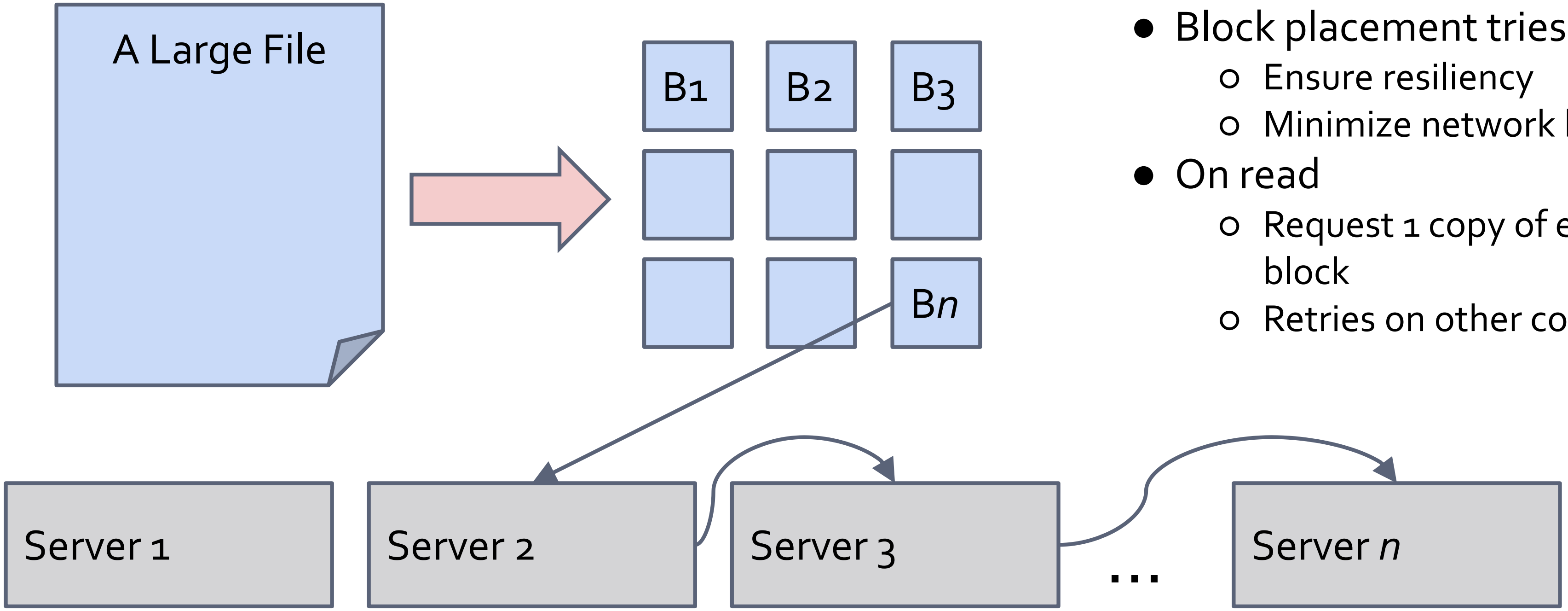
Two distributed approaches to data storage

- **HDFS (Hadoop Distributed File System)**
  - Presents like a local filesystem
  - Distribution mechanics handled automatically

- **NoSQL Databases (Key/Value Stores)**
  - Typically store records as “**key-value pairs**”
  - Distribution mechanics tied to record keys

How Does HDFS Work?

File divided into **blocks**
(Typically between 64MB and 256MB)



A Large File

B1 B2 B3

B*n*

Server 1

Server 2

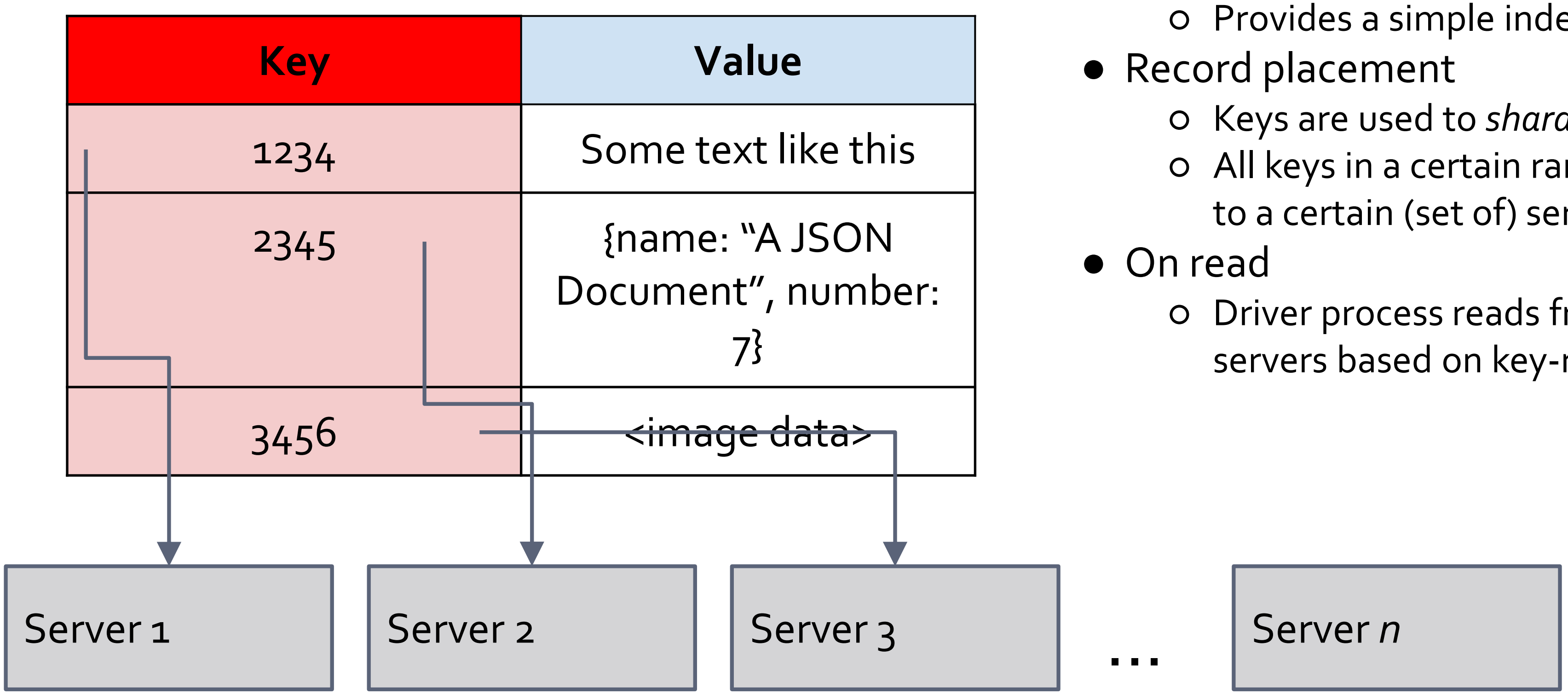
Server 3

…

Server *n*

- Blocks replicated *k* times
  - Typically: k >= 3
- Block placement tries to
  - Ensure resiliency
  - Minimize network hops
- On read
  - Request 1 copy of each block
  - Retries on other copies

How Do Key-Value Stores Work?



Key	Value
1234	Some text like this
2345	{name: "A JSON Document", number: 7}
3456	<image data>

Server 1

Server 2

Server 3

…

Server *n*

- Records stored by **key**
  - Provides a simple index
- Record placement
  - Keys are used to *shard*
  - All keys in a certain range go to a certain (set of) servers
- On read
  - Driver process reads from servers based on key-ranges

When Are They Useful?

HDFS

- Popular bulk data store
- Many, large files
  - File size >= Block size
- Agnostic to file content
- Good as an immutable data store
- Good for parallel reads of lots of blocks
- Bad for small, specific reads
- Bad for fast writes

Key-Value Stores

- Many popular choices
  - Redis, Berkeley DB
  - MongoDB
  - Cassandra (column-families imposed on value)
- Good for fast, key-based access
- Good for fast writes
- Bad for off-key access
- Complicated for merging datasets

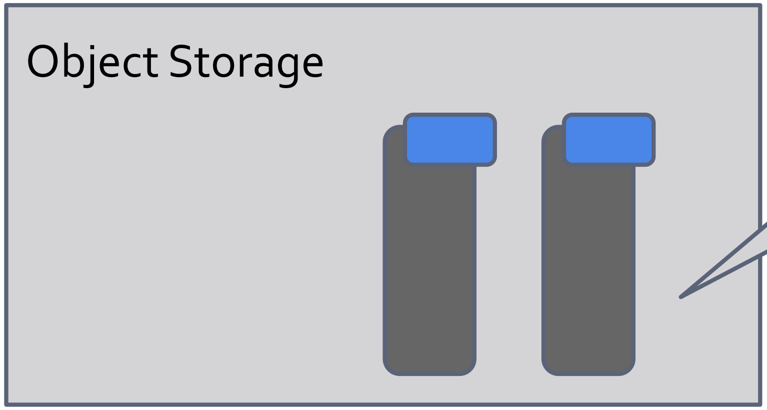
OS and SDS Storage

Two Concepts

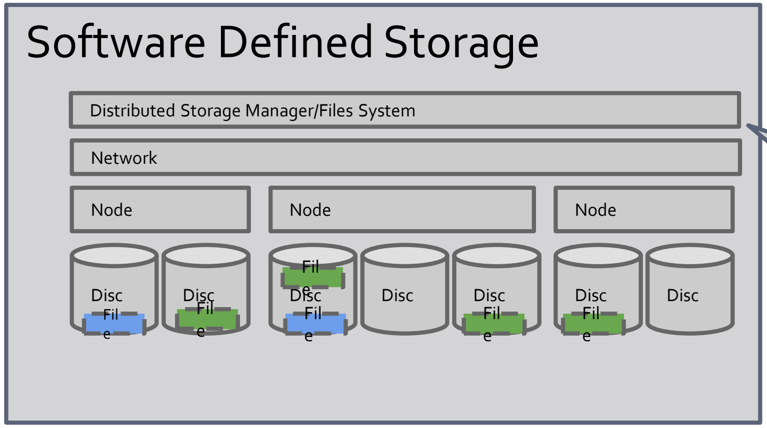
- **Object Storage (OS)**: as a new abstraction for storing data
- **Software Defined Storage (SDS)**: An architecture that enables cost effective, scalable, highly available (HA) storage systems

Combining OS and SDS provides an efficient solution for certain data applications

What is it?



Manage data as one (large) logical object
Consists of meta data and data
Unique identifier across system
Data is an uninterpreted set of bytes



Data Replication for resilience and HA
Store anything
Runs on commodity hardware
Manages data automatically, blocks hidden

What Problem Does it Solve?

- Simplified model for managing data growth
- Lowers management cost
- Lowers hardware cost
- Meet Resiliency and HA needs and lower cost

How does it work?

- Simple API with an Object Abstraction
- Data is partitioned, partitions are replicated for resiliency and HA
- Software layer
  - manages replication and data placement
  - automatically re-distributes data in case of expansion, contraction or failure

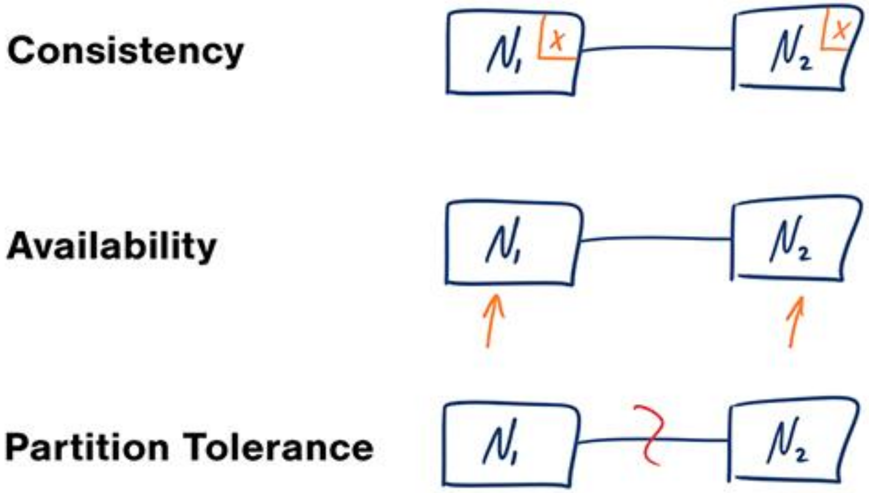
Examples

Oracle Storage Service	OpenStack SWIFT based Storage. HA, scalable storage with eventual consistency
Amazon S3	HA, scalable storage with eventual consistency
Google Cloud Storage	HA, scalable storage with strong consistency
Windows Azur Storage	HA, scalable storage with strong consistency
Rackspace Files	OpenStack SWIFT based Storage. HA, scalable storage with eventual consistency

Strong consistency offers **up-to-date** data but at the cost of **high latency**
Eventual consistency offers **low latency** but may reply to read requests with **stale data** since all nodes of the database may not have the updated data.

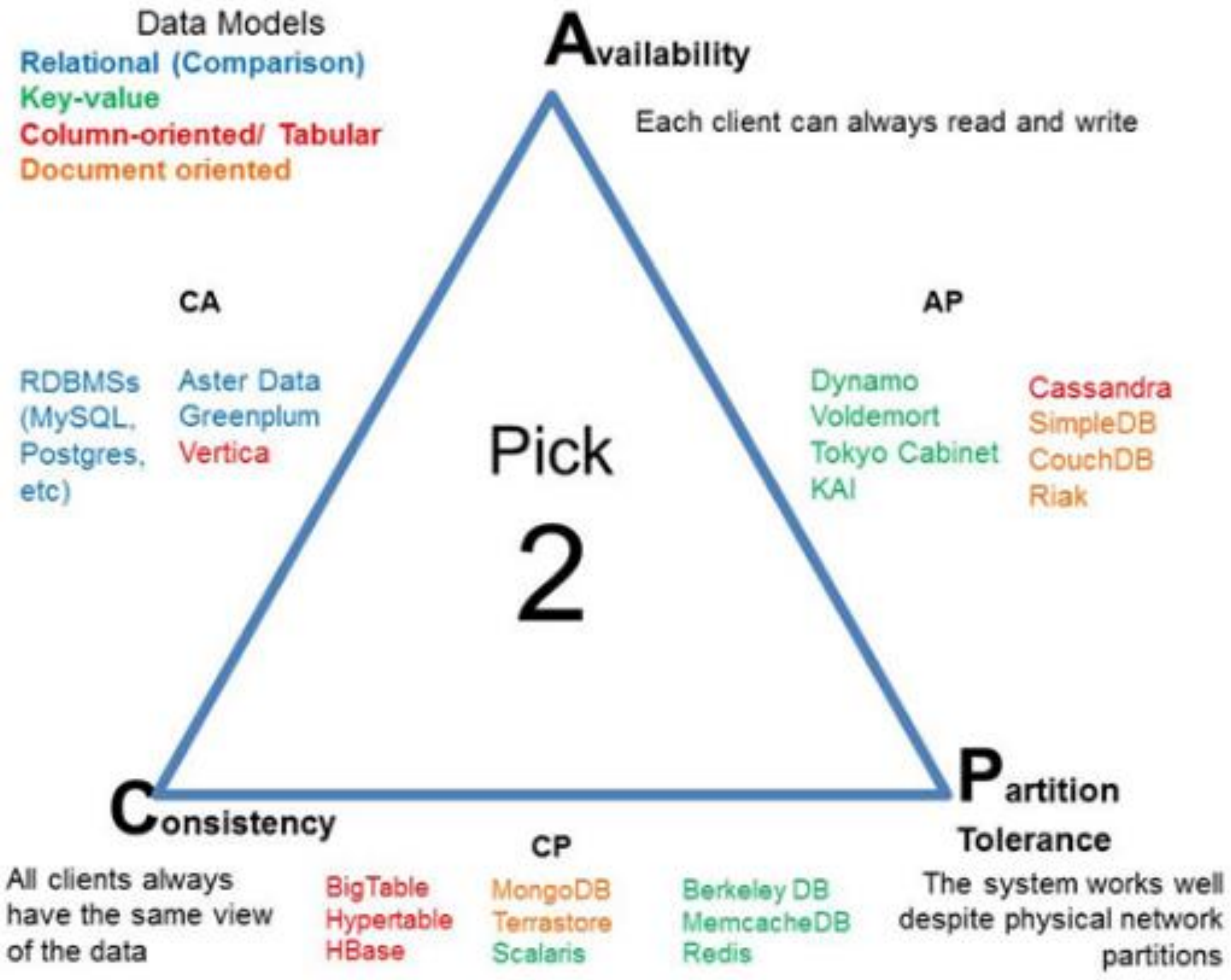
CAP Theorem

It is impossible for a distributed data store to simultaneously provide more than two out of the following three guarantees



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

CAP Theorem (Simplified)



Data Models

- Relational (Comparison)
- Key-value
- Column-oriented/ Tabular
- Document oriented

Availability

Each client can always read and write

CA

RDBMSs (MySQL, Postgres, etc)

Aster Data
Greenplum
Vertica

AP

Dynamo
Voldemort
Tokyo Cabinet
KAI

Cassandra
SimpleDB
CouchDB
Riak

Pick 2

Consistency

All clients always have the same view of the data

CP

BigTable
Hypertable
HBase

MongoDB
Terrastore
Scalaris

Berkeley DB
MemcacheDB
Redis

Partition Tolerance

The system works well despite physical network partitions

Moving Large Data Considerations

Moving Large Data

- If data is distributed how can you leverage parallelism?
- What kind of source and sink is involved?
- How do you use network bandwidth efficiently?
- How to handle different formats and structures?
- Large files take a long-time, how are failures handled?

As a data scientist you need to understand how to think about data transfer and movement

Performance Measures

- **Bandwidth** measured in bits/sec is the maximum transfer rate
- **Throughput** is the actual rate that information is transferred
- **Latency** the delay between the sender and the receiver, this is a function of the calls/signals travel time and intermediate processing time
- **Jitter** variation in the time of arrival at the receiver of the information
- **Error rate** # of corrupted bits as a percentage or fraction of the total sent

Transfer Times

Limiting Factors:

- Available Network Bandwidth
- Read/Write performance
- Error rates

Some info (for Disk storage we use base 10)

- 1 byte = 8 bits
- 1000 Bytes = 1 Kilobyte
- 1000 Kilobytes = 1 Megabyte
- 1000 Megabytes = 1 Gigabyte
- 1000 Gigabytes = 1 Terabyte

Example

How long would it take to transfer **2 TB file** over a **100 Mbit / sec** connection?

Answer

2TB = 2*1000*1000*1000*1000*8 = 1.6E+13 bit

100 Mbit = 100*1000*1000 = 100000000

seconds = 1.6E+13 / 100000000 = 160000

hours = 160000 / 60 / 60 = **44 hours**

Example Tools

Tool	What
Sqoop	RDBMS, BDW to Hadoop
distcp2	HDFS to HDFS copy
Rsync	FS to FS copy, FS to FS synchronization

Tools Comparison

	Sqoop	rsync	Distcp
Type(s) of source and sink	RDBMS to HDFS	A unix / linux system inter transfer tool	HDFS to HDFS Storage Service (S3) to HDFS
Network usage	High	Smart use of bandwidth for sync	Uses available bandwidth
Level of parallelism	Low	No built-in parallelism	High. Configurable
Structures and formats	Per table or free form SQL	Agnostic to file content	Agnostic to structure in files
Resilience to failures	If task fails it will be rolled back and result in a partial export	Need to be reinitiated/ restarted	High, will retry per job. If one job fails it will be restarted

Summary: Moving Large Data

- Understand the bottleneck and your use case
- Define your time constraints, can you move all the data or do you need to segment
- Pick the right tool

SQL DDL, Avro, Protobuf, CSV

Data Definition

When is Schema Applied?

- Schemas represent the logical view of data
- We can apply them
  - When data is **written**
  - When data is **read**
- The application of schema comes with trade-offs

Schema-on-Read

- Data is stored without constraint
  - Store data without validation
- Apply the plan to the data stream on every read
  - Extract the record from the data stream
  - Extract the details from the record
  - Validate the record

Examples of Schema-on-Read

- File systems
  - The local disk on your computer
- "Big Data Frameworks"
  - Apache Hadoop
  - Apache Spark

Rely on runtime logic to apply schema

- Some NoSQL Databases
  - MongoDB
  - CouchDB

Rely on self-describing data to apply schema

Example: Avro Schema

Consider this Avro schema expressed in JSON

```
{
   "type": "record",
   "name": "Person",
   "fields": [
        {"name": "userName", "type": "string"},
       {"name": "favoriteNumber", "type": ["null", "long"]},
       {"name": "interests","type":{"type":"array","items":"string"}}]
}
```

Other Schema-encod. Formats

- Google protobuf
- messagepack
- Cap’n Proto
- Parquet
  - Designed for large, column-oriented data

Trade-Offs in Schema-on-Read

Pros

- Data can be subject to varying interpretation
- Validation can be as strict as needed
- Schema can mutate over time

Cons

- Higher cost to read data
  - Assemble records
  - Validate records
  - Access details
- No implicit guarantees about data contents

Schema-on-Write

- Data is stored only if it fits constraints
  - Validate the schema before persisting
    - # and type of attributes
    - uniqueness, size, etc.
- Extract data quickly, without re-validation
  - Data shape, size, and location is already known

Examples of Schema-on-Write

- Databases (Typically Relational or Object-Relational)
  - MySQL
  - PostgreSQL
  - Oracle Database
  - Microsoft SQL Server
  - and many more

Trade-Offs in Schema-on-Write

Pros

- Data characteristics are guaranteed
- Storage can be optimized to speed retrieval
  - Lower-cost reads

Cons

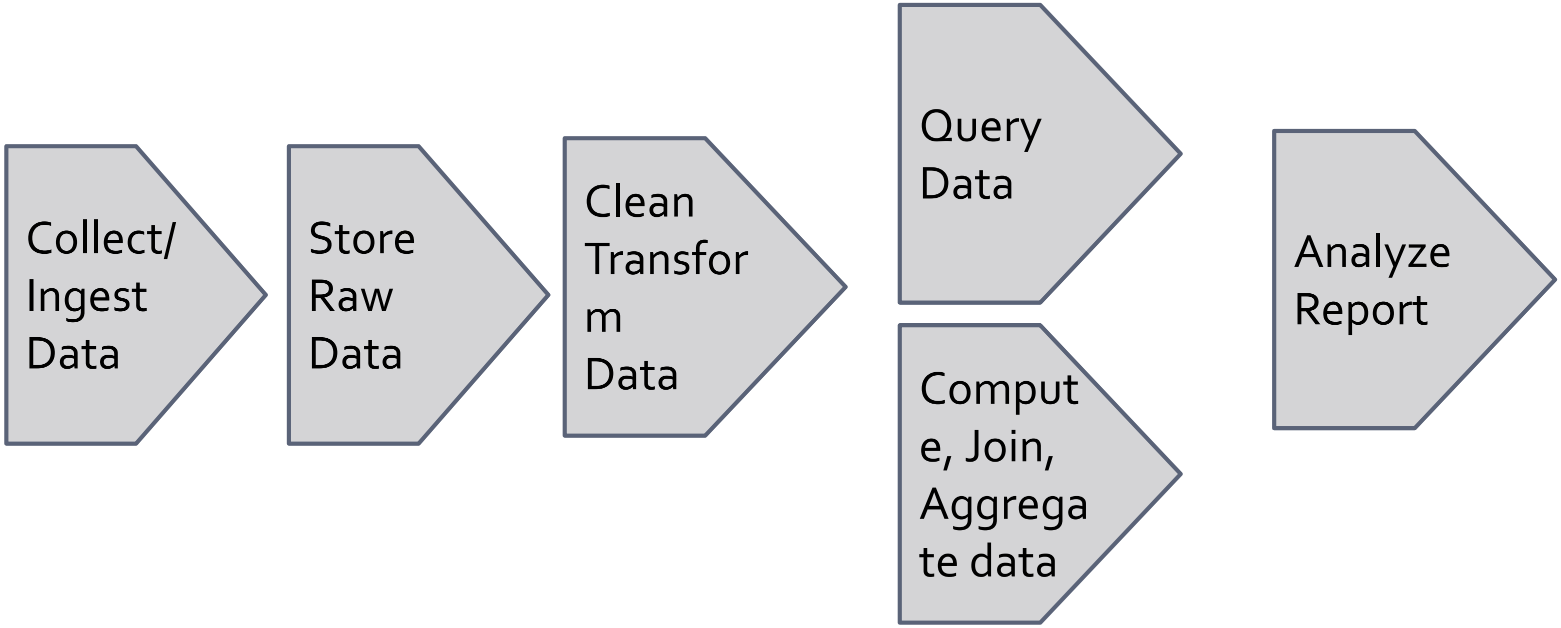
- Schema must be provided **before** data is written
- Schema modifications may cause writes to existing data
- Multiple interpretations require
  - Duplicate definitions
  - Sometimes duplicate materializations

BigTable: a Hybrid Approach

- Column-Family Database
  - Organize data into a hierarchy
    - Columns → record details
    - Column families → groups of columns
  - Column families are **schema-on-write**
  - Columns are **schema-on-read**
    - Can add columns, interpret bytes variably
- Examples:
  - Apache HBase
  - Apache Cassandra

Big Data Architectures

Elements of DAV Architecture



Collect/ Ingest Data

Store Raw Data

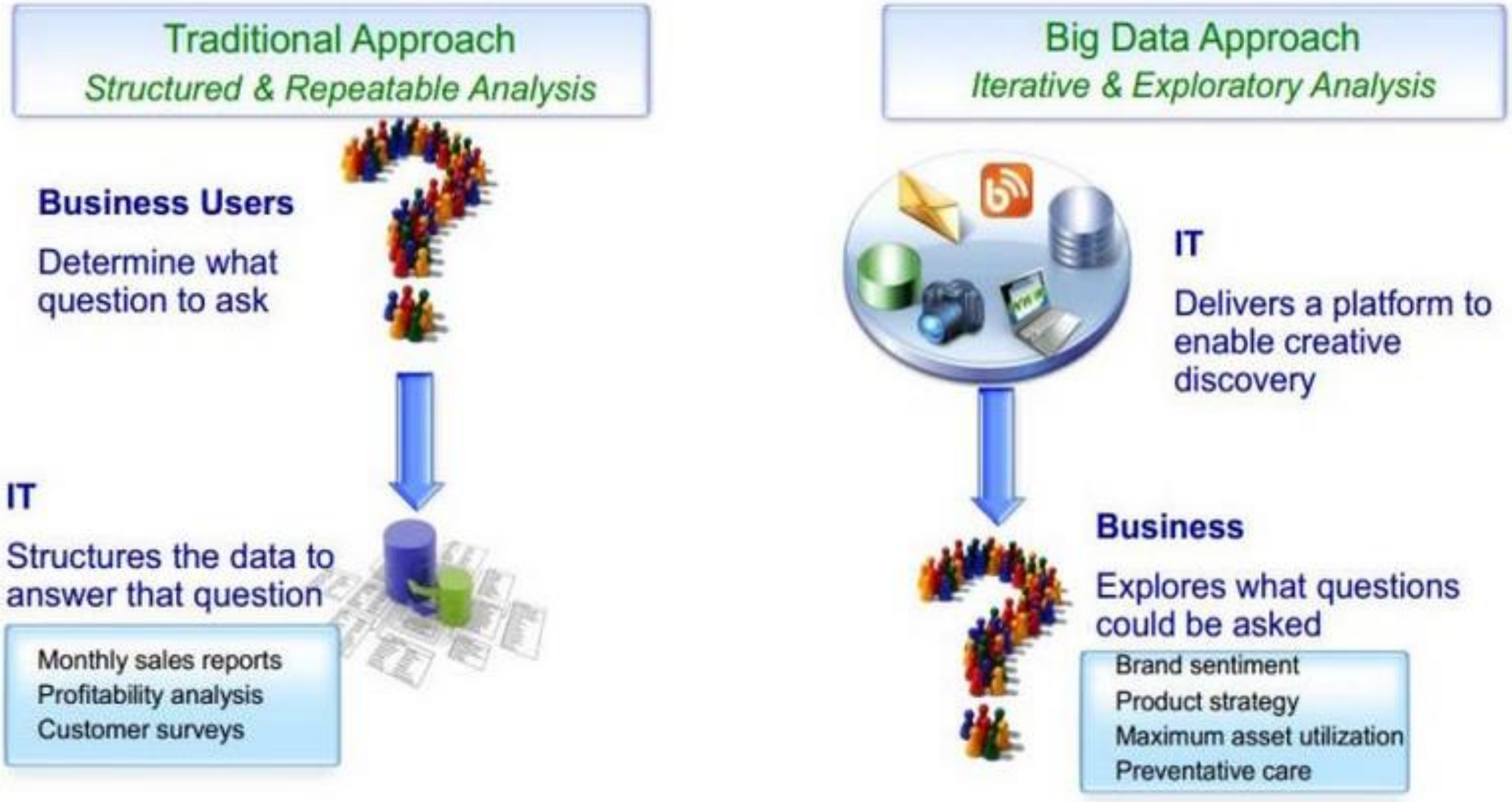
Clean Transform Data

Query Data

Compute, Join, Aggregate data

Analyze Report

Difference in Approach



Traditional Approach

Structured & Repeatable Analysis

Business Users

Determine what question to ask

IT

Structures the data to answer that question

- Monthly sales reports
- Profitability analysis
- Customer surveys

Big Data Approach

Iterative & Exploratory Analysis

IT

Delivers a platform to enable creative discovery

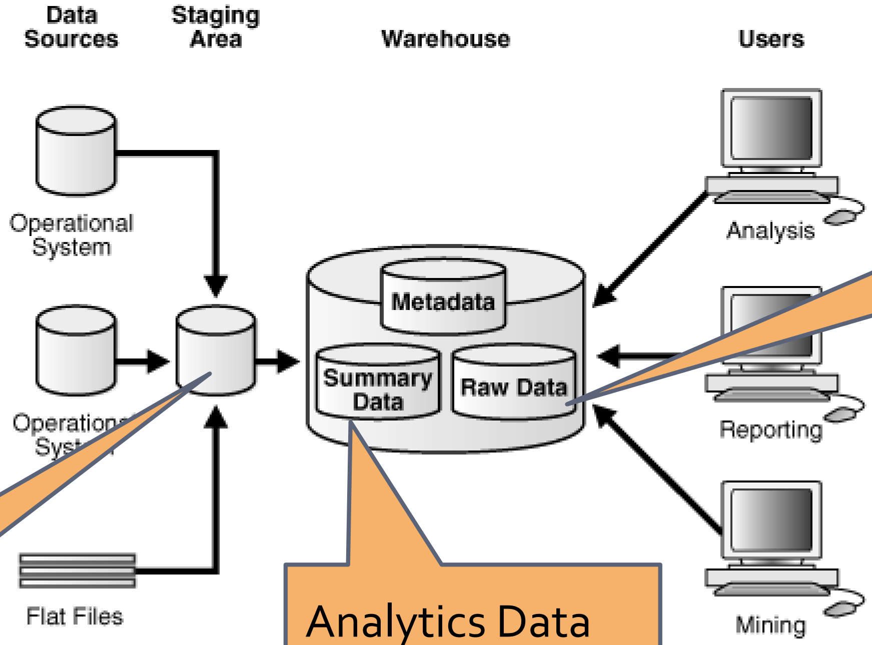
Business

Explores what questions could be asked

- Brand sentiment
- Product strategy
- Maximum asset utilization
- Preventative care

Notice the difference!

Traditional Business Warehouse



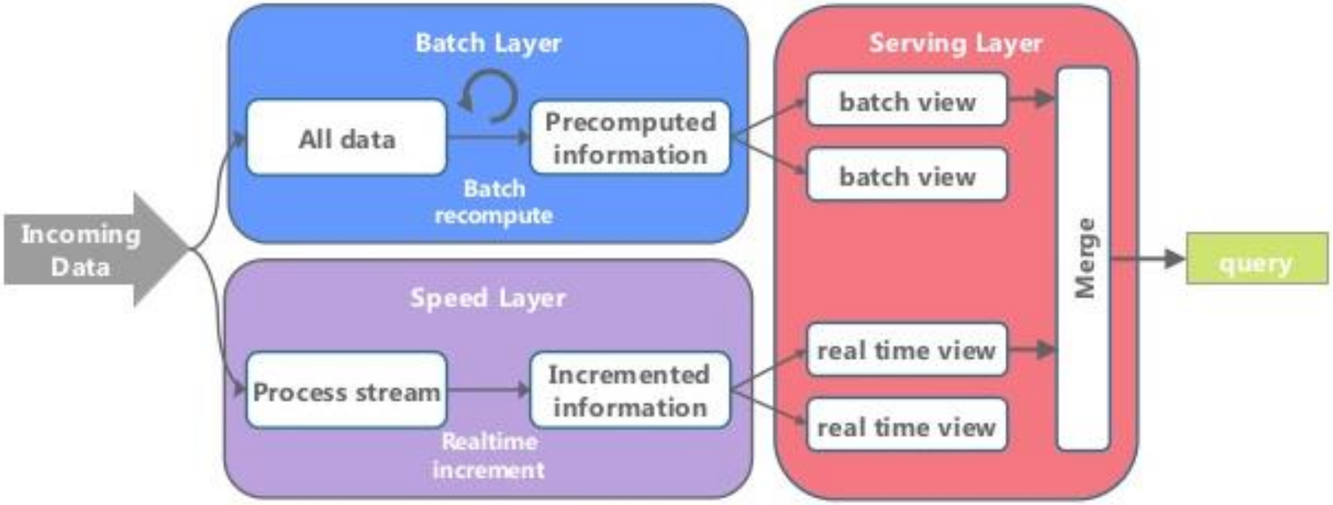
Transaction data and Fact based data model

New transactions and facts

Analytics Data

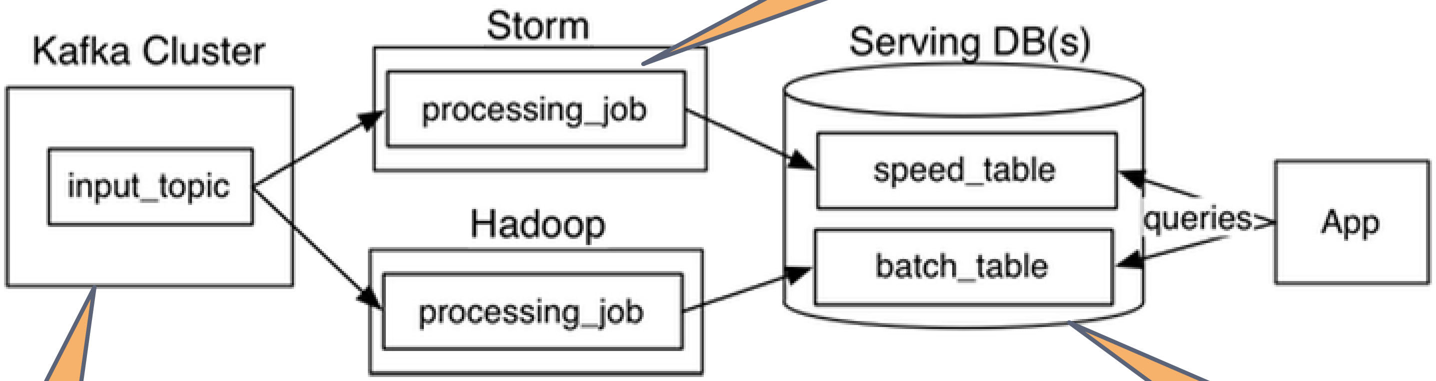
Big Data Analytics Architecture

Example:
Lambda Architecture



Other examples:
Kappa Architecture
Netflix Architecture

Lambda Architecture



Streaming analytics

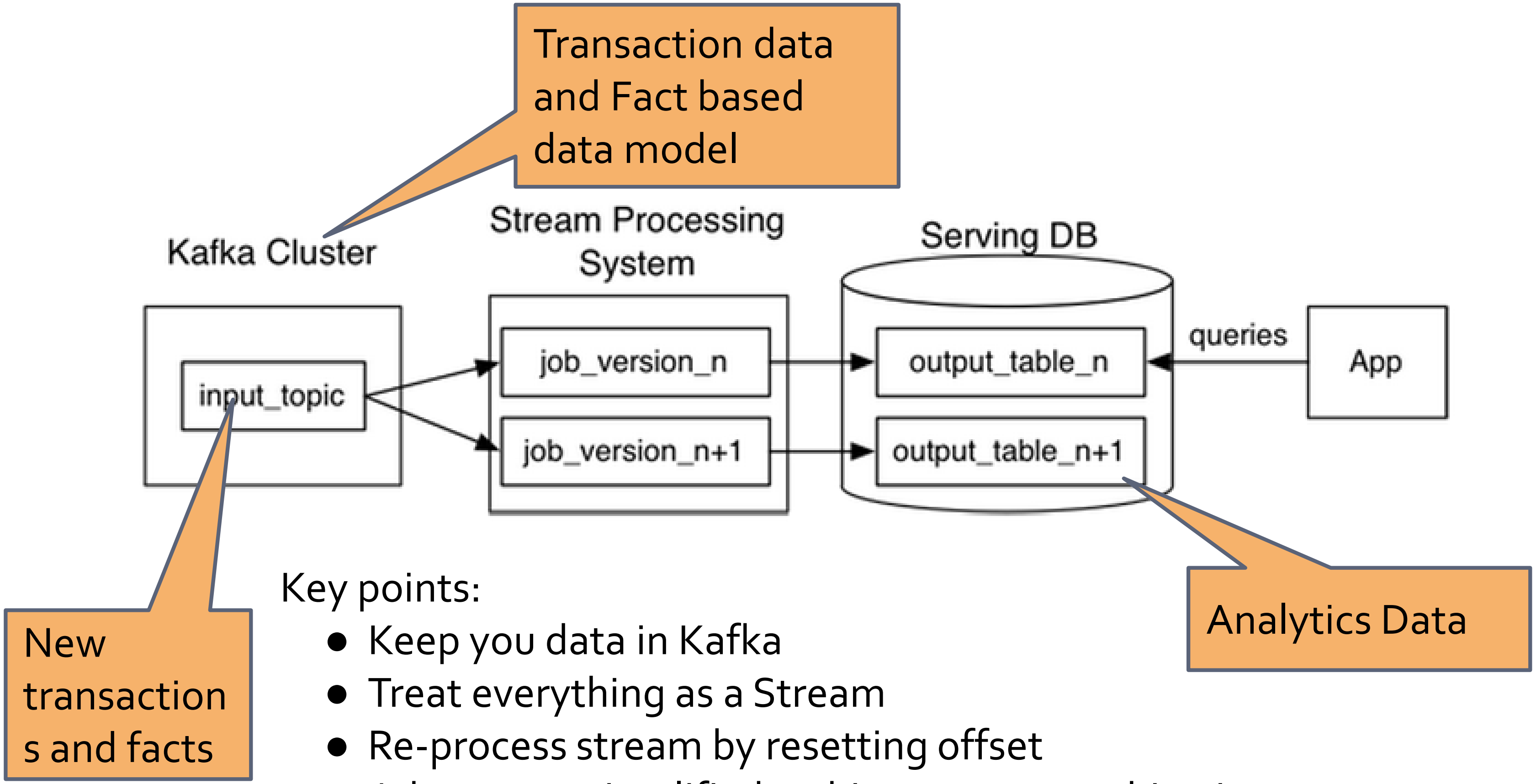
Ingest

Analytics Data

Key points:

- Keep you data in Kafka and HDFS
- Low latency processing as a stream
- Re-process and batch processing in Hadoop

Kappa Architecture



Transaction data and Fact based data model

New transactions and facts

Analytics Data

Key points:

- Keep you data in Kafka
- Treat everything as a Stream
- Re-process stream by resetting offset
- Advantage: simplified architecture, everything is a stream

MapReduce, Spark, BigQuery, …

Processing Platforms

Processing Platforms

- Batch Processing
  - Google GFS/MapReduce (2003)
  - Apache Hadoop HDFS/MapReduce (2004)
- SQL
  - BigQuery (based on Google Dremel, 2010)
  - Apache Hive (HiveQL) (2012)
- Streaming Data
  - Apache Storm (2011) / Twitter Huron (2015)
- Unified Engine (Streaming, SQL, Batch, ML)
  - Apache Spark (2012)