Distributed Big Data Frameworks A Panorama



This project has received funding from the European Union's Horizon 2020 Research and Innovation programme under grant agreement No 809965.



BIG DATA & AI LANDSCAPE 2018

INFRASTRUCTURE	ANALYTICS	APPLICATIONS – ENTERPRISE
HADOOP ON PREMISE Cloudera Motomonos MADRO PIVOCAL IBM InfoSphere' Bobledata jethro C A Z E NA SC CenturyLink: HADOOP IN THE CLOUD Bightsdats Coogle Cloud InfoSphere C A Z E NA SC CenturyLink: Bightsdats C A Z E NA SC CenturyLink: Bightsdats Bightsd	DATA ANALYST PLATFORMS Microsoft © pentebe alteryx @ Batteryx @ UAVUS AYASDI ATTIV/O Datameer: Quid Incorta. Interjana ClearStary Origani ENDOR MADE Bottlense wijkthead	SALS MARKETING - 828 MARKETING - 828
Nosol DATABASES Sopole Cloud WS Crock CLus Trix Composition Clusteria mongo DB Mark Logic Crock Charles Clusteria mongo DB Mark Logic Crock Clusteria Mark Clusteria Crock Clusteria Cro	BI PLATFORMS Microsoft Wiscower W	HUMAN CAPITAL ANAPCE
DATA TRAINSFORMATION *talend @ pentoho alteryx @ rarActa % tomr @Pactata % tomr @Pactatatatatatatatatatatatatatatatatatat	COMPUTER VISION Microsoft Azure Emission Religibilition Confination Religibilition Confination Religibility Confination Religibility Confinati	ADVERTISING ADVER
STORAGE avs Content of the source of the so	SEARCH LOG ANALYTICS Splunk - Splunk - Splunk - Sumologic Lusseward TUIVO O withope G adolt Heboño omnicus SINEOLA (Sineoreach bibly predata (Sineareach bibly predata (Sineareach bibly predata (Sineareach bibly predata (Sineareach bibly predata (Sineareach bibly predata (Sineareach bibly predata (Sineareach (Sinearea	HEALTHCARE HEALTH
Coogle Cloud Microsoft IBM COV SSRS 1010DATA VM RAMEWORK Soci Sol	VARY TIBCO TERADATA CRACLE TRANSF Syncson WARR clouders OPEN SOURCE STAT TOOLS AI/ MACHINE LEARNING / DEEP LEA talend Sport (mark) (mar	Image: Security of the secure of the security of the security of the security of the security
HEALTH VALIDIC Practice fusion Fibit GARMIN Kinso Kin	Quandi Airwaro Airababrica Sector S	Image: Construction Qualitrics Qua
Final 2018 version, updated 07/15/2018 © Matt Turck (@ma	ttturck), Demi Obayomi (@demi_obayomi), & FirstMark (@firstmarl	kcap) mattturck.com/bigdata2018 FIRSTMARK



This project has received funding from the European Union's Horizon 2020 Research and Innovation programme under grant agreement No 809965.



Database Paradigms



Database Paradigms

• Relational (RDBMS) — The SQL world...!

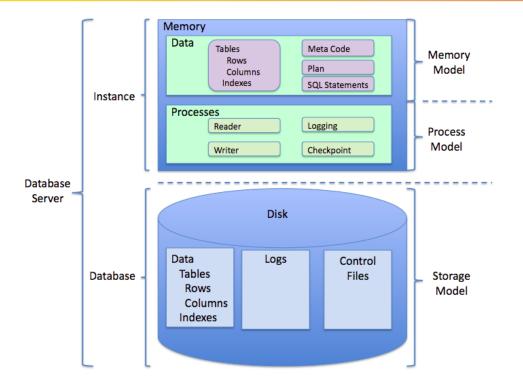


Relational (a quick reminder)

- ACID set of properties *i.e.* atomicity, consistency, isolation and durability.
- SQL is the canonical query language
- MySQL, PostgreSQL, Oracle, ...



Relational (a quick reminder)



https://en.wikipedia.org/wiki/Relational_database#/media/File:RDBMS_structure.png

LEARNING, APPLYING, MULTIPLYING BIG DATA ANALYTICS

Database Paradigms

- Relational (RDBMS) The SQL world...!
- NoSQL
 - Key-Value stores



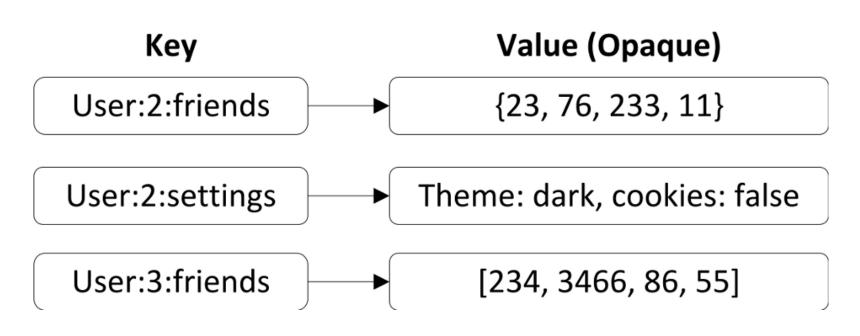
Key-Value stores

- Paradigm \rightarrow One key = One value
 - Without duplicate
 - Usually sorted
- Key is like a hash
- Value is seen as a binary object
- Examples:
 - Amazon Dynamo
 - MemcacheDB

RNING, APPLYING, MULTIPLYING BIG DATA ANALYTIC

– Apache Accumulo

Key-Value stores





Database Paradigms

- Relational (RDBMS) The SQL world...!
- NoSQL
 - Key-Value stores
 - Document databases



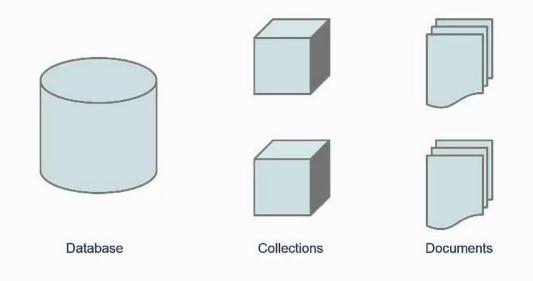
Document databases

- Key-Value store, but the value is structured and *understood* by the DB.
- Querying data is possible (by other means than just a key).
- Examples:
 - Amazon SimpleDB
 - CouchDB
 - Riak
 - MongoDB

rning, Applying, Multiplying Big Data Analytic

Document databases

Documents are gathered together in collections within the database.





Database Paradigms

- Relational (RDBMS) The SQL world...!
- NoSQL
 - Key-Value stores
 - Document databases
 - Wide Column stores (*e.g.* BigTable and its variations)



Wide Column stores

- Often referred as BigTables systems
- "Sparse, distributed mutli-dimensional sorted map"
- Examples:
 - Google BigTable
 - Cassandra (Facebook)
 - HBase



Wide Column stores

		Column	Column	Column
Row Row Key		Name	Name	Name
	Row Key	Value	Value	Value
	Timestamp	Timestamp	Timestamp	

https://database.guide/wp-content/uploads/2016/06/wide_column_store_database_example_row-1.png

Database Paradigms

- Relational (RDBMS) The SQL world...!
- NoSQL
 - Key-Value stores
 - Document databases
 - Wide Column stores (e.g. BigTable and its variations)
 - Graph databases

• Other ones...

LEARNING, APPLYING, MULTIPLYING BIG DATA ANALYTIC

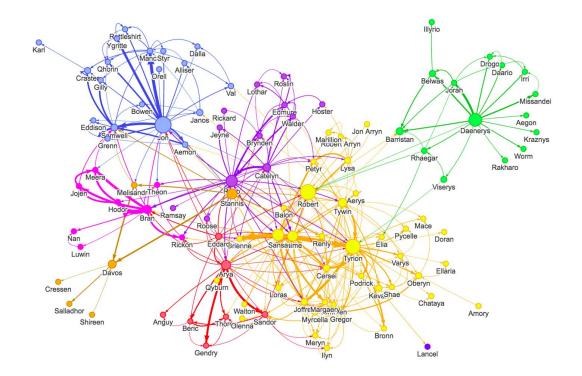
Graph databases

- Multi-relational graph
- Put emphasis on links between data pieces

- Examples:
 - Neo4j
 - InfoGrid
 - Triplestores...



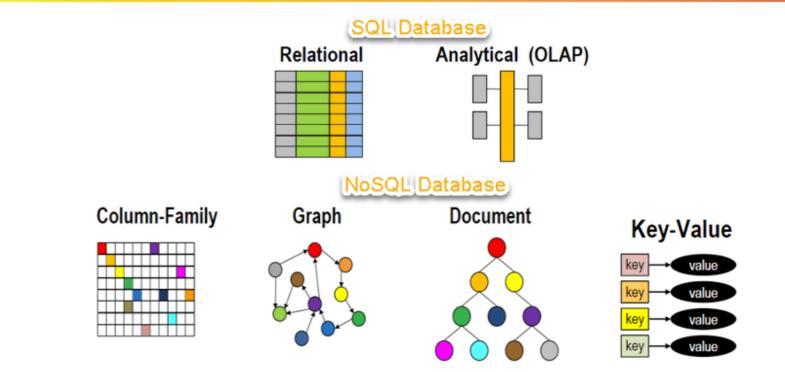
Graph databases



Learning, Applying, Multiplying Big Data Analytics

https://neo4j.com/blog/graph-of-thrones/

Database Paradigms (Visually)





https://www.guru99.com/nosql-tutorial.html

Selected Storage Systems



MongoDB



- Document database (NoSQL)
 - scalability and flexibility
 - querying and indexing
- Stores data in
 - JSON-like documents
 - schema free database
- Open-Source



What is MongoDB great for?

- RDBMS replacement for Web Applications
- Semi-structured Content Management
- Real-time Analytics & High-Speed Logging
- Caching and Scalability

Apache Hive



- Apache Hive is a data warehouse
 - Developed by Facebook
 - On top of Apache Hadoop
- Provides
 - Data summarization
 - Query
 - Analysis
- Open-Source
- Gives an SQL-like interface



Apache Hive - Some Facts



Most Queries Per Hour

100,000 Queries Per Hour (Yahoo Japan)

Largest Hive Warehouse

300+ PB Raw Storage (Facebook) **Analytics Performance**

100 Million rows/s Per Node (with Hive LLAP)

Largest Cluster

4,500+ Nodes (Yahoo)



https://www.slideshare.net/MahmoodRezaEsmailiZa/apache-hive-

Apache Hive - Limitations



- Not design for online transaction processing
- Not suited for real-time queries
- Not made for low-latency query
- Certain standard SQL functions do not exist
 - NOT IN
 - NOT LIKE
 - NOT EQUAL



Apache Cassandra



- Facebook inbox search feature
- millisecond read and write times
- Designed for linear, incremental scalability on top of commodity hardware.
- Open-Source since 2008





Cassandra - Strenghts

- Linear scale performance when adding node
- Peer-to-peer architecture instead of master-slave
- Fault tolerant in case of node failure
- High performance
- Schema-free/Schema-less





Cassandra - Limitations

Use cases where it is better to avoid using Cassandra

- If there are too many joins required
- To store configuration data
- During compaction, things slow down
- Aggregation Operator support is limited
- Can update or delete data but not designed for



Distributed Stream Processing



Apache Kafka



- Distributed event streaming platform
- Able to handle up to trillions of events a day
- Initially conceived as a messaging queue
- Open-sourced by LinkedIn in 2011
- Useful for:
 - Stream processing
 - Website activity tracking
 - Metrics collection and monitoring
 - Log aggregation



Apache Kafka



Three key capabilities

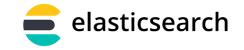
- Publish and Subscribe
 - Stream of records
- Process
 - Streams of records as they occur
- Store
 - Streams of records in fault tolerant manner



Search, Indexing, visualization



ElasticSearch



- Distributed and highly available search engine
 - Indexes are sharded (replicas)
 - read/search on any replica shards
- Multi-tenant
 - Support for more than one index
- Various set of APIs
- Document oriented
- Reliable
- Near real time search



ElasticSearch



- Data into ElasticSearch
 - Receive data in form of JSON documents
 - Ingest data using Logstash
 - Connectors to other data stores
- Stores and add searchable reference to the document
- All data is indexed by default
- Every field has a dedicated inverted index
- All of inverted indexes can be used in a query



Visualization

LEARNING, APPLIED, MULTIPLING BIG DATA ANALYTICS

Kibana



- Browser-based analytics and search dashboard for Elasticsearch
 - search
 - view
 - interact

with the data stored in Elasticsearch indices

- Visualize data
 - Charts
 - Tables
 - Maps

LEARNING, APPLYING, MULTIPLYING BIG DATA ANALYTIC

Kibana



- Display changes in real time
- Discover
 - Explore data using selected index patterns
- Visualize
 - Create visualizations of data based on
 - ElasticSearch queries, Search saved from Discover
 - Stored as dashboards
- Dashboard
 - collection of visualizations and searches



Processing Frameworks



Analytic Frameworks

- Batch-only
 - Apache Hadoop MapReduce
- Stream and In-Memory Computing
 - Apache Spark
 - Apache Flink





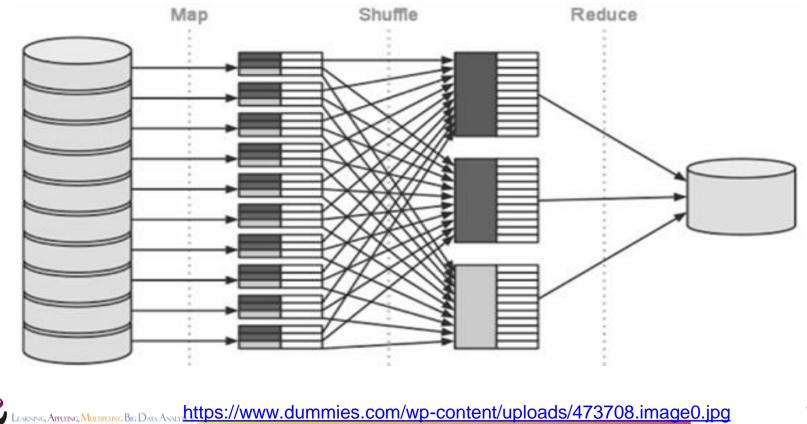


Hadoop MapReduce



- Distributed framework to process vast amounts of data ullet(multi-terabyte data-sets)
 - Cluster of commodity hardware
 - Reliable
 - Fault tolerant
- MapReduce job ۲
 - Divides the large data into independent chunks
 - Processed by Map-tasks in parallel
 - Sorted output is passed to the reduce-tasks
 - Typically both input and output are stored in filesystem (HDFS)

MapReduce Engine



Map reduce

- First popular data flow model
- In the Map-Reduce model, the user provides two functions (map and reduce)
 - Map() must output key-value pairs
 - Input to the reduce is partitioned by key across machines (shuffled)
 - reduce() output the aggregated values





Processing of Map tasks

- Given a file divided into multiple parts (splits).
- Each record (line) is processed by a Map function,
 - written by the user,
 - takes an input key/value pair
 - produces a set of intermediate key/value pairs.
 - e.g. (doc-id, doc-content)
- Draws an analogy to SQL group-by clause



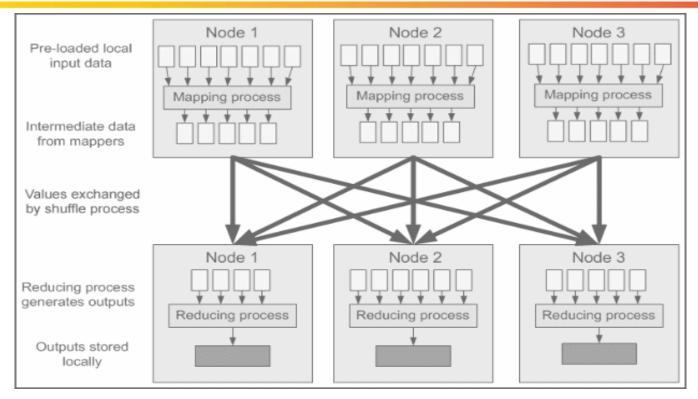
Processing of Reduce Tasks

Given a set of (key, value) records by map tasks

- The intermediate values are combined into a list based on keys and given to a reducer.
- Each reducer further performs an *aggregate* function (e.g., average) computed over all the rows with the same "key"



Visualizing map and reduce tasks



https://cdn.intellipaat.com/mediaFiles/2015/07/hadoop-mapreduce1.jpg.png

Example: Word counting in class

"Consider the problem of counting the number of occurrences of each word in a large collection of documents"



Divide a collection of documents among the class

ARNING, APPLYING, MULTIPLYING BIG DATA ANALYTICS

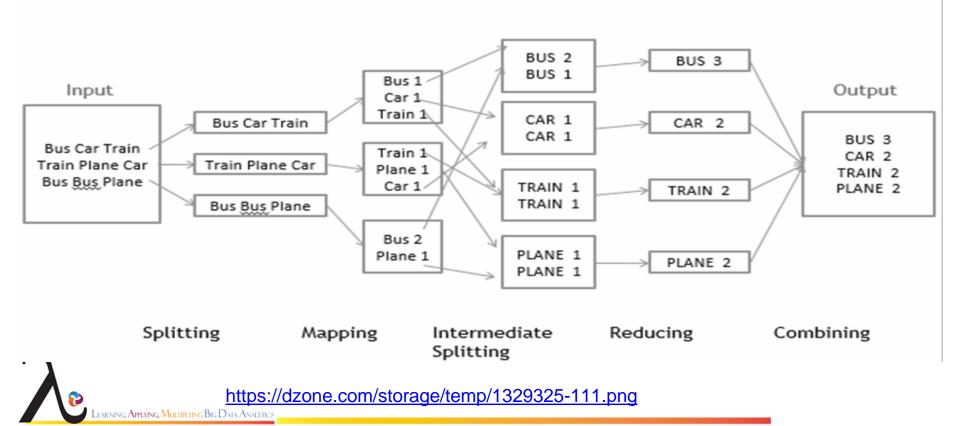
Each person calculates counts of individual words in the documents

independent

Gather the words and counts

Sum up the counts from all the documents for all the words

Word Count MapReduce



Drawbacks of MapReduce

- Forces data analysis workflow into a map and a reduce phase
 - You might need
 - Join
 - Filter
 - Sample
 - Complex workflows that do not fit into map/Reduce
 - Mapreduce relies on reading data from disk
 - Performance bottleneck
 - Especially for iterative algorithms
 - e.g. Machine Learning



Requirement..

- A tool, compatible with the existing environment
- Without replacing the stack
 - replace map-reduce only
- Generic
 - Provides a rich API, more functions
- Reduces Disk I/O
 - Faster
 - In-memory computations
- Provides an interactive shell



Apache Flink



- Distributed stream processing engine
- Process bounded and unbounded streams
- Generic deployment
- Scalable
 - Trillions of events
 - Terabytes of states
 - Thousands of cores
- In-Memory performance

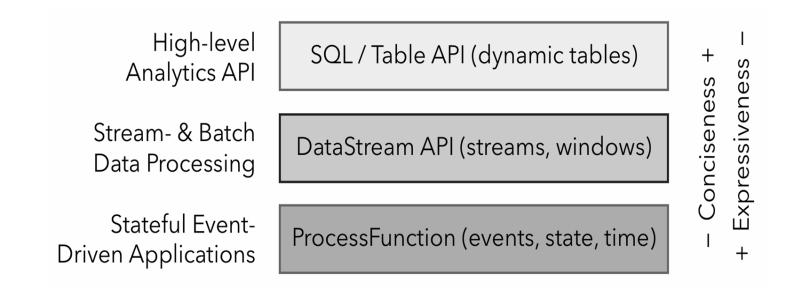


Apache Flink APIs

- Data Stream API
 - bounded or unbounded streams of data
- Dataset API
 - bounded data sets
 - Transformations (Filter, map, join)
- Table API
 - SQL-like expression language for relational stream



Apache Flink Layered APIs



LEARNING, APPLYING, MULTIPLYING BKG DATA ANALYTICS

Apache Flink Libraries

- Complex Event Processing (CEP)
 - Pattern detection from events
- DataSet API
 - Map, Reduce, join, iterate
- Gelly
 - Scalable Graph processing library



References

https://flink.apache.org/





This project has received funding from the European Union's Horizon 2020 Research and Innovation programme under grant agreement No 809965.

