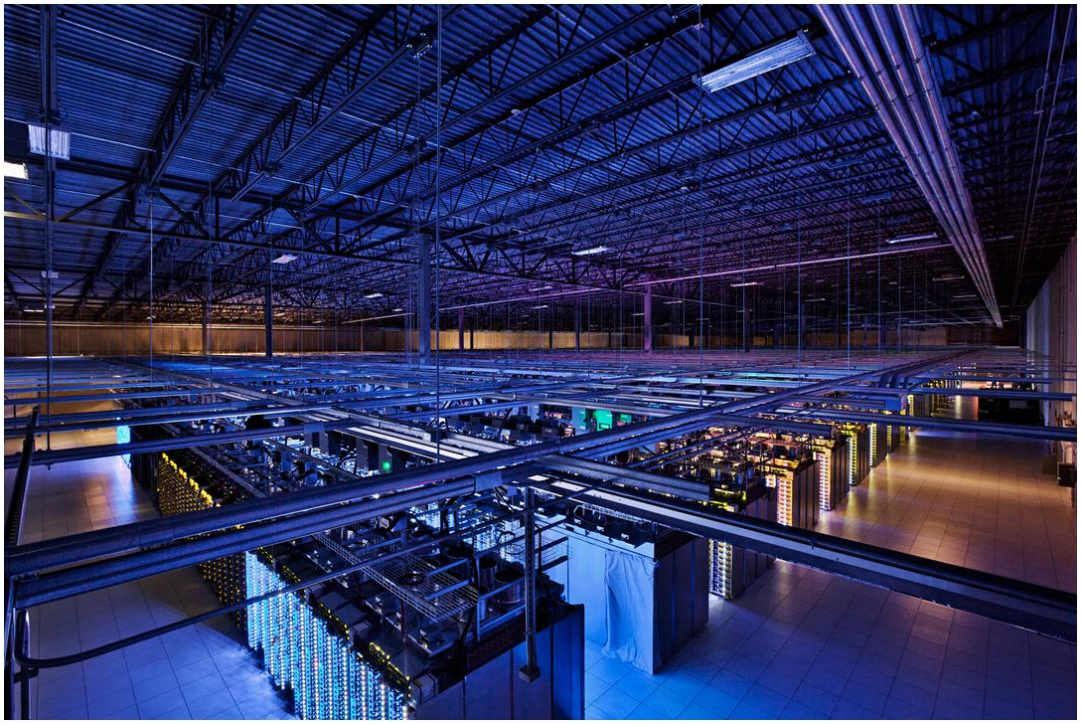
The Spark Framework



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What is Spark?

- Fast and expressive cluster computing system interoperable with Apache Hadoop
- Improves efficiency through:
  - In-memory computing primitives
  - General computation graphs

→ Up to 100 × faster (2-10 × on disk)

- Improves usability through:
  - Rich APIs in Scala, Java, Python
  - Interactive shell

→ Often 5 × less code

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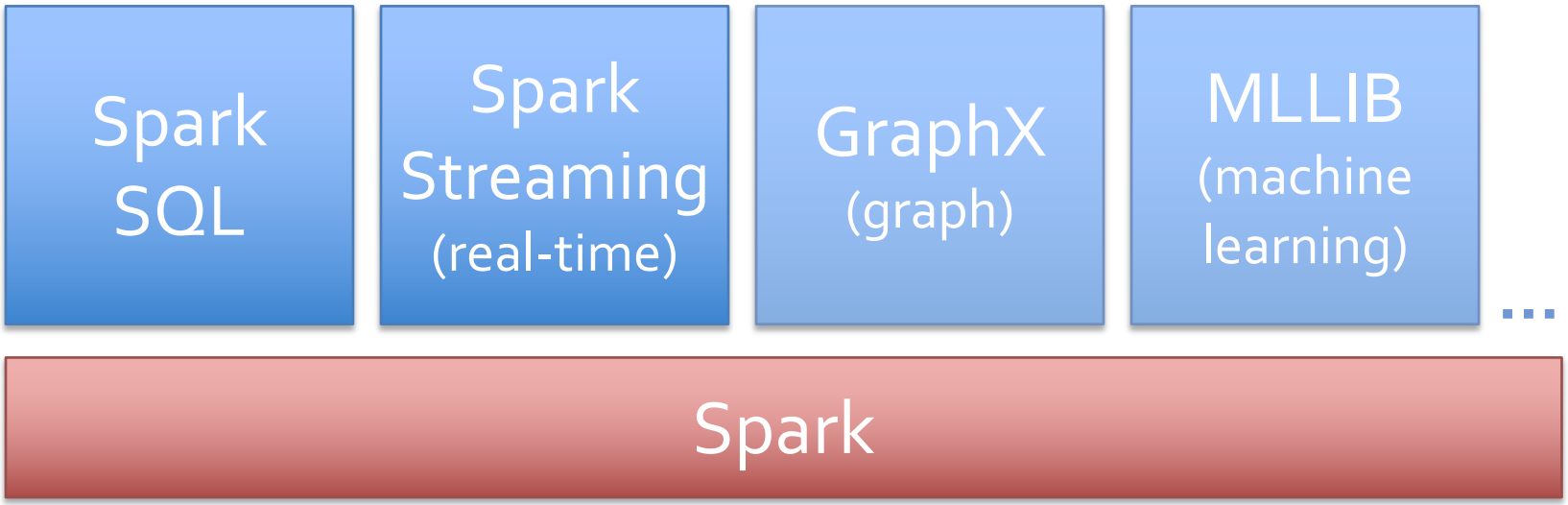
The Spark Stack

- Spark is the basis of a wide set of projects in the Berkeley Data Analytics Stack (BDAS)



More details: amplab.berkeley.edu

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Why a New Programming Model?

- MapReduce greatly simplified big data analysis
- But as soon as it got popular, users wanted more:
  - More **complex**, multi-pass analytics (e.g. ML, graph)
  - More **interactive** ad-hoc queries
  - More **real-time** stream processing
- All 3 need faster **data sharing** across parallel jobs

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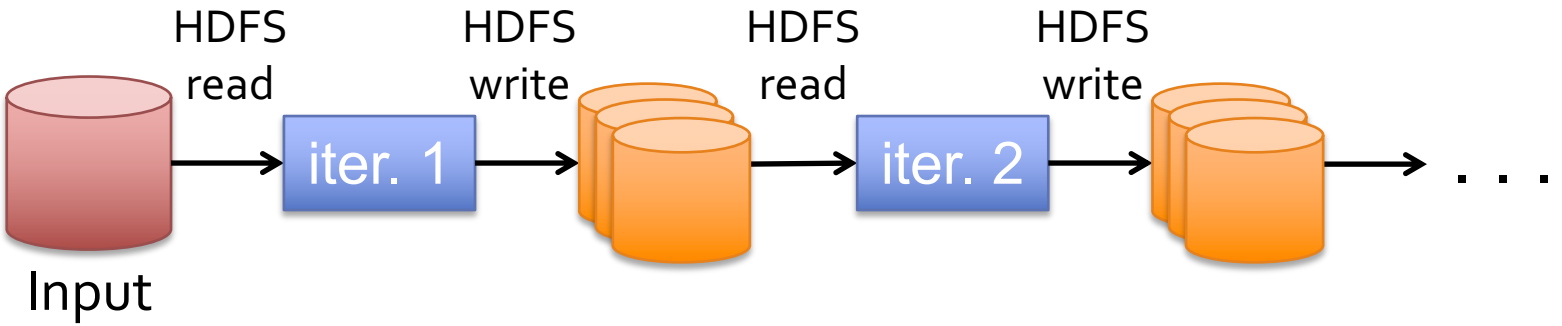
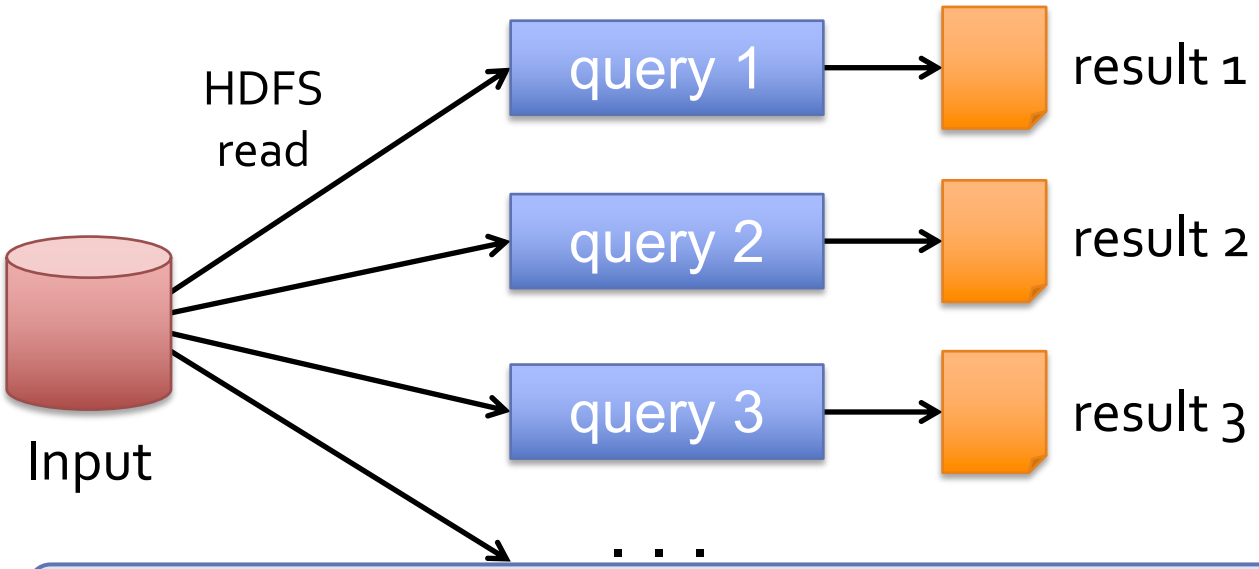
Data Sharing in MapReduce





Slow due to replication, serialization, and disk IO

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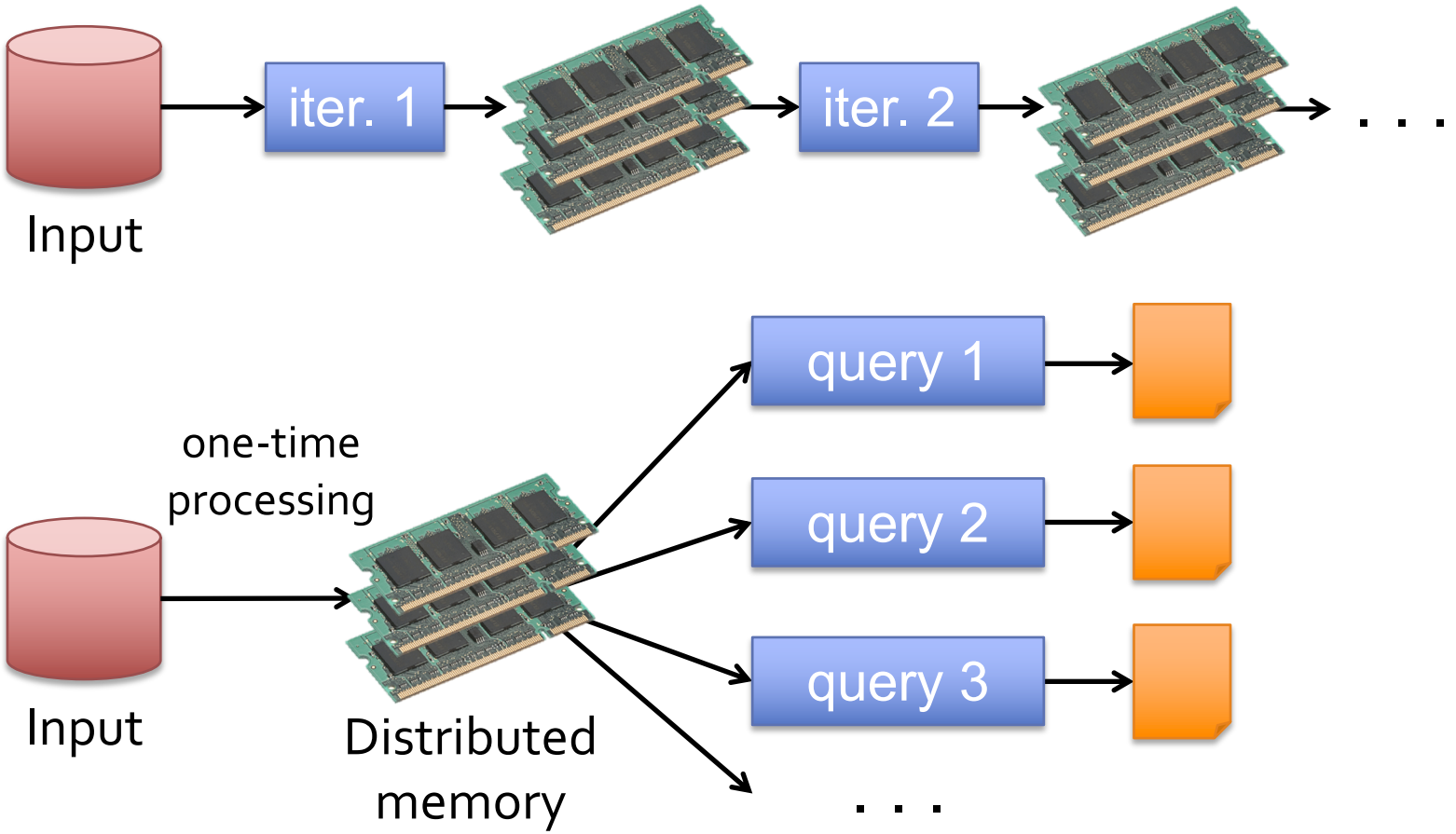
Data Sharing in Spark



~10× faster than network and disk

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Spark Programming Model

- Key idea: *resilient distributed datasets (RDDs)*
  - Distributed collections of objects that can be cached in memory across the cluster
  - Manipulated through parallel operators
  - Automatically *recomputed* on failure
- Programming interface
  - Functional APIs in Scala, Java, Python
  - Interactive use from Scala shell

Example: Log Mining

Load error messages from a log into memory, then interactively search for various patterns

```
lines = spark.textFile(“hdfs://...”)
errors = lines.filter(lambda x: x.startswith(“ERROR”))
messages = errors.map(lambda x: x.split(‘\t’)[2])
messages.cache()
```

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Lambda Functions

```
errors = lines.filter(lambda x: x.startswith("ERROR"))
messages = errors.map(lambda x: x.split('\t')[2])
```

Lambda function ← functional programming!

= implicit function definition

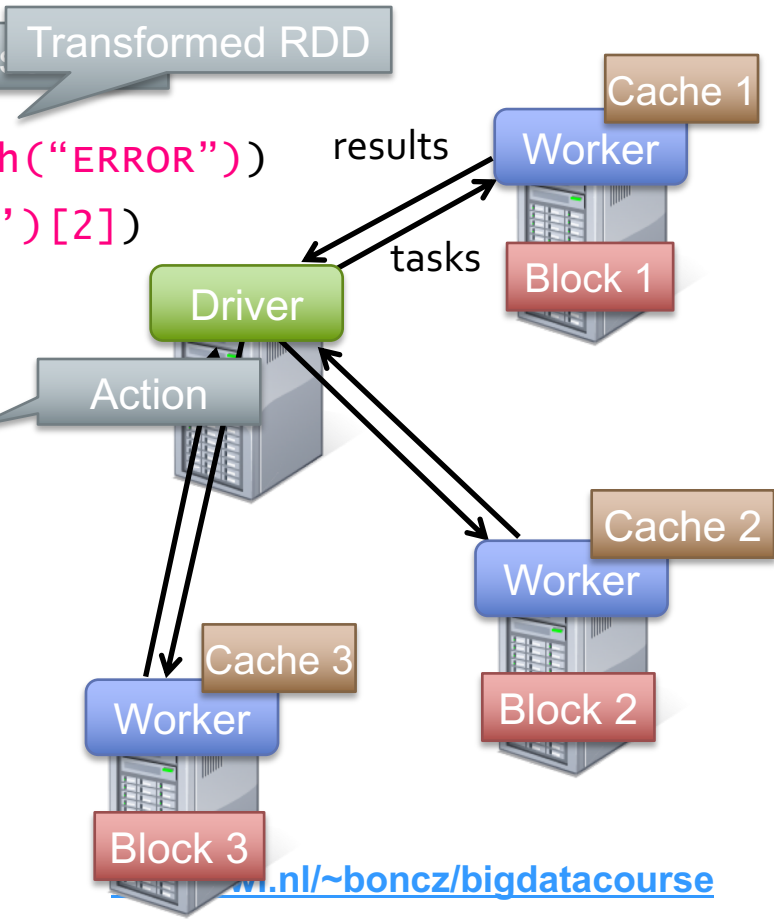
```
bool detect_error(string x) {
    return x.startswith("ERROR");
}
```

Example: Log Mining

Load error messages from a log into memory, then interactively search for various patterns

```
lines = spark.textFile("hdfs://...")
errors = lines.filter(lambda x: x.startswith("ERROR"))
messages = errors.map(lambda x: x.split('\t')[2])
messages.cache()

messages.filter(lambda x: "foo" in x).count
messages.filter(lambda x: "bar" in x).count
```



Result: scaled to 1 TB data in 5-7 sec (vs 170 sec for on-disk data)

Result: full-text search of Wikipedia in <1 sec (vs 20 sec for on-disk data)

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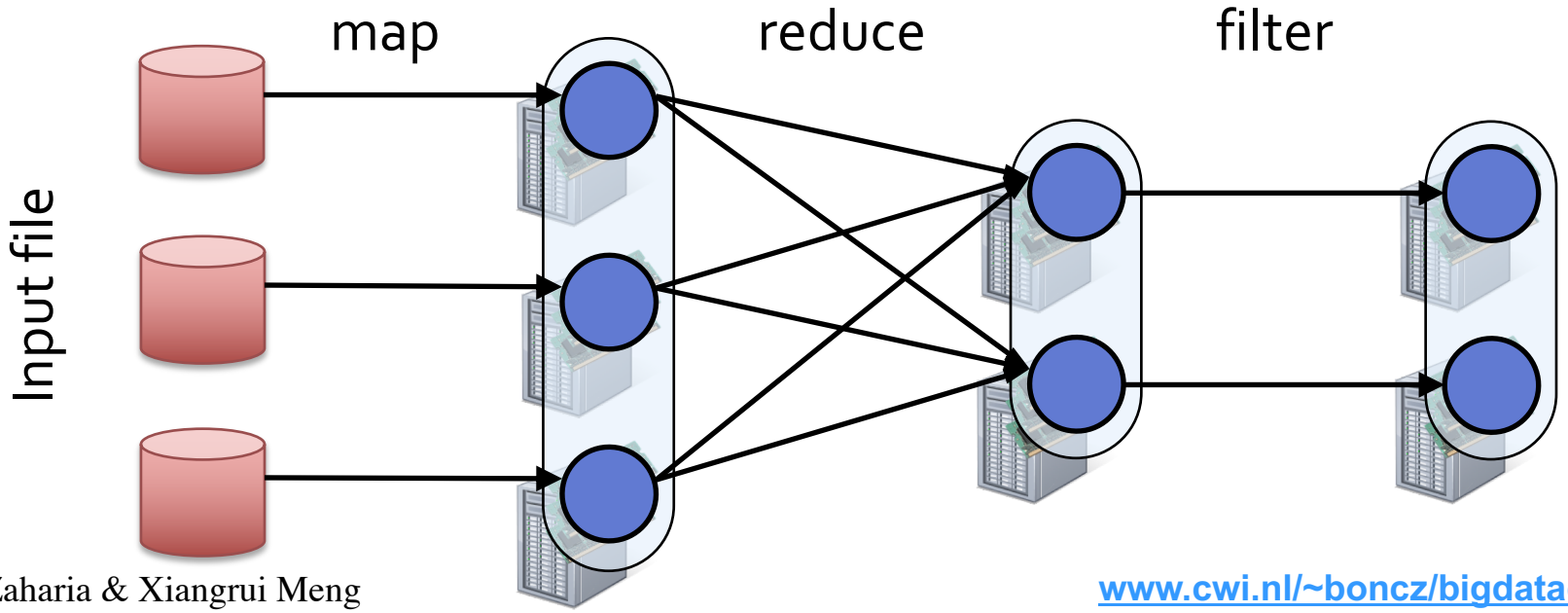
Fault Tolerance

RDDs track *lineage* info to rebuild lost data

```
file.map(lambda rec: (rec.type, 1))
    .reduceByKey(lambda x, y: x + y)
    .filter(lambda (type, count): count > 10)
```



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Fault Tolerance

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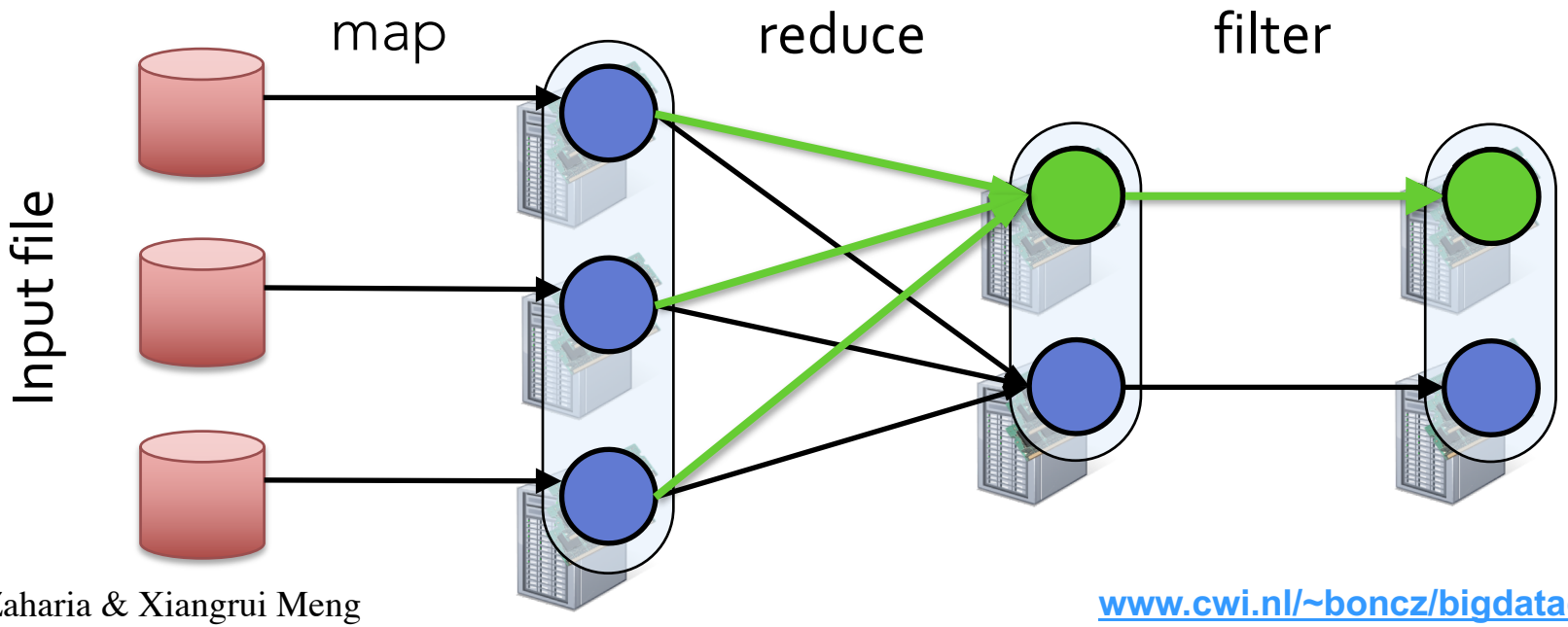

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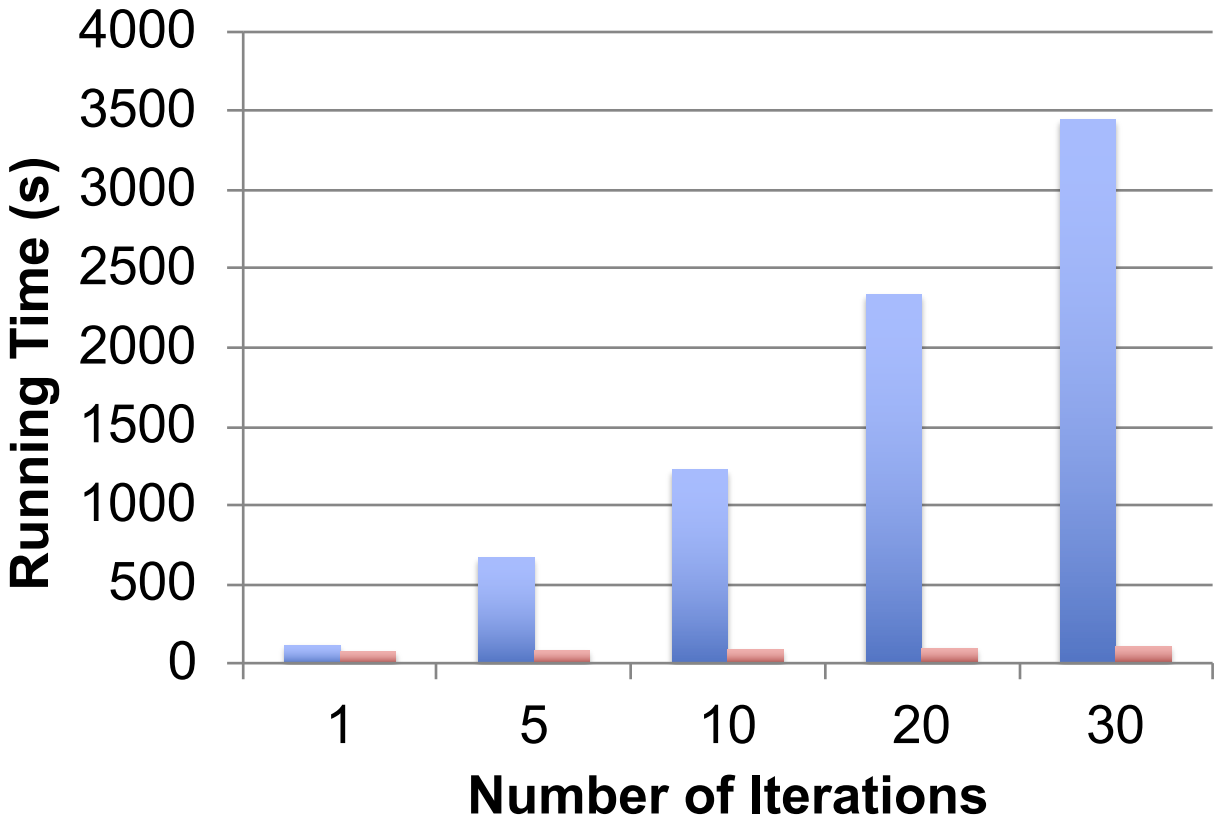
Example: Logistic Regression



110 s / iteration

Hadoop

Spark

first iteration 80 s
further iterations 1 s

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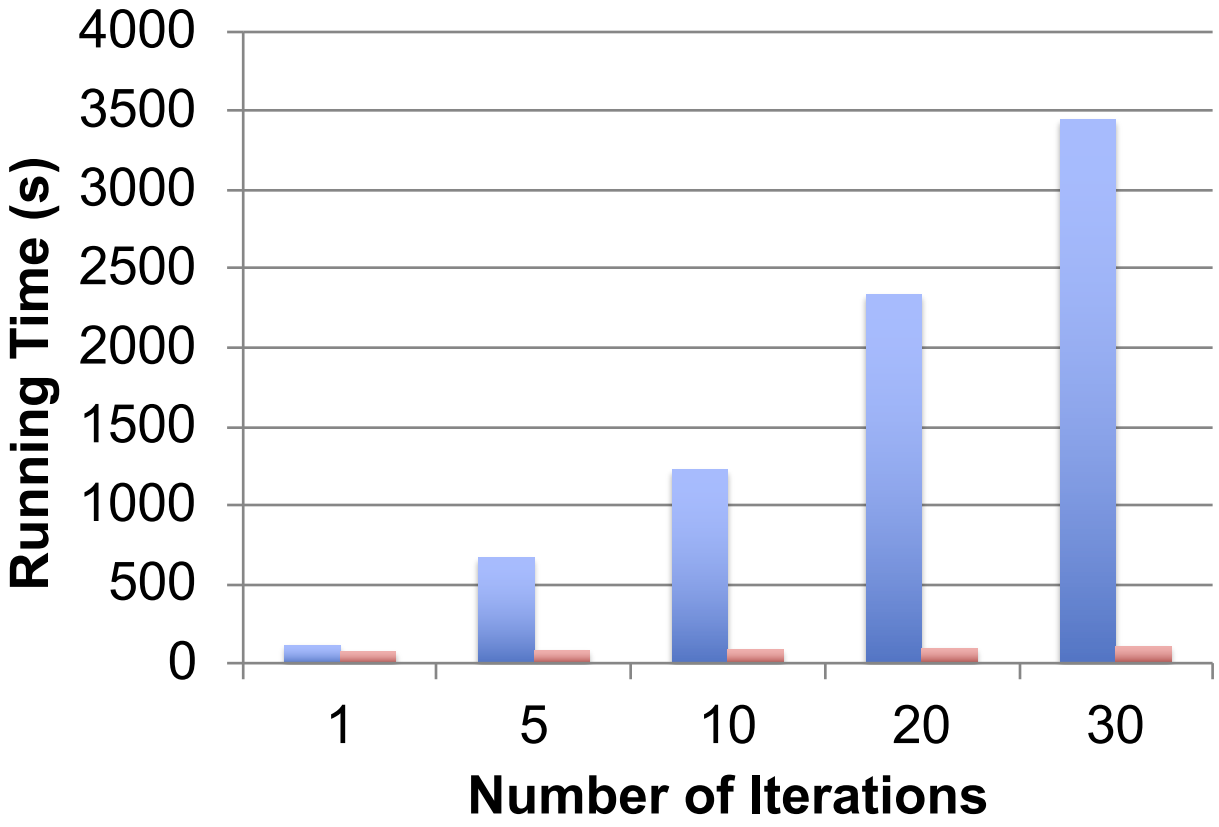
Example: Logistic Regression



110 s / iteration

Hadoop

Spark

first iteration 80 s
further iterations 1 s

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Spark in Scala and Java

```
// Scala:

val lines = sc.textFile(...)
lines.filter(x => x.contains("ERROR")).count()


// Java:

JavaRDD<String> lines = sc.textFile(...);
lines.filter(new Function<String, Boolean>() {
  Boolean call(String s) {
    return s.contains("error");
  }
}).count();
```

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Matei Zaharia & Xiangrui Meng

Supported Operators

- `map`
- `filter`
- `groupBy`
- `sort`
- `union`
- `join`
- `leftOuterJoin`
- `rightOuterJoin`
- `reduce`
- `count`
- `fold`
- `reduceByKey`
- `groupByKey`
- `cogroup`
- `cross`
- `zip`

`sample`

`take`

`first`

`partitionBy`

`mapWith`

`pipe`

`save`

`...`

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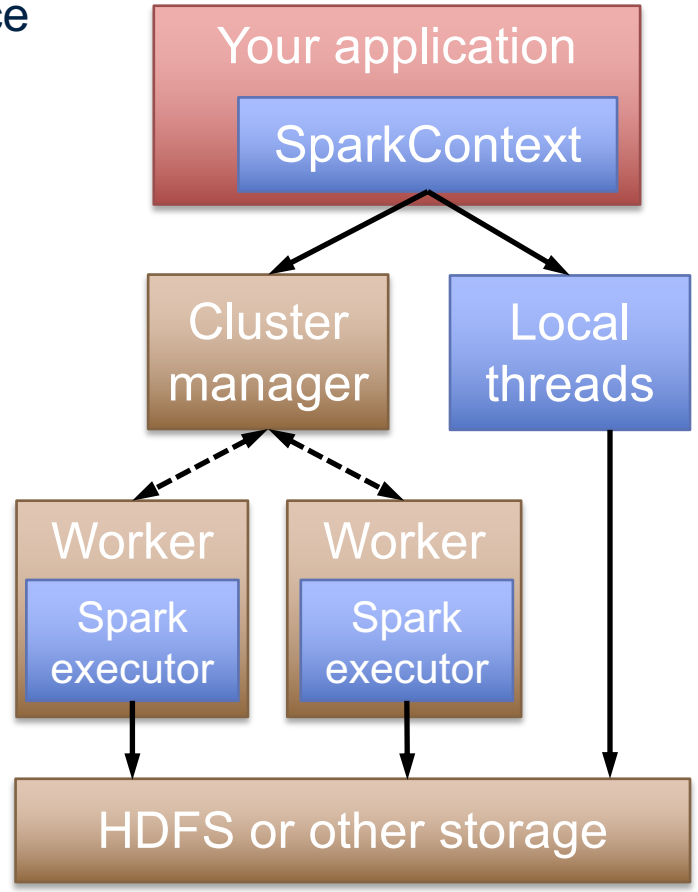
Software Components

- Spark client is library in user program (1 instance per app)
- Runs tasks locally or on cluster
  - Mesos, YARN, standalone mode
- Accesses storage systems via Hadoop InputFormat API
  - Can use HBase, HDFS, S3, …



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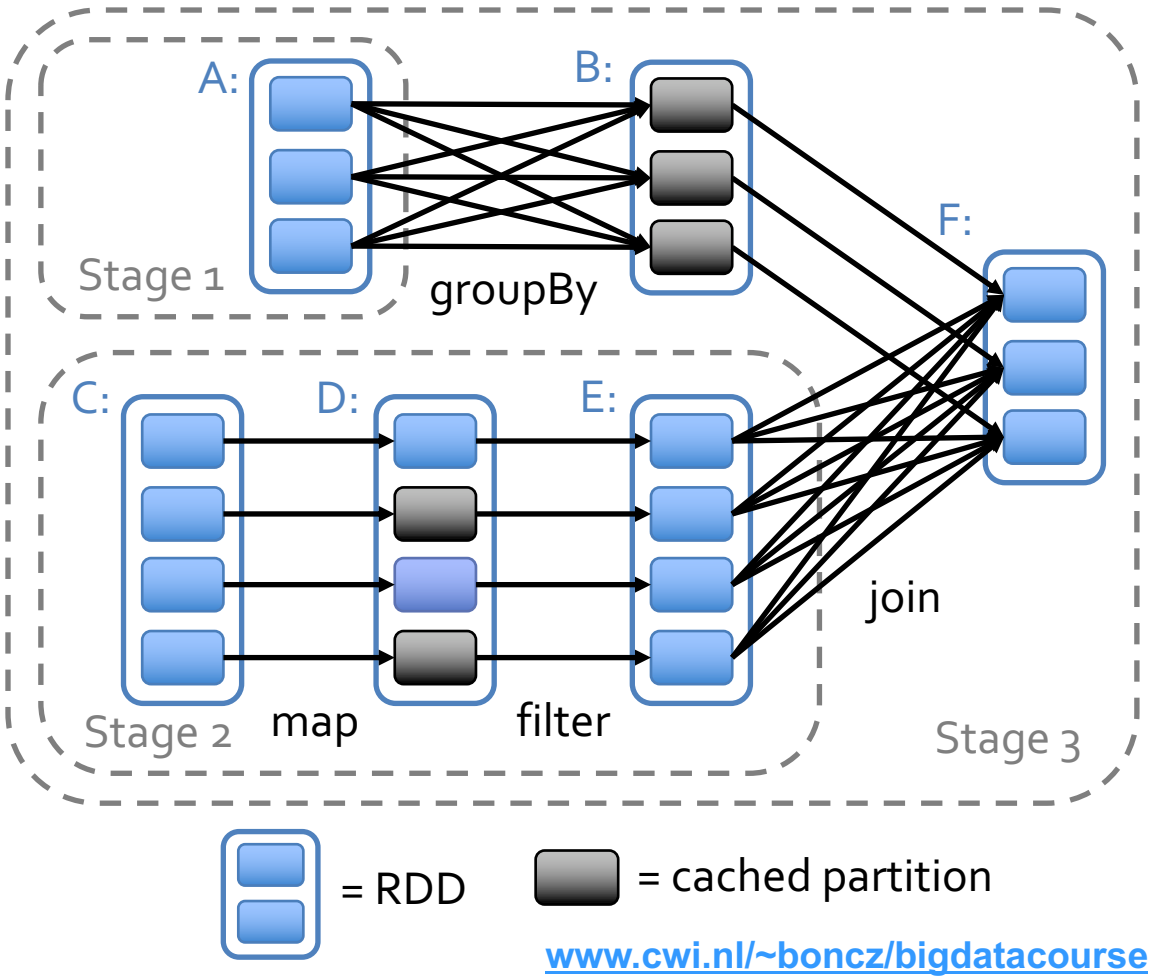
Task Scheduler

- General task graphs
- Automatically pipelines functions
- Data locality aware
- Partitioning aware to avoid shuffles



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Spark SQL

- Columnar SQL analytics engine for Spark
  - Support both SQL and complex analytics
  - Columnar storage, JIT-compiled execution, Java/Scala/Python UDFs
  - Catalyst query optimizer (also for DataFrame scripts)

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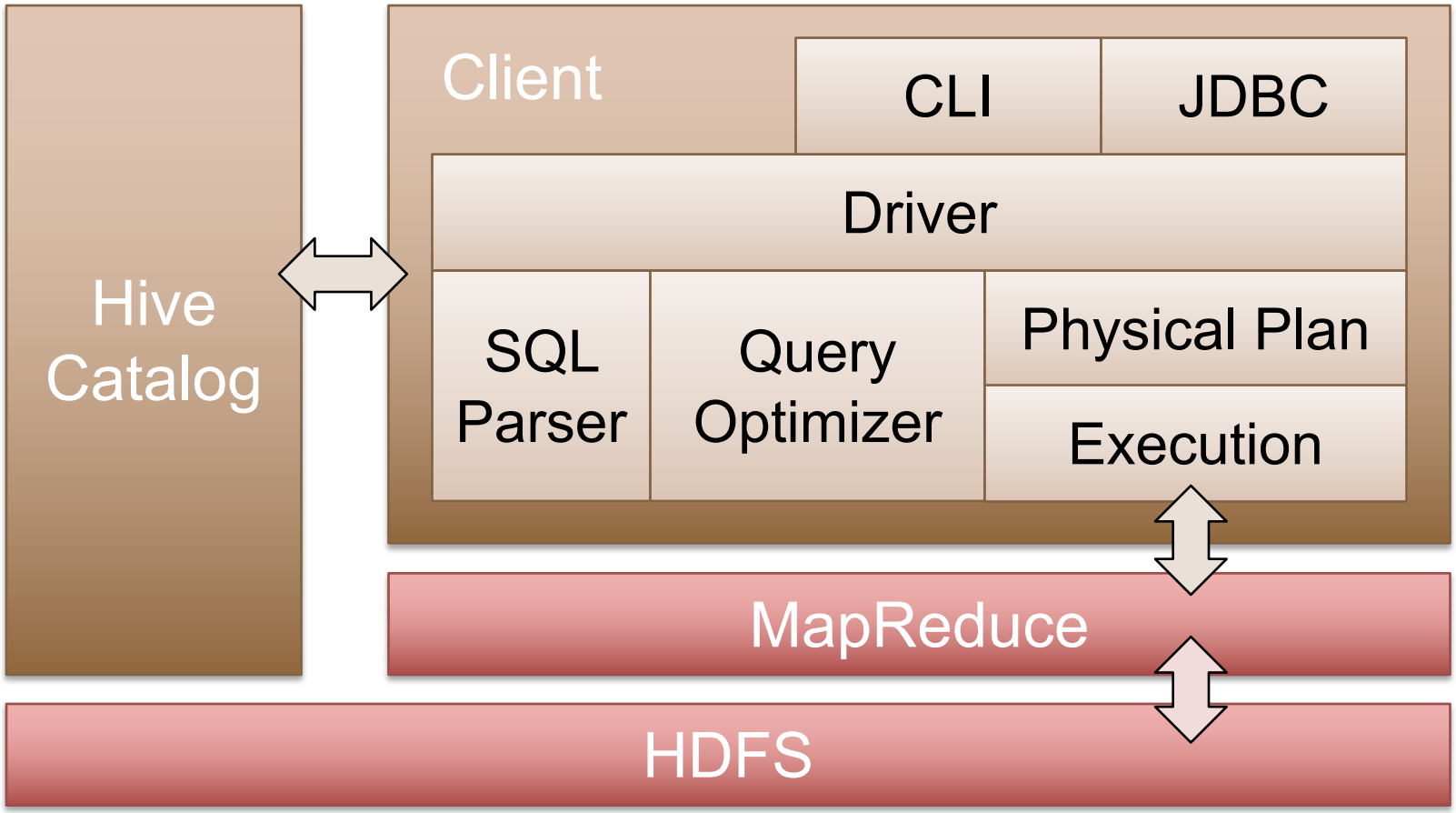
Hive Architecture



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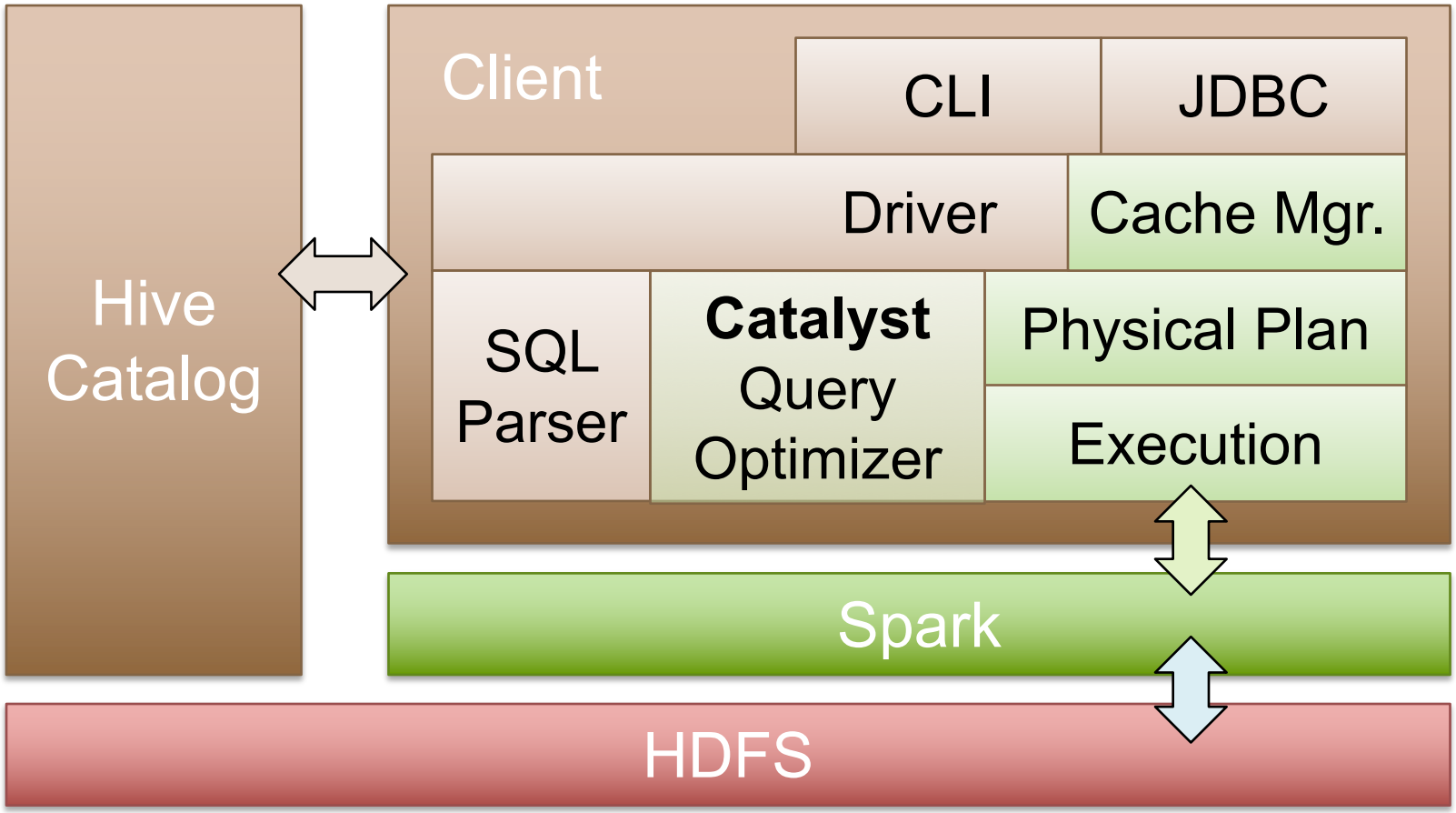
Spark SQL Architecture



[Engle et al, SIGMOD 2012]

From RDD to DataFrame

```
users = ctx.table("users")
young = users.where(users("age") < 21)
println(young.count())
```

- A distributed collection of rows with the same schema (RDDs suffer from type erasure)
- Can be constructed from external data sources or RDDs into essentially an RDD of Row objects (SchemaRDDs as of Spark < 1.3)
- Supports relational operators (e.g. *where*, *groupby*) as well as Spark operations.
- Evaluated lazily → non-materialized *logical* plan

DataFrame: Data Model

- Nested data model
- Supports both primitive SQL types (boolean, integer, double, decimal, string, data, timestamp) and complex types (structs, arrays, maps, and unions); also user defined types.
- First class support for complex data types

DataFrame Operations

- Relational operations (select, where, join, groupBy) via a DSL
- Operators take *expression* objects
- Operators build up an abstract syntax tree (AST), which is then optimized by *Catalyst*.

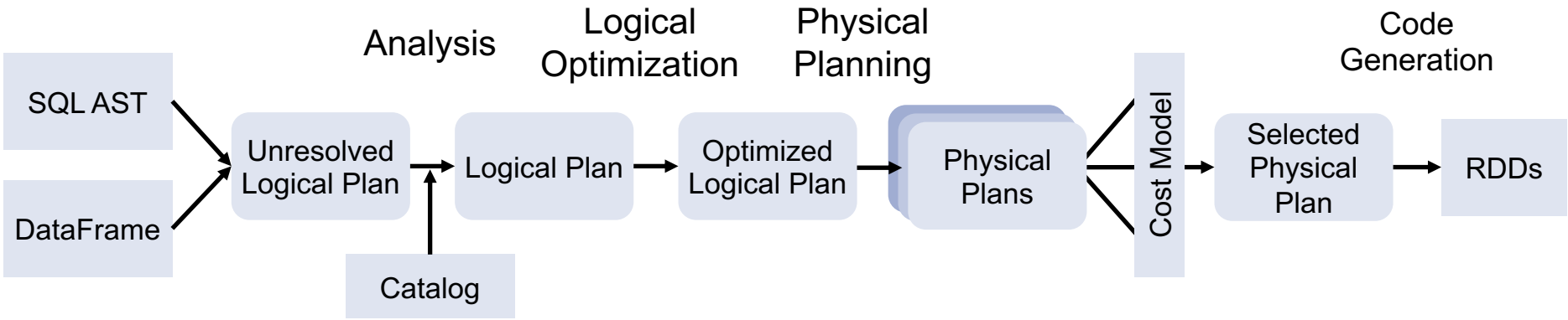
```
employees
  .join(dept, employees("deptId") === dept("id"))
  .where(employees("gender") === "female")
  .groupBy(dept("id"), dept("name"))
  .agg(count("name"))
```

- Alternatively, register as temp SQL table and perform traditional SQL query strings

```
users.where(users("age") < 21)
     .registerTempTable("young")
ctx.sql("SELECT count(*), avg(age) FROM young")
```

credits:
Matei Zaharia & Reynold Xin

Catalyst: Plan Optimization & Execution



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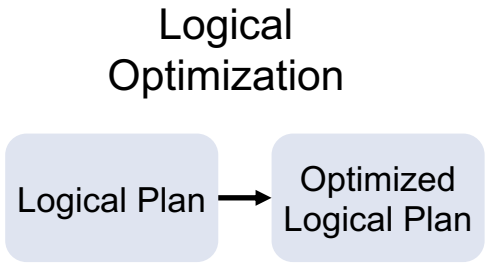
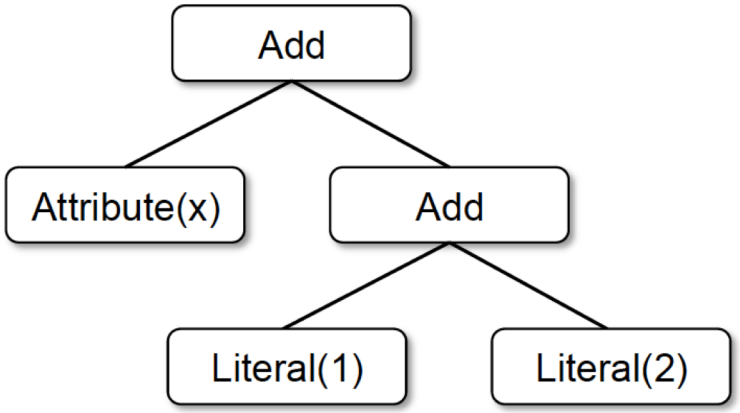
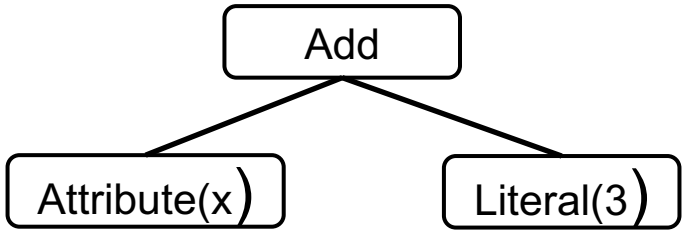
Catalyst Optimization Rules



- Applies standard rule-based optimization (constant folding, predicate-pushdown, projection pruning, null propagation, boolean expression simplification, etc)

```
tree.transform {
  case Add(Literal(c1), Literal(c2)) => Literal(c1+c2)
}
```





$x + (1 + 2)$

$x + 3$

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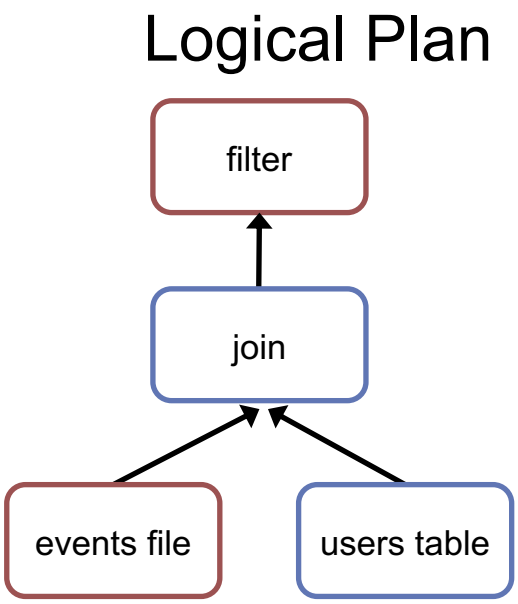
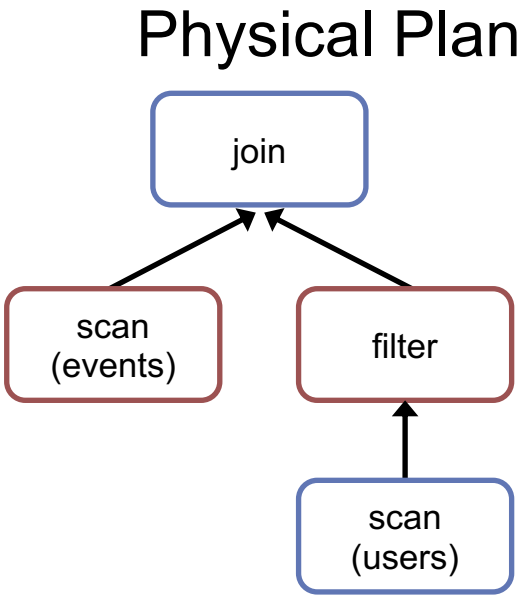
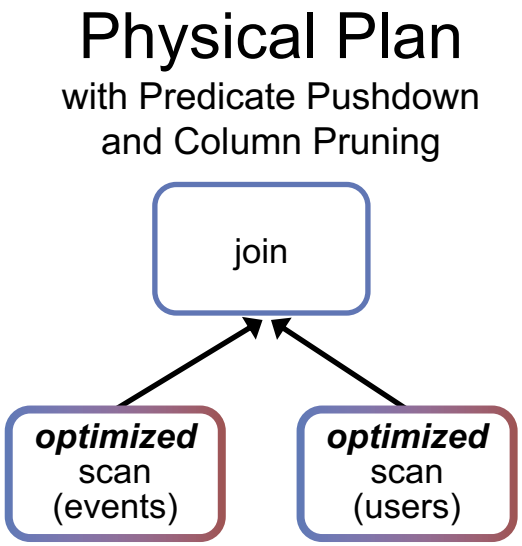
```
def add_demographics(events):
   u = sqlCtx.table("users")                        # Load partitioned Hive table
   events \
     .join(u, events.user_id == u.user_id) \        # Join on user_id
     .withColumn("city", zipToCity(df.zip))         # Run udf to add city column
events = add_demographics(sqlCtx.load("/data/events",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







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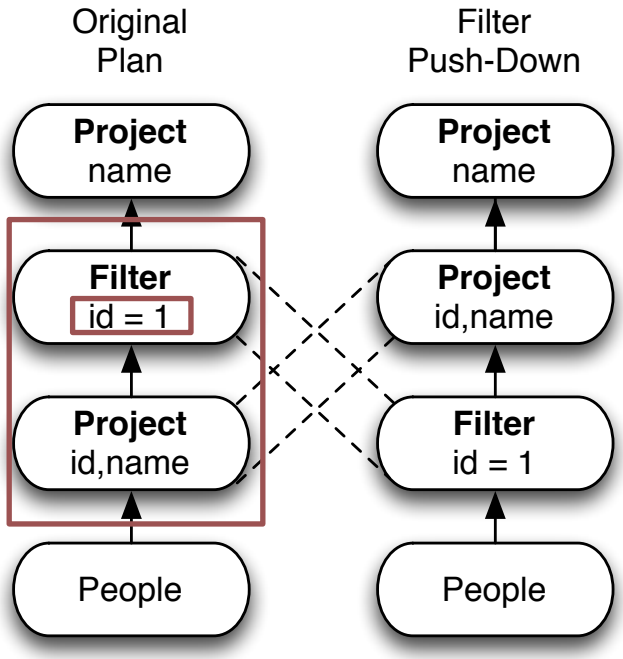
An Example Catalyst Transformation

1. Find filters on top of projections.
2. Check that the filter can be evaluated without the result of the project.
3. If so, switch the operators.



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Other Spark Stack Projects

We will revisit **Spark SQL** in the **SQL on Big Data** lecture

- **Structured Streaming:** stateful, fault-tolerant stream

```
sc.twitterStream(...)
  .flatMap(_.getText.split(" "))
  .map(word => (word, 1))
  .reduceByWindow("5s", _ + _)
```

  - we will revisit **structured streaming** in the Data Streaming lecture

this lecture, still:

- **GraphX & GraphFrames:** graph-processing framework
- **MLlib:** Library of high-quality machine learning algorithms

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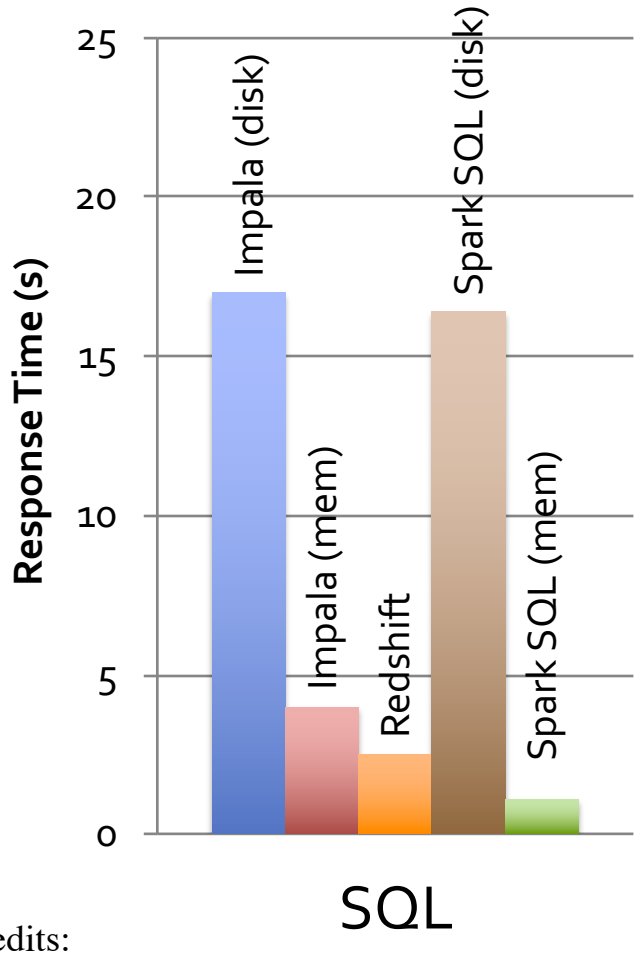
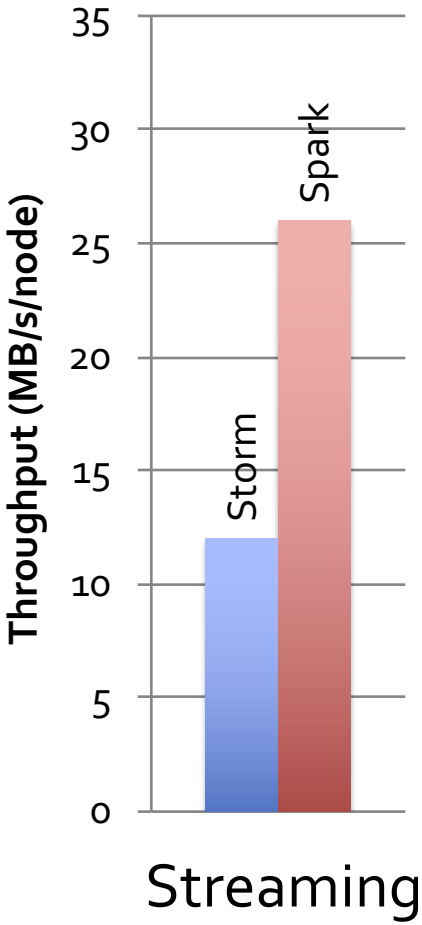
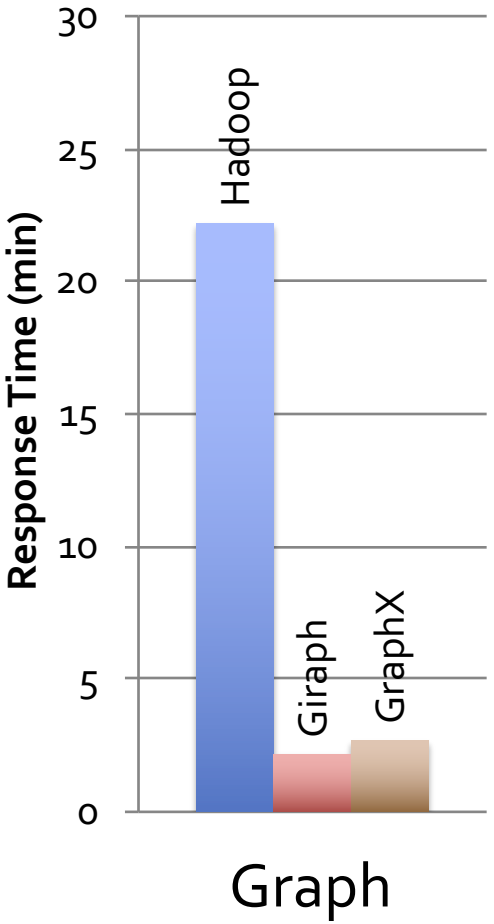
Performance







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CWI
Centrum Wiskunde & Informatica

SPARK MLLIB

credits:
Matei Zaharia & Xiangrui Meng

www.cwi.nl/~boncz/bigdatacourse

What is MLLIB?

MLlib is a Spark subproject providing machine learning primitives:

- initial contribution from AMPLab, UC Berkeley
- shipped with Spark since version 0.8

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What is MLLIB?

Algorithms:

- **classification**: logistic regression, linear support vector machine (SVM), naive Bayes
- **regression**: generalized linear regression (GLM)
- **collaborative filtering**: alternating least squares (ALS)
- **clustering**: k-means
- **decomposition**: singular value decomposition (SVD), principal component analysis (PCA)

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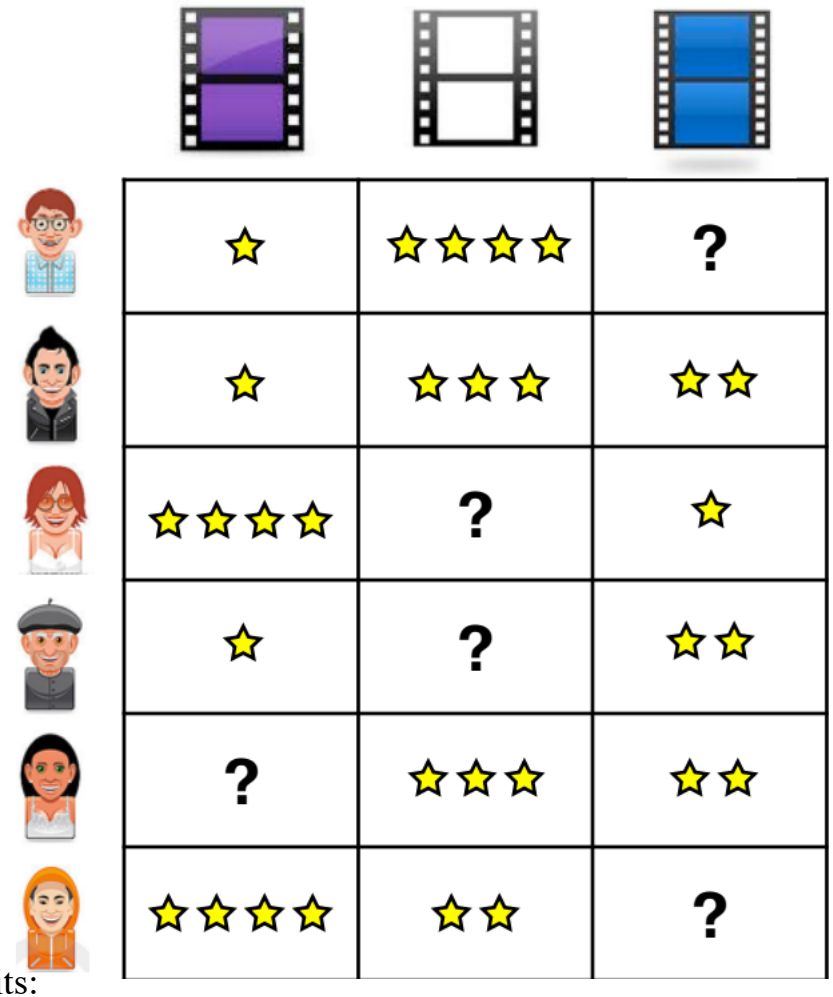
Collaborative Filtering



- Recover a rating matrix from a subset of its entries.

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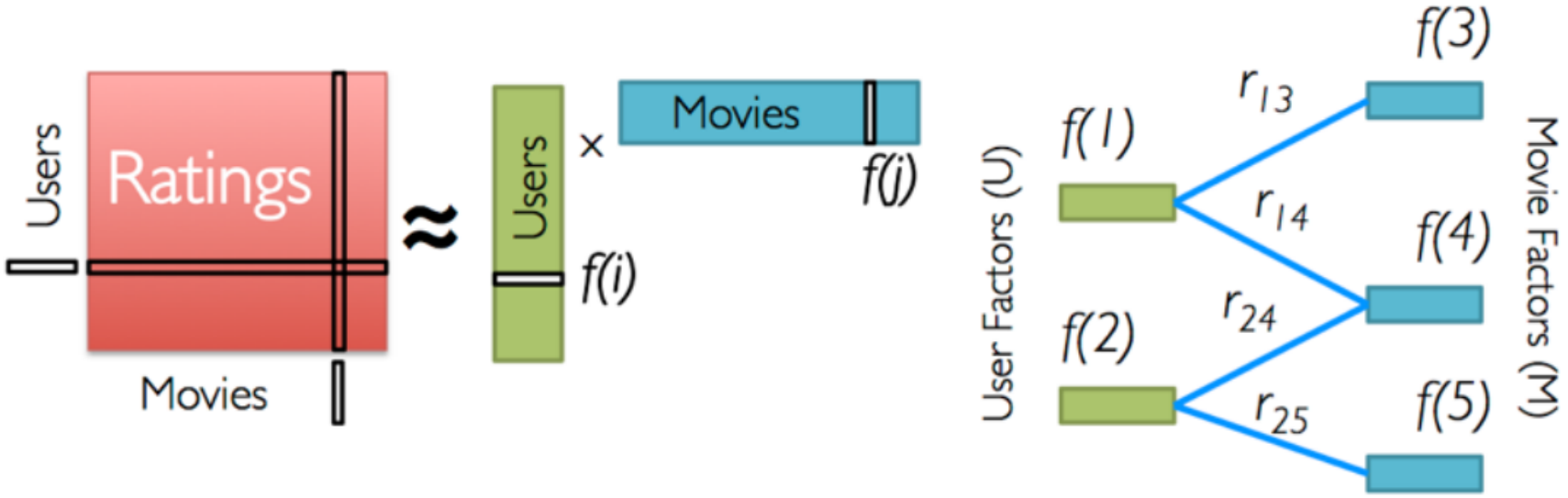
Alternating Least Squares (ALS)



Iterate:

$$f[i] = \arg\min_{w \in \mathbb{R}^d} \sum_{j \in \text{Nbrs}(i)} \left(r_{ij} - w^T f[j]\right)^2 + \lambda ||w||_2^2$$

credits:
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Collaborative Filtering in Spark MLLIB

```
trainset =
  sc.textFile("s3n://bads-music-dataset/train_*.gz")
    .map(lambda l: l.split('\t'))
    .map(lambda l: Rating(int(l[0]), int(l[1]), int(l[2])))

model = ALS.train(trainset, rank=10, iterations=10) # train

testset =                                    # load testing set
  sc.textFile("s3n://bads-music-dataset/test_*.gz")
    .map(lambda l: l.split('\t'))
    .map(lambda l: Rating(int(l[0]), int(l[1]), int(l[2])))

# apply model to testing set (only first two cols) to predict
predictions =
   model.predictAll(testset.map(lambda p: (p[0], p[1])))
        .map(lambda r: ((r[0], r[1]), r[2]))
```

credits:
Matei Zaharia & Xiangrui Meng

Spark MLLIB – ALS Performance

System	Wall-clock /me (seconds)
Matlab	15443
Mahout	4206
GraphLab	291
MLlib	481

- Dataset: Netflix data
- Cluster: 9 machines.
- MLlib is an order of magnitude faster than Mahout.
- MLlib is within factor of 2 of GraphLab.

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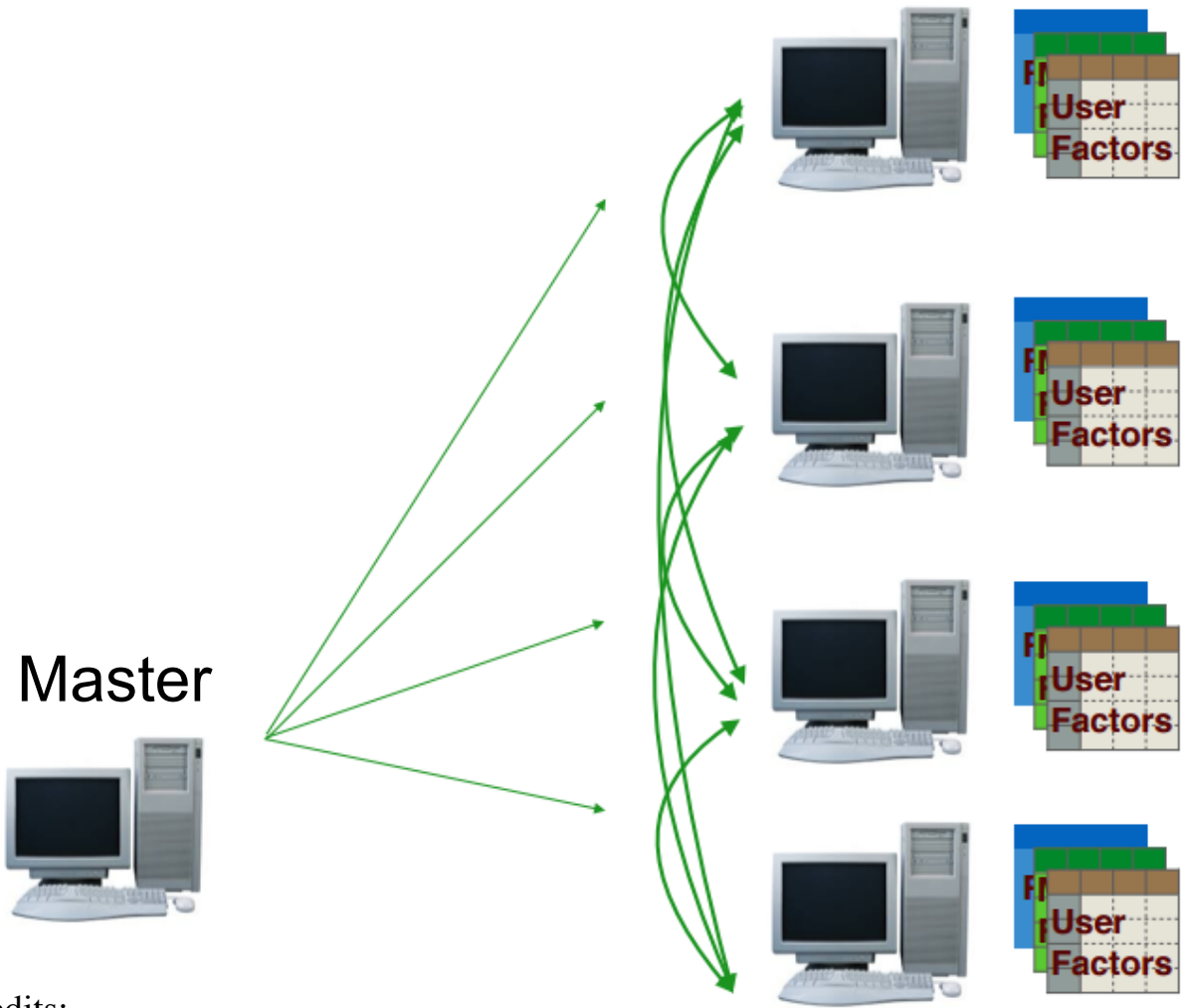
Spark Implementation of ALS



- Workers load data
- Models are instantiated at workers.
- At each iteration, models are shared via join between workers.
- Good scalability.
- Works on large datasets

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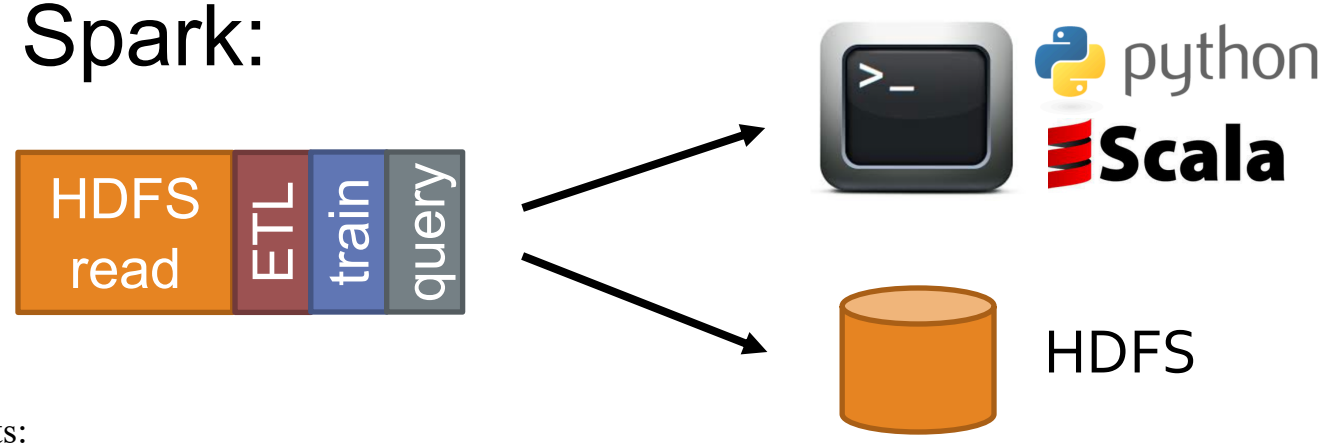
What it Means for Users

- Separate frameworks:

Spark:



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Summary

- The Spark Framework
  - Generalize Map(),Reduce() to a much larger set of operations
    - Join, filter, group-by, …➔ closer to database queries
  - High(er) performance (than MapReduce)
    - In-memory caching, catalyst query optimizer, JIT compilation, ..
    - Low-level RDD API ➔ Higher-level DataFrame API (+SQL)
- Spark GraphX: Graph Analytics (similar to Pregel/Giraph/Gelly)
  - Graph algorithms are often iterative (multi-job) ➔ a pain in MapReduce
  - Vertex-centric programming model:
    - Who to send messages to (halt if none)
    - How to compute new vertex state from messages
- Spark MLlib: scalable Machine learning
  - classification, regression, ALS, k-means, decomposition
  - Parallel DataFrame operations: allows analyzing data > RAM

Conclusion

- Big data analytics is evolving to include:
  - More **complex** analytics (e.g. machine learning)
  - More **interactive** ad-hoc queries
  - More **real-time** stream processing
- Spark is a fast platform that *unifies* these apps
- More info: spark-project.org

credits:
Matei Zaharia & Xiangrui Meng