UC San Diego

DSC 102
Systems for Scalable Analytics

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Topic 4: Dataflow Systems

Spark Book; Chapter 2.2 of MLSys Book

Tentative Course Schedule

Week	Topic
	Basics of Machine Resources: Computer Organization
	Basics of Machine Resources: Operating Systems
4	Basics of Cloud Computing
4-5	Parallel and Scalable Data Processing: Parallelism Basics
	Midterm Exam on TBD
6-7	Parallel and Scalable Data Processing: Scalable Data Access
7-8	Parallel and Scalable Data Processing: Data Parallelism
9	Dataflow Systems
10	ML Model Building Systems
11	**Final Exam on Dec 15**

Systems Principles

Scalability Principles

Scalable Analytics Systems

Remaining quarter

- Last lecture: Review for final exam.
- Final exam.
- Triton Test Center
- 90%+ CAPE response for class yields => 0.5% collective boost to final score.

Outline

- Beyond RDBMSs: A Brief History
- MapReduce/Hadoop Craze
- Spark and Dataflow Programming
- Scalable BGD with MapReduce/Spark
- Dataflow Systems vs Task-Parallel Systems

Q: *How to shield users from needing to think about moving raw pages between disk/RAM/network to scale data-intensive programs?*

Parallel RDBMSs

- Parallel RDBMSs are highly successful and widely used
- Typically shared-nothing data parallelism
- Optimized **runtime performance** + enterprise-grade features:
  - ANSI SQL & more
  - Business Intelligence (BI) dashboards/APIs
  - Transaction management; crash recovery
  - Indexes, auto-tuning, etc.

Q: *So, why did people need to go beyond parallel RDBMSs?*

Ad: Take CSE 132C for more on parallel RDBMSs

Beyond RDBMSs: A Brief History

- DB folks got blindsided by the rise of Web/Internet giants

- 4 new concerns of Web giants vs RDBMSs built for enterprises:
  - **Developability:** Custom data models and computations hard to program on SQL/RDBMSs; need for simpler APIs
  - **Fault Tolerance:** Need to scale to 1000s of machines; need for graceful handling of worker failure
  - **Elasticity:** Need to be able to easily upsize or downsize cluster size based on workload
  - **Cost:** Commercial RDBMSs licenses too costly; hired own software engineers to build custom new systems

A new breed of parallel data systems called **Dataflow Systems** jolted the DB folks from being smug and complacent!

What is MapReduce?

- A programming model for parallel programs on **sharded data** + **distributed system** architecture
- **Map** and **Reduce** are terms from functional PL; software/data/ML engineer implements logic of Map, Reduce
- System handles data distribution, parallelization, fault tolerance, etc. under the hood
- Created by Google to solve "simple" data workload: index, store, and search the Web!
- Google's engineers started with MySQL! Abandoned it due to reasons listed earlier (developability, fault tolerance, elasticity, etc.)

https://static.googleusercontent.com/media/research.google.com/en//archive/mapreduce-osdi04.pdf

Programming Language Background

- Declarative?
- While coding, you will not be interested in how you want the job done. The focus is on what result you want to obtain. (e.g., SQL*)
- Imperative?
- The micromanaging boss who gives instructions down to the final detail. (e.g., Python*)
- Object-Oriented Programming?
- Organizes data and the software structure based on the concept of classes and objects.
- Functional?
- A paradigm of building computer programs using expressions and functions without mutating state and data

What is MapReduce?

- **Standard example**: count word occurrences in a doc corpus
- **Input**: A set of text documents (say, webpages)
- **Output**: A dictionary of unique words and their counts

function map (String docname, String doctext) :

Hmmm, sounds suspiciously familiar! :)

  for each word w **in** doctext :

    emit (w, 1)

Part of MapReduce API

function reduce (String word, Iterator partialCounts) :

  sum = 0

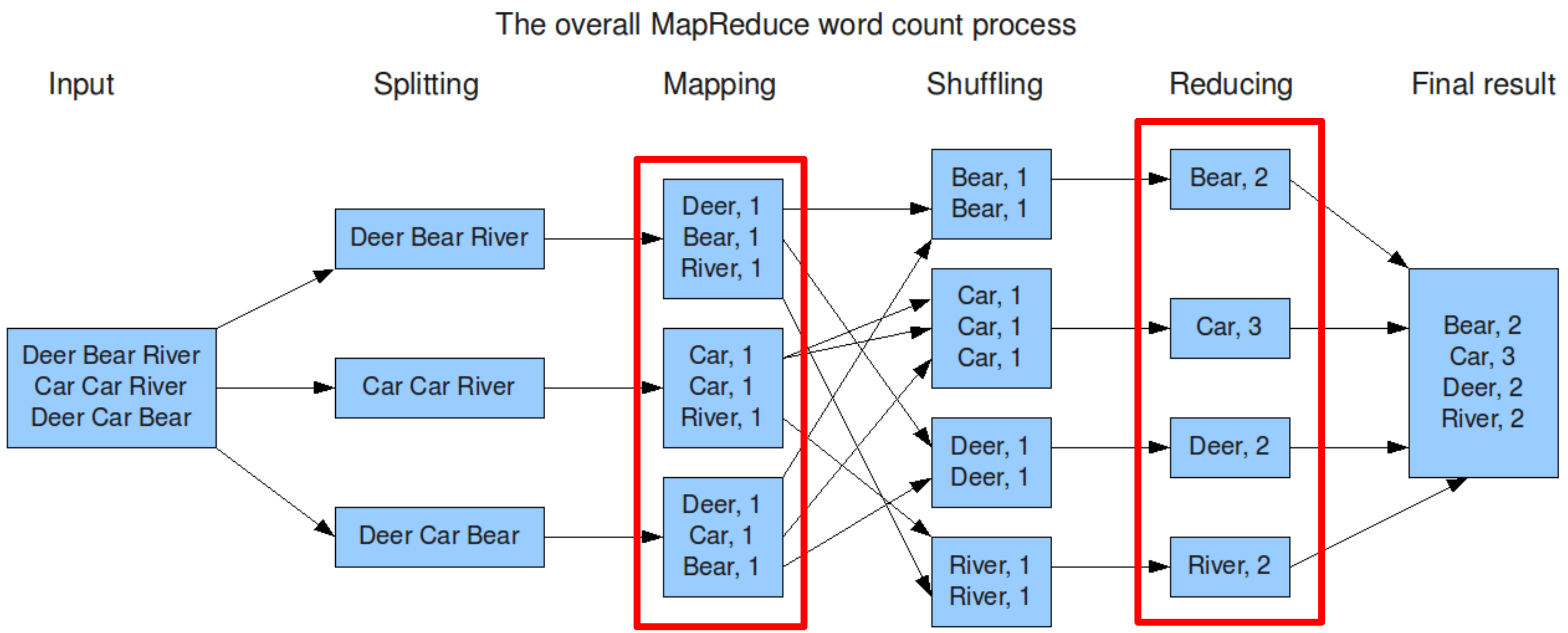
  for each pc **in** partialCounts :

    sum += pc

  emit (word, sum)

How MapReduce Works

Parallel flow of control and data during MapReduce execution:



Under the hood, each **Mapper** and **Reducer** is a separate process; Reducers face barrier synchronization (BSP)

Fault tolerance achieved using **data replication**

Benefits and Catch of MapReduce

- **Goal:** High-level *functional* ops to simplify data-intensive programs
- **Key Benefits:**
  - Map() and Reduce() are highly general; any data types/structures; great for ETL, text/multimedia
  - Native scalability, large cluster parallelism
  - System handles fault tolerance automatically
  - Decent FOSS stacks (Hadoop and later, Spark)
- **Catch:** Users must learn "art" of casting program as MapReduce
  - Map operates record-wise; Reduce aggregates globally
  - But MR libraries now available in many PLs: C/C++, Java, Python, R, Scala, etc.

Abstract Semantics of MapReduce

- **Map():** Process one “record” at a time *independently*
  - A record can physically *batch* multiple data examples/tuples
  - Dependencies across Mappers *not* allowed
  - *Emit* 1 or more key-value pairs as output(s)
  - Data types of input vs. output can be different
- **Reduce():** Gather all Map outputs across workers sharing same key into an Iterator (list)
  - Apply *aggregation* function on Iterator to get final output(s)
- **Input Split:**
  - Physical-level shard to batch many records to one file “block” (HDFS default: 128MB?)
  - User/application can create *custom* Input Splits

Emulate MapReduce in SQL?

Q: How would you do the word counting in RDBMS / in SQL?

- First step: **Transform** text docs into relations and load:
  - Part of the ETL stage
  - Suppose we pre-divide each doc into words w/ schema:
  - **DocWords** (DocName, Word)
- Second step: a single, simple SQL query!

```
SELECT      Word, COUNT (*)
FROM        DocWords
GROUP BY    Word
[ORDER BY   Word]
```

Parallelism, scaling, etc. done by RDBMS under the hood

More MR Examples: Select Operation

- **Input Split**:
  - Shard table tuple-wise
- **Map():**
  - On tuple, apply selection condition; if satisfies, emit KV pair with dummy key, entire tuple as value
- **Reduce():**
  - Not needed! No cross-shard aggregation here
- These kinds of MR jobs are called "**Map-only**" jobs

More MR Examples: Simple Agg.

- Suppose it is *algebraic* aggregate (SUM, AVG, MAX, etc.)
- **Input Split**:
  - Shard table tuple-wise
- **Map():**
  - On agg. attribute, compute incr. stats; emit pair with single global dummy key and incr. stats as value
- **Reduce():**
  - Since only one global dummy key, Iterator has *all* suff. stats to unify into global agg.

More MR Examples: GROUP BY Agg.

- Assume it is *algebraic* aggregate (SUM, AVG, MAX, etc.)
- **Input Split**:
  - Shard table tuple-wise
- **Map():**
  - On agg. attribute, compute incr. stats; emit pair with *grouping attribute as key* and stats as value
- **Reduce():**
  - Iterator has all suff. stats *for a single group*; unify those to get result for that group
  - Different reducers will output different groups' results

More MR Examples: Matrix Norm

- Assume it is *algebraic* aggregate ($L_{p,q}$ norm)
- Very similar to simple SQL aggregates
- **Input Split**:
  - Shard table tuple-wise
- **Map():**
  - On agg. attribute, compute incr. stats; emit pair with single global dummy key and stats as value
- **Reduce():**
  - Since only one global dummy key, Iterator has *all* suff. stats to unify into global agg.

What is Hadoop then?

- FOSS system implementation with MapReduce as prog. model and HDFS as filesystem
- MR user API; input splits, data distribution, shuffling, fault tolerances handled by Hadoop under the hood
- Exploded in popularity in 2010s: 100s of papers, 10s of products
- A “revolution” in scalable+parallel data processing that took the DB world by surprise
- But nowadays Hadoop largely supplanted by Spark

NB: Do not confuse MR for Hadoop or vice versa!

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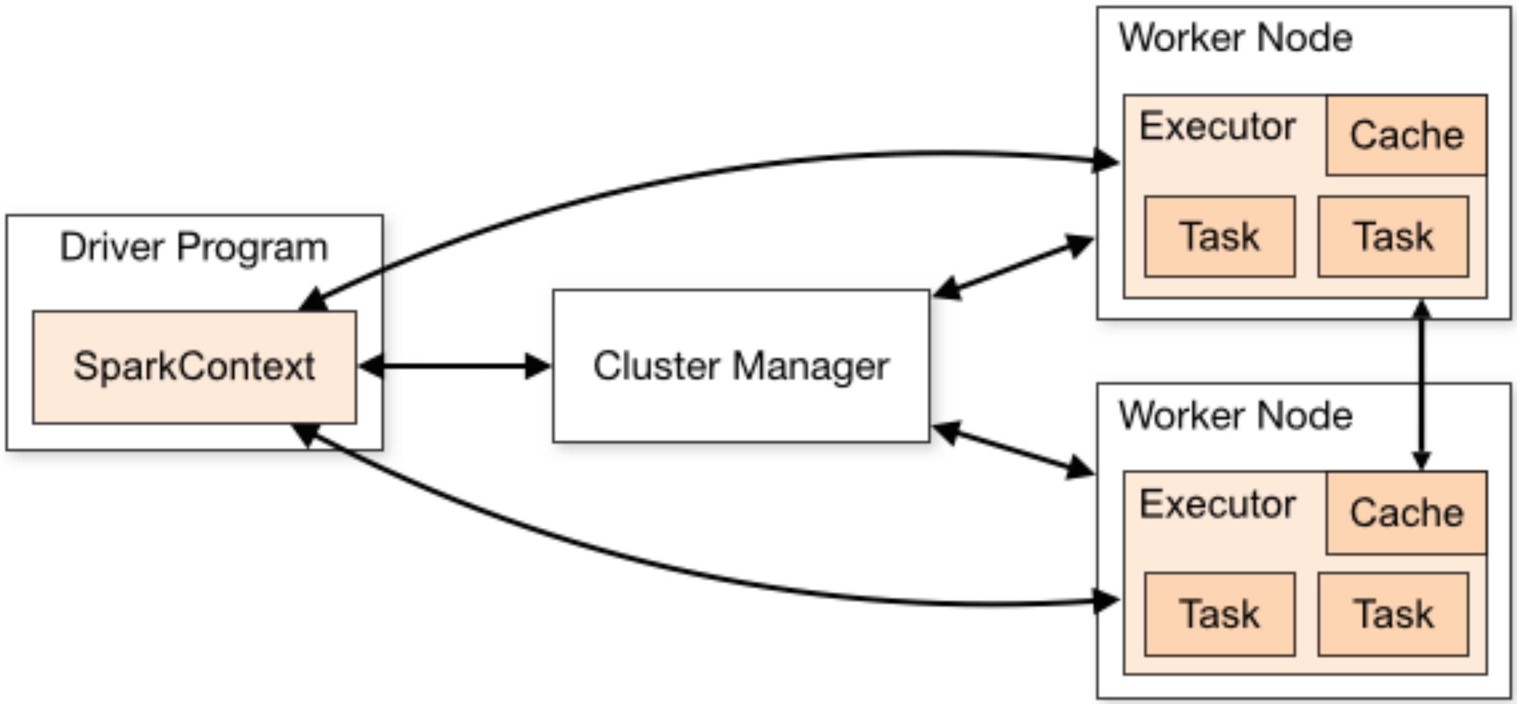
Apache Spark

- **Dataflow programming** model (subsumes most of RA; MR)
  - Inspired by Python Pandas style of chaining functions
  - Unified storage of relations, text, etc.; custom programs
  - System impl. (re)designed from scratch
- Tons of sponsors, gazillion bucks, unbelievable hype!
- **Key idea vs Hadoop**: exploit distributed memory to cache data
- **Key novelty vs Hadoop**: lineage-based fault tolerance
- Open-sourced to Apache; commercialized as Databricks

Distributed Architecture of Spark



https://spark.apache.org/docs/latest/cluster-overview.html

Spark's Dataflow Programming Model

Transformations are relational ops, MR, etc. as functions

Actions are what force computation; aka ***lazy evaluation***

Transformations	$map(f : \mathrm{T} \Rightarrow \mathrm{U})$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{RDD[U]}$
	$filter(f : \mathrm{T} \Rightarrow \mathrm{Bool})$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{RDD[T]}$
	$flatMap(f : \mathrm{T} \Rightarrow \mathrm{Seq[U]})$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{RDD[U]}$
	$sample(fraction : \mathrm{Float})$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{RDD[T]}$ (Deterministic sampling)
	$groupByKey()$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, Seq[V])]}$
	$reduceByKey(f : (\mathrm{V}, \mathrm{V}) \Rightarrow \mathrm{V})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, V)]}$
	$union()$	:	$(\mathrm{RDD[T]}, \mathrm{RDD[T]}) \Rightarrow \mathrm{RDD[T]}$
	$join()$	:	$(\mathrm{RDD[(K, V)]}, \mathrm{RDD[(K, W)]}) \Rightarrow \mathrm{RDD[(K, (V, W))]}$
	$cogroup()$	:	$(\mathrm{RDD[(K, V)]}, \mathrm{RDD[(K, W)]}) \Rightarrow \mathrm{RDD[(K, (Seq[V], Seq[W]))]}$
	$crossProduct()$	:	$(\mathrm{RDD[T]}, \mathrm{RDD[U]}) \Rightarrow \mathrm{RDD[(T, U)]}$
	$mapValues(f : \mathrm{V} \Rightarrow \mathrm{W})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, W)]}$ (Preserves partitioning)
	$sort(c : \mathrm{Comparator[K]})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, V)]}$
	$partitionBy(p : \mathrm{Partitioner[K]})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, V)]}$
Actions	$count()$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{Long}$
	$collect()$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{Seq[T]}$
	$reduce(f : (\mathrm{T}, \mathrm{T}) \Rightarrow \mathrm{T})$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{T}$
	$lookup(k : \mathrm{K})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{Seq[V]}$ (On hash/range partitioned RDDs)
	$save(path : \mathrm{String})$	:	Outputs RDD to a storage system, *e.g.,* HDFS

[Resilient Distributed Datasets: A Fault-tolerant Abstraction for In-memory Cluster Computing. In NSDI 2012](#)

Word Count Example in Spark

Spark RDD API available in Python, Scala, Java, and R

```
text_file = sc.textFile("hdfs://...")
counts = text_file.flatMap(lambda line: line.split(" ")) \
             .map(lambda word: (word, 1)) \
             .reduceByKey(lambda a, b: a + b)
counts.saveAsTextFile("hdfs://...")
```

```
val textFile = sc.textFile("hdfs://...")
val counts = textFile.flatMap(line => line.split(" "))
                 .map(word => (word, 1))
                 .reduceByKey(_ + _)
counts.saveAsTextFile("hdfs://...")
```

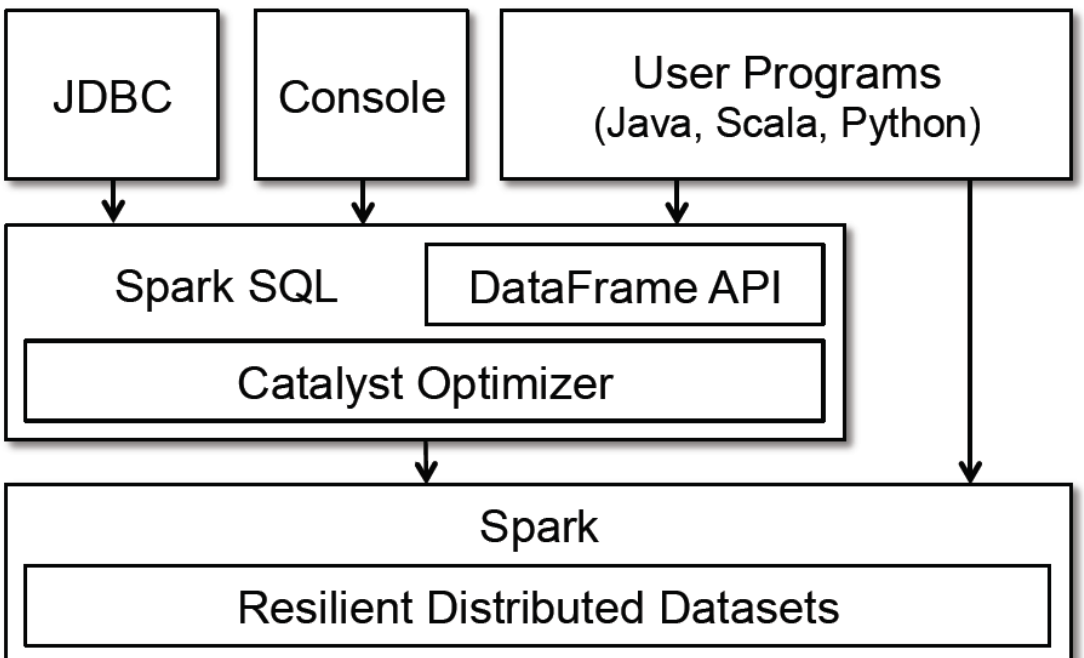
```
JavaRDD<String> textFile = sc.textFile("hdfs://...");
JavaPairRDD<String, Integer> counts = textFile
    .flatMap(s -> Arrays.asList(s.split(" ")).iterator())
    .mapToPair(word -> new Tuple2<>(word, 1))
    .reduceByKey((a, b) -> a + b);
counts.saveAsTextFile("hdfs://...");
```

Spark DataFrame API of SparkSQL offers an SQL interface

Can also interleave SQL with DF-style function chaining!

Spark DF API and SparkSQL

- Databricks now recommends SparkSQL/DataFrame API; avoid RDD API unless really needed!
- **Key Reason:** Automatic query optimization becomes more feasible
  - AKA (painfully) re-learn 40 years of database systems research! :)



Spark SQL: Relational Data Processing in Spark. In SIGMOD 2015.

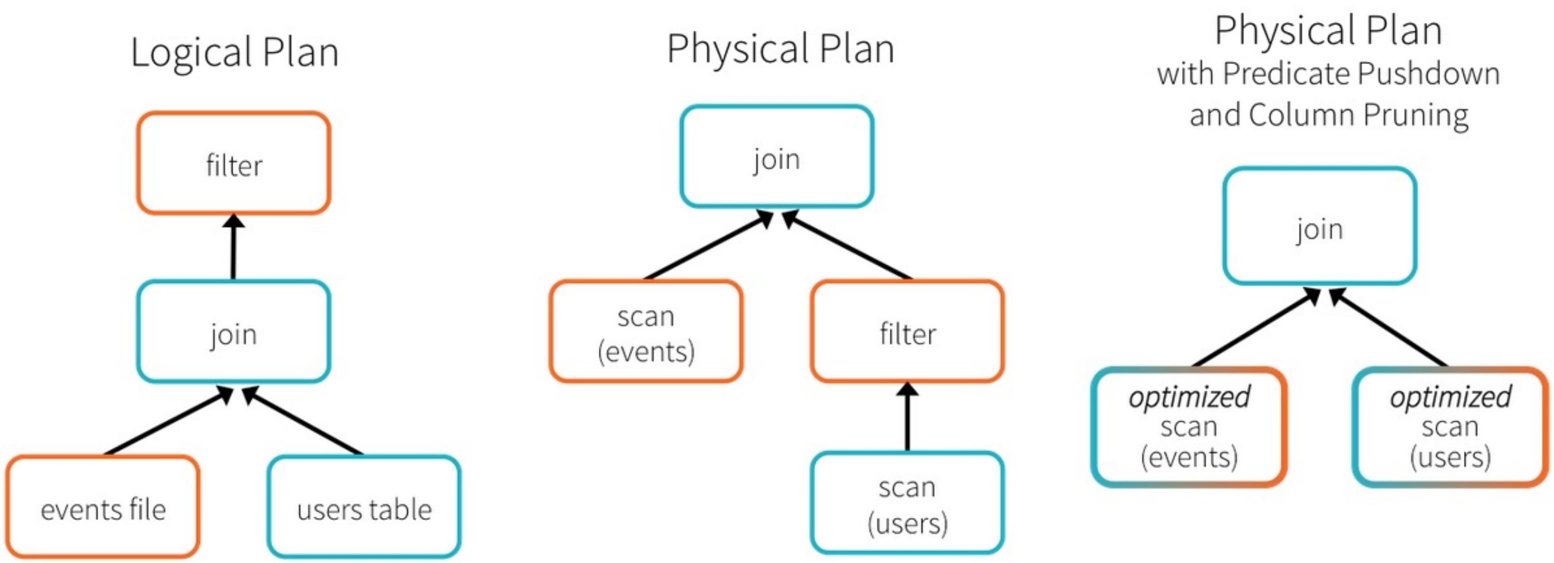
Query Optimization in Spark

- Common automatic query optimizations (from RDBMS world) are now performed in Spark's Catalyst optimizer:
- **Projection pushdown:**
  - Drop unneeded columns early on
- **Selection pushdown:**
  - Apply predicates close to base tables
- **Join order optimization:**
  - Not all joins are equally costly
- Fusing of aggregates
- …

Spark SQL: Relational Data Processing in Spark. In SIGMOD 2015.

Query Optimization in Spark

```
def add_demographics(events):
   u = sqlCtx.table("users")                     # Load partitioned Hive table
   events \
     .join(u, events.user_id == u.user_id) \      # Join on user_id
     .withColumn("city", zipToCity(df.zip))       # Run udf to add city column
events = add_demographics(sqlCtx.load("/data/events", "parquet"))
training_data = events.where(events.city == "New York").select(events.timestamp).collect()
```



Databricks is building yet another parallel RDBMS! :)

[Spark SQL: Relational Data Processing in Spark](). In SIGMOD 2015.

Reinventing the Wheel?

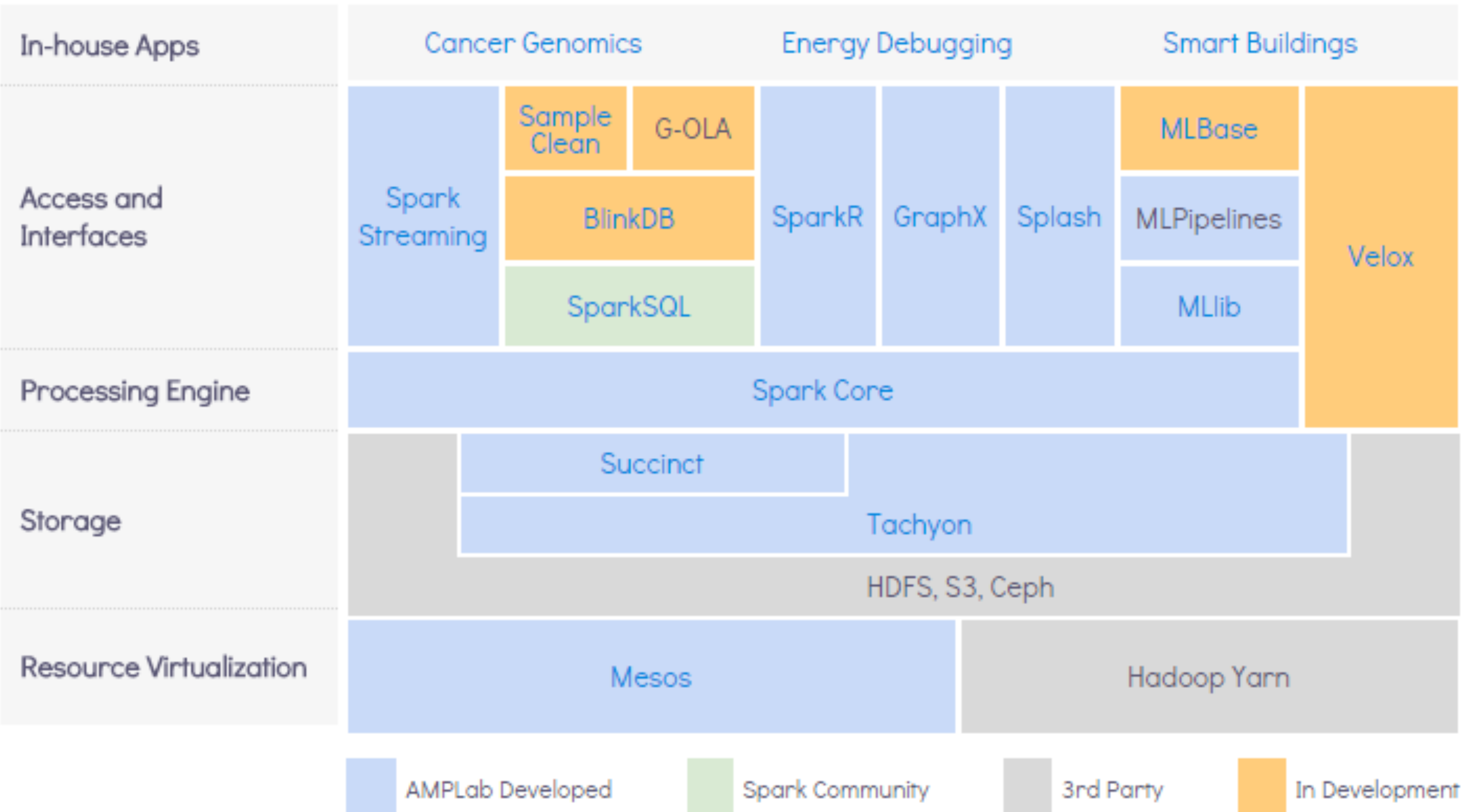
Comparing Spark's APIs

Check out TA's PA 2 slides for more on Spark APIs

	RDD	DataFrame	Koalas
Abstraction Level	Low	High	High
Named Columns	No	Yes	Yes
Support for Query Optimization	No	Yes	Yes
Programming Mode	map-reduce	Dataflow, SQL	Pandas-like
Best suited for	Unstructured data Low-level ops Folks who like func. PLs and MapReduce	Structured data High-level ops Folks who know SQL, Python, R	Structured data Lower barrier to entry for folks who only know Pandas or Dask

Ad: Take Yoav's DSC 291 to learn more Spark programming

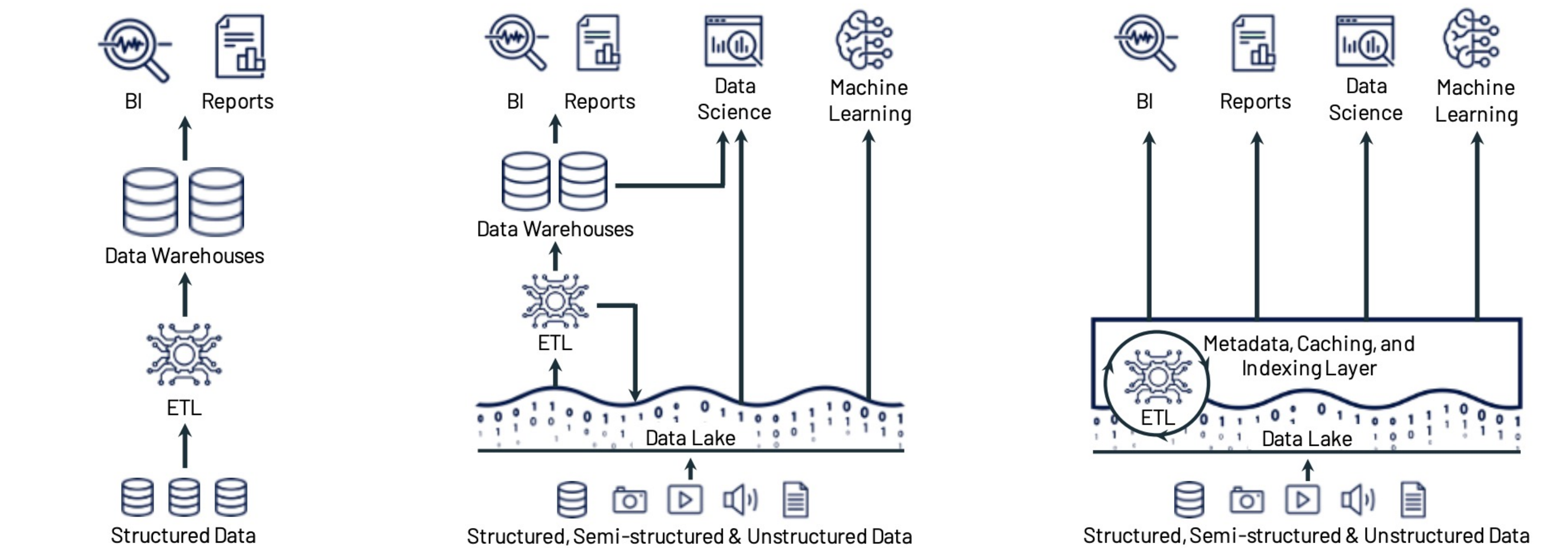
Spark-based Ecosystem of Tools



The Berkeley Data Analytics Stack (BDAS)

New Paradigm of Data “Lakehouse”

- **Data “Lake”:** *Loose coupling* of data file format and data/query processing stack (vs RDBMS’s tight coupling); many frontends



(a) First-generation platforms. **(b) Current two-tier architectures.** **(c) Lakehouse platforms.**

If interested, check out this vision paper on the future of data lakes and data lakehouses: http://cidrdb.org/cidr2021/papers/cidr2021_paper17.pdf

References and More Material

- **MapReduce/Hadoop:**
  - MapReduce: Simplified Data Processing on Large Clusters. Jeffrey Dean and Sanjay Ghemawat. In OSDI 2004.
  - More Examples: http://bit.ly/2rkSRj8
  - Online Tutorial: http://bit.ly/2rS2B5j

- **Spark:**
  - Resilient Distributed Datasets: A Fault-tolerant Abstraction for In-memory Cluster Computing. Matei Zaharia and others. In NSDI 2012.
  - More Examples: http://bit.ly/2rhkhEp, http://bit.ly/2rkT8Tc
  - Online Guide: https://spark.apache.org/docs/2.1.0/sql-programming-guide.html

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Example: Batch Gradient Descent

$$\nabla L(\mathbf{w}^{(k)}) = \sum_{i=1}^{n} \nabla l(y_i, f(\mathbf{w}^{(k)}, x_i))$$

- Very similar to algebraic SQL; vector addition
- **Input Split**: Shard table tuple-wise
- **Map():**
  - On tuple, compute per-example gradient; add these across examples in shard; emit partial sum with single dummy key
- **Reduce():**
  - Only one global dummy key, Iterator has partial gradients; just add all those to get full batch gradient

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Dataflow Sys. vs. Task-Par. Sys.

- **Pros:**
  Discussion in class

- **Cons:**
  Discussion in class

More Specific to Spark vs. Dask?

- **Pros:**

  Discussion in class

- **Cons:**

  Discussion in class

Optional: Advanced examples of use of MapReduce to scale ML algorithms

Not included in syllabus

Primer: K-Means Clustering

- **Basic Idea:** Identify clusters based on Euclidean distances; formulated as an optimization problem
- **Llyod's algorithm:** Most popular heuristic for K-Means
- **Input:** *n x d* examples/points
- **Output:** *k* clusters and their centroids

1. Initialize *k* centroid vectors and point-cluster ID assignment
2. **Assignment step:** Scan dataset and assign each point to a cluster ID based on which centroid is *nearest*
3. **Update step:** Given new assignment, scan dataset again to recompute centroids for all clusters
4. Repeat 2 and 3 until convergence or fixed # iterations

K-Means Clustering in MapReduce

- **Input Split:** Shard the table tuple-wise
  - Assume each tuple/example/point has an *ExampleID*
- Need 2 jobs! 1 for Assignment step, 1 for Update step
- 2 external data structures needed for both jobs:
  - Dense matrix A: $k \times d$ centroids; ultra-sparse matrix B: $n \times k$ assignments
  - A and B first broadcast to all Mappers via HDFS; Mappers can read small data directly from HDFS files
  - Job 1 read A and creates new B
  - Job 2 reads B and creates new A

K-Means Clustering in MapReduce

- A: *k x d* centroid matrix; B: *n x k* assignment matrix
- **Job 1 Map():** Read A from HDFS; compute point's distance to all *k* centroids; get nearest centroid; emit new assignment as output pair (PointID, ClusterID)
- No Reduce() for Job 1; new B now available on HDFS
- **Job 2 Map():** Read B from HDFS; look into B and see which cluster point got assigned to; emit point as output pair (ClusterID, point vector)
- **Job 2 Reduce():** Iterator has all point vectors of a given ClusterID; add them up and divide by count; got new centroid; emit output pair as (ClusterID, centroid vector)

Ad: Take Yoav's DSC 291 to write more MR/Spark programs