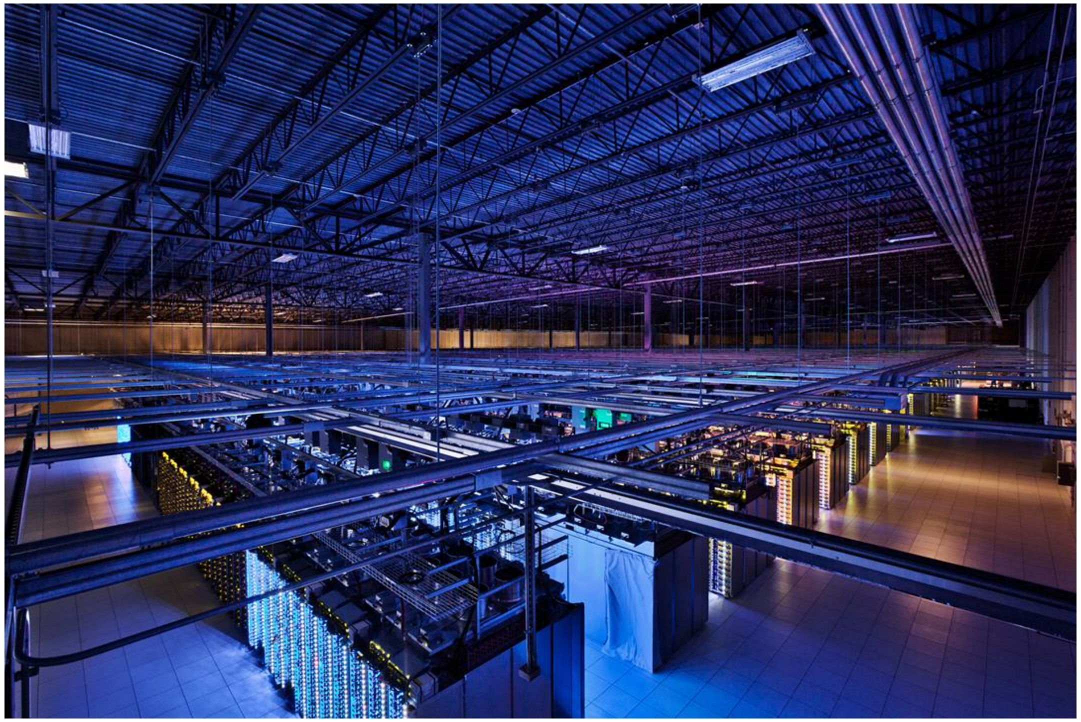
Big Data Infrastructures & Technologies

Hadoop Streaming Revisit



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ENRON Mapper

```python
#!/usr/bin/env python

import sys

for line in sys.stdin:
    line = line.strip().split('\t')
    if len(line) != 3:
        continue
    date, sender, recipient = line
    date = date[:10]
    if (date <= "2001-11-05" or date >= "2001-11-08"):
        continue
    if "enron" in recipient or not "enron" in sender:
        continue
    print sender + '\t' + recipient
```

ENRON Mapper Output (Excerpt)

acomnes@enron.com edward.snowden@cia.gov

blake.walker@enron.com alex.berenson@nyt.com

ENRON Reducer

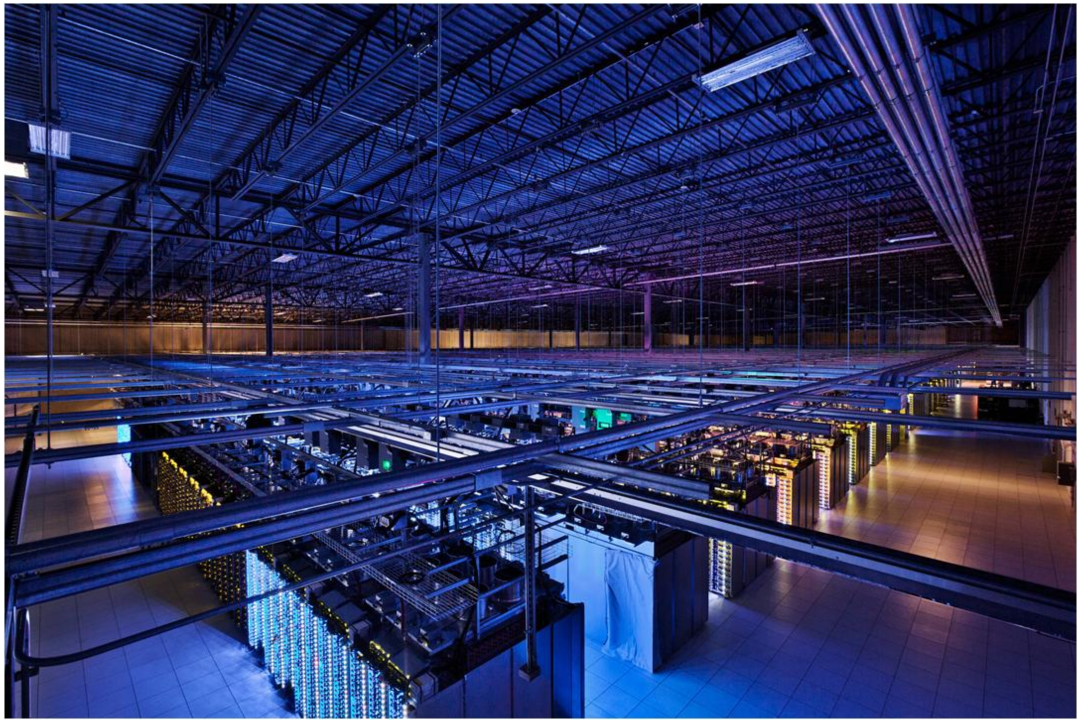
```
#!/usr/bin/env python

import sys

current_sender = ''
current_count = 0
for line in sys.stdin:
    line = line.strip().split('\t')
    if len(line) != 2:
        continue
    sender, recipient = line
    if (sender != current_sender):
        if (current_count > 1):
            print current_sender + '\t' + str(current_count)
        current_sender = sender
        current_count = 0
    current_count += 1
if (current_count > 1):
    print current_sender + '\t' + str(current_count)
```

Optimization?

ENRON Final Results (Excerpt)

acomnes@enron.com	32
anne.jolibois@enron.com	18
billy.lemmons@enron.com	11
brad.guilmino@enron.com	11

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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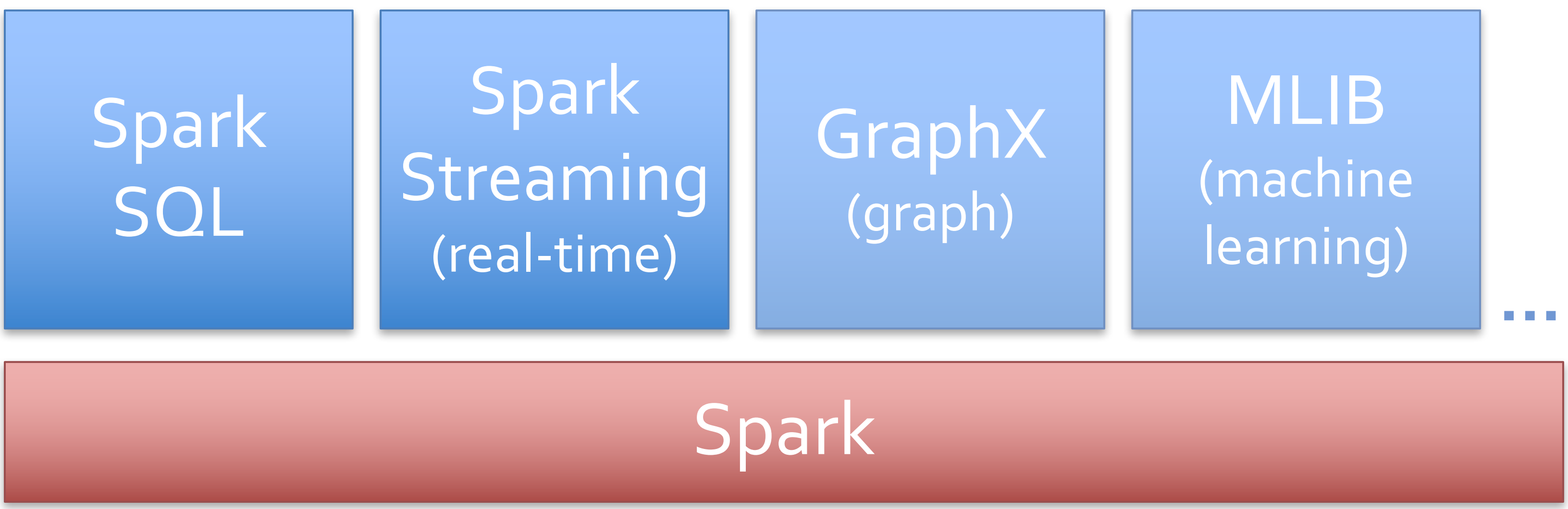
The Spark Stack

- 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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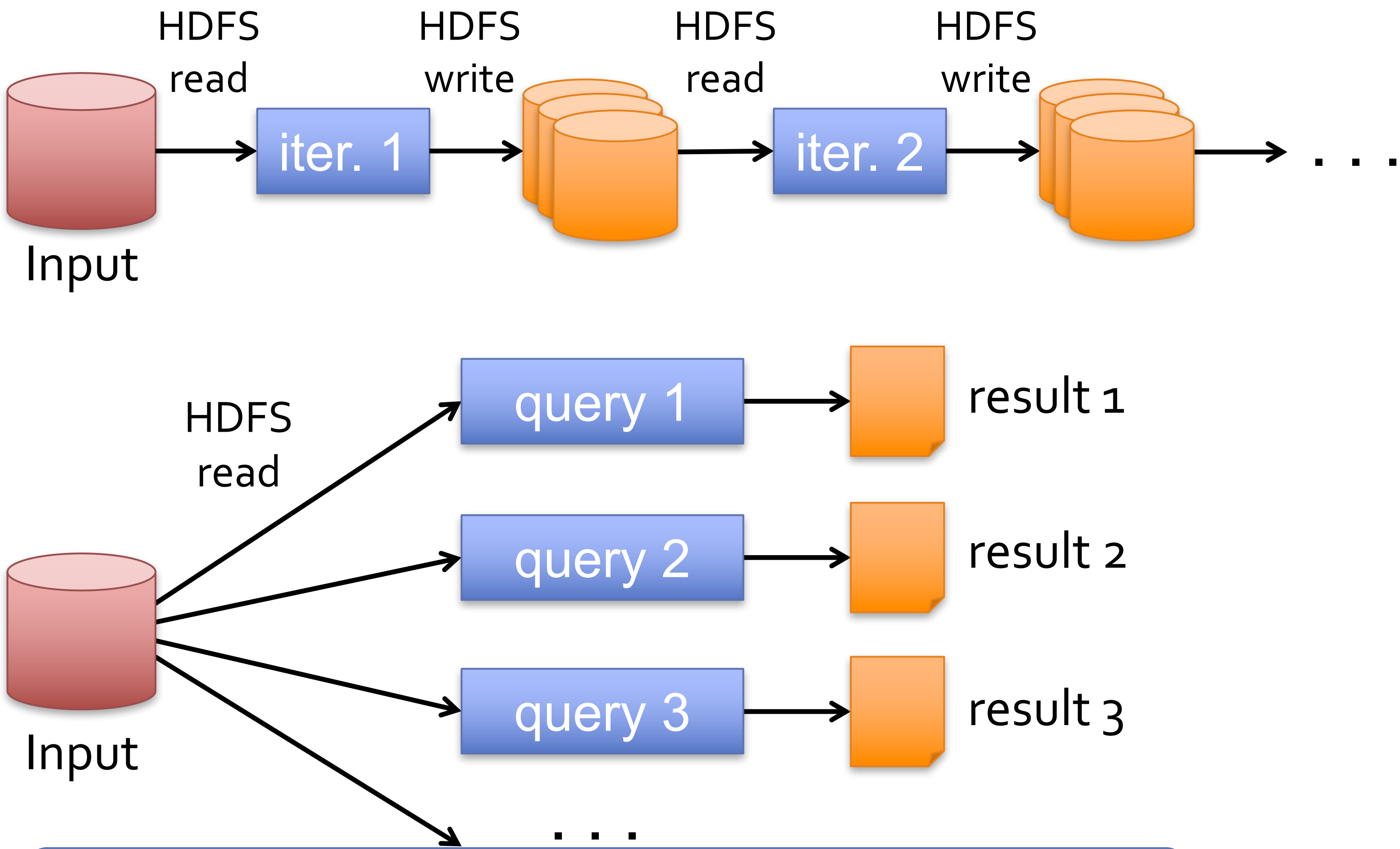
Data Sharing in MapReduce



Slow due to replication, serialization, and disk IO

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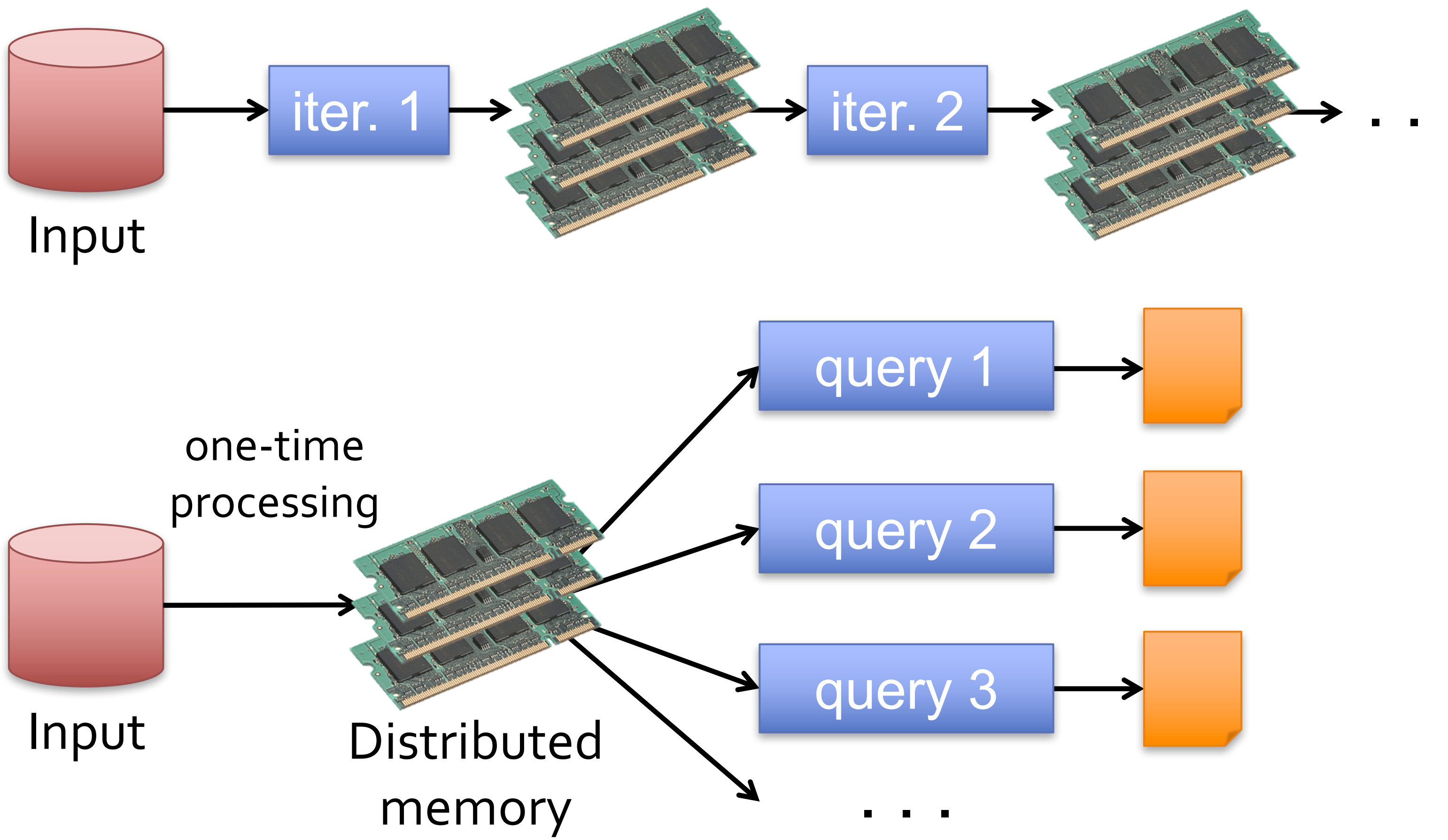
Data Sharing in Spark



~10 × faster than network and disk

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Spark Programming Model

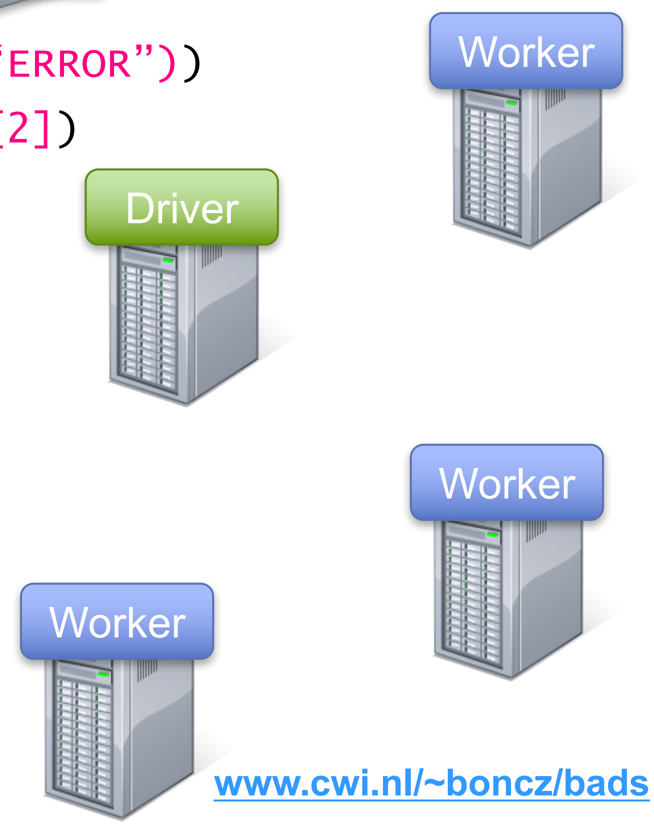
- Key idea: *resilient distributed datasets (RDDs)*
  - Distributed collections of objects that can be cached in memory across the cluster
  - Manipulated through parallel operators
  - Automatically *recomputed* on failure
- Programming interface
  - Functional APIs in Scala, Java, Python
  - Interactive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

Example: Log Mining

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

Transformed RDD

```
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

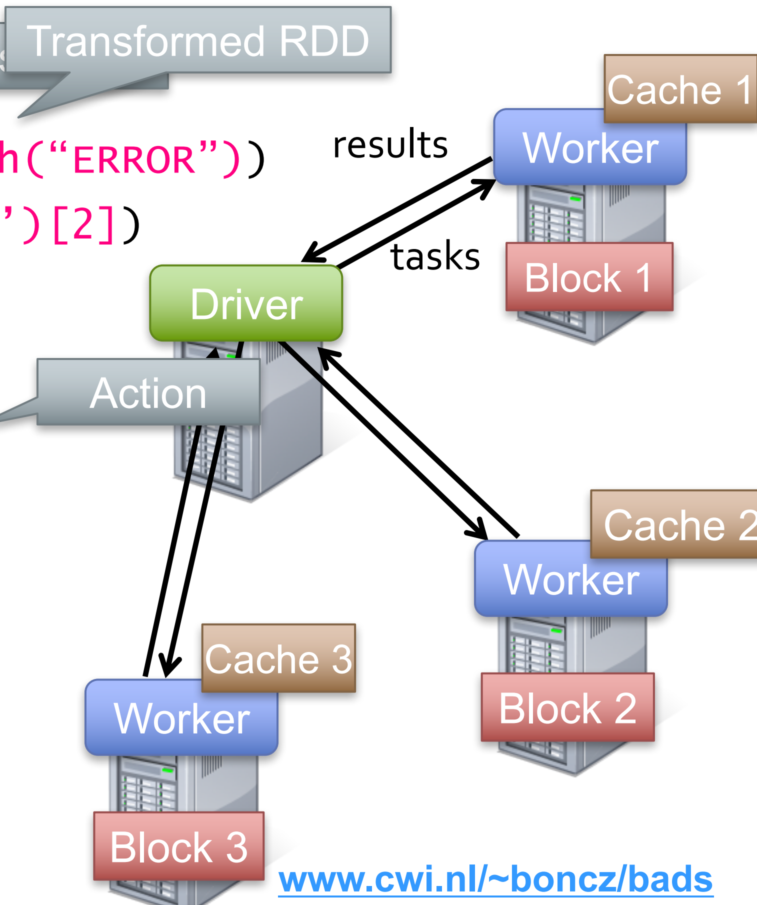
```
bool detect_error(string x) {
    return x.startswith("ERROR");
}
```

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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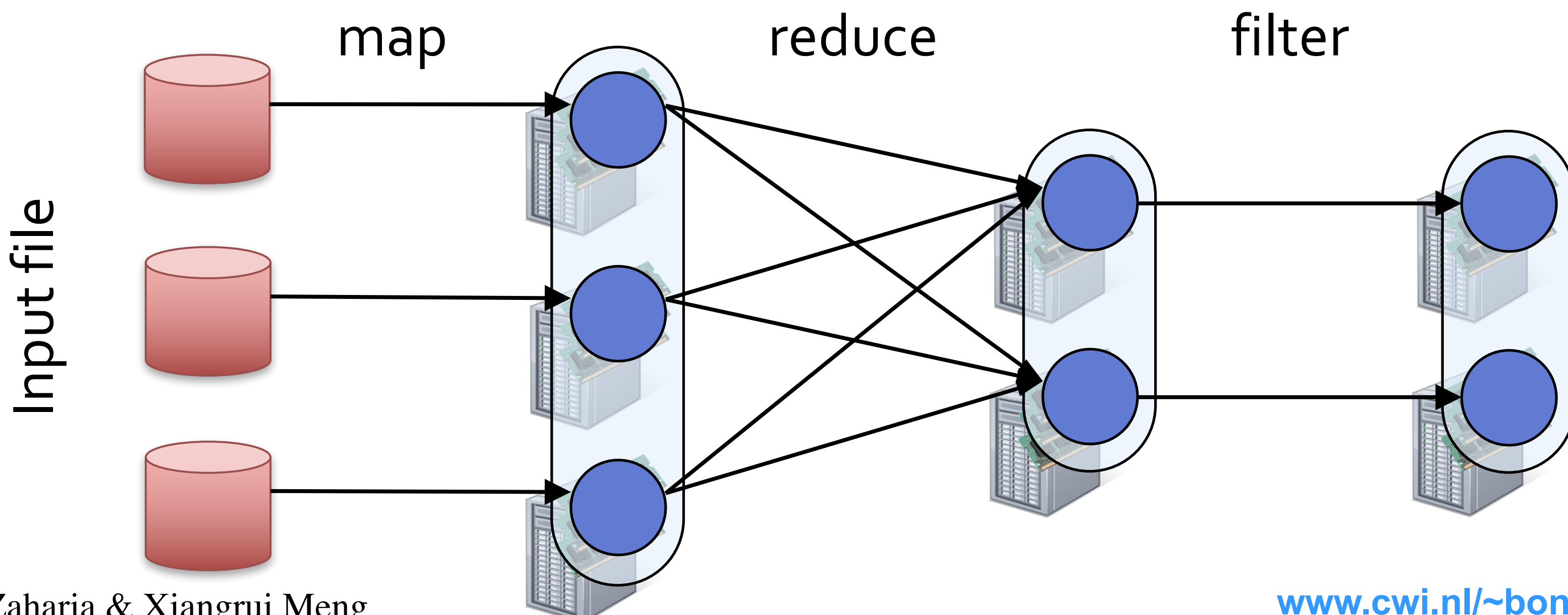
Fault Tolerance

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)
  ```



credits:
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  ```

Fault Tolerance

RDDs track *lineage* info to rebuild lost data

```
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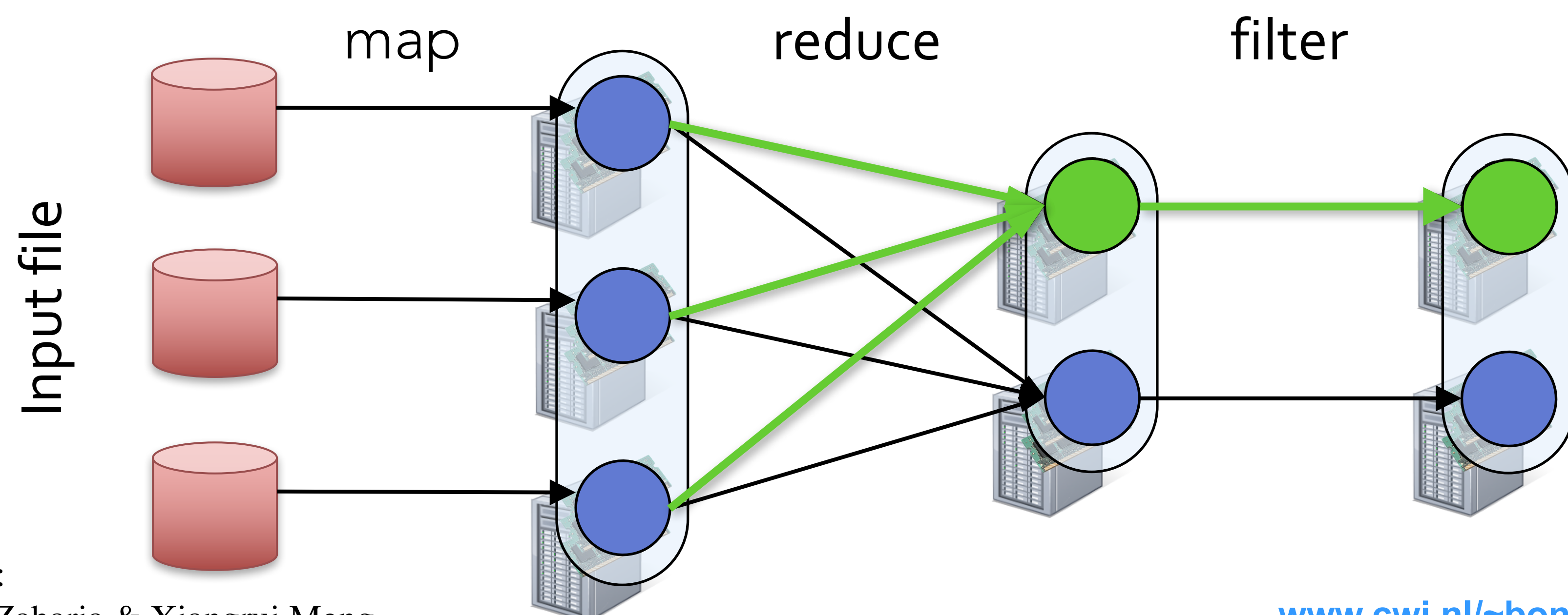

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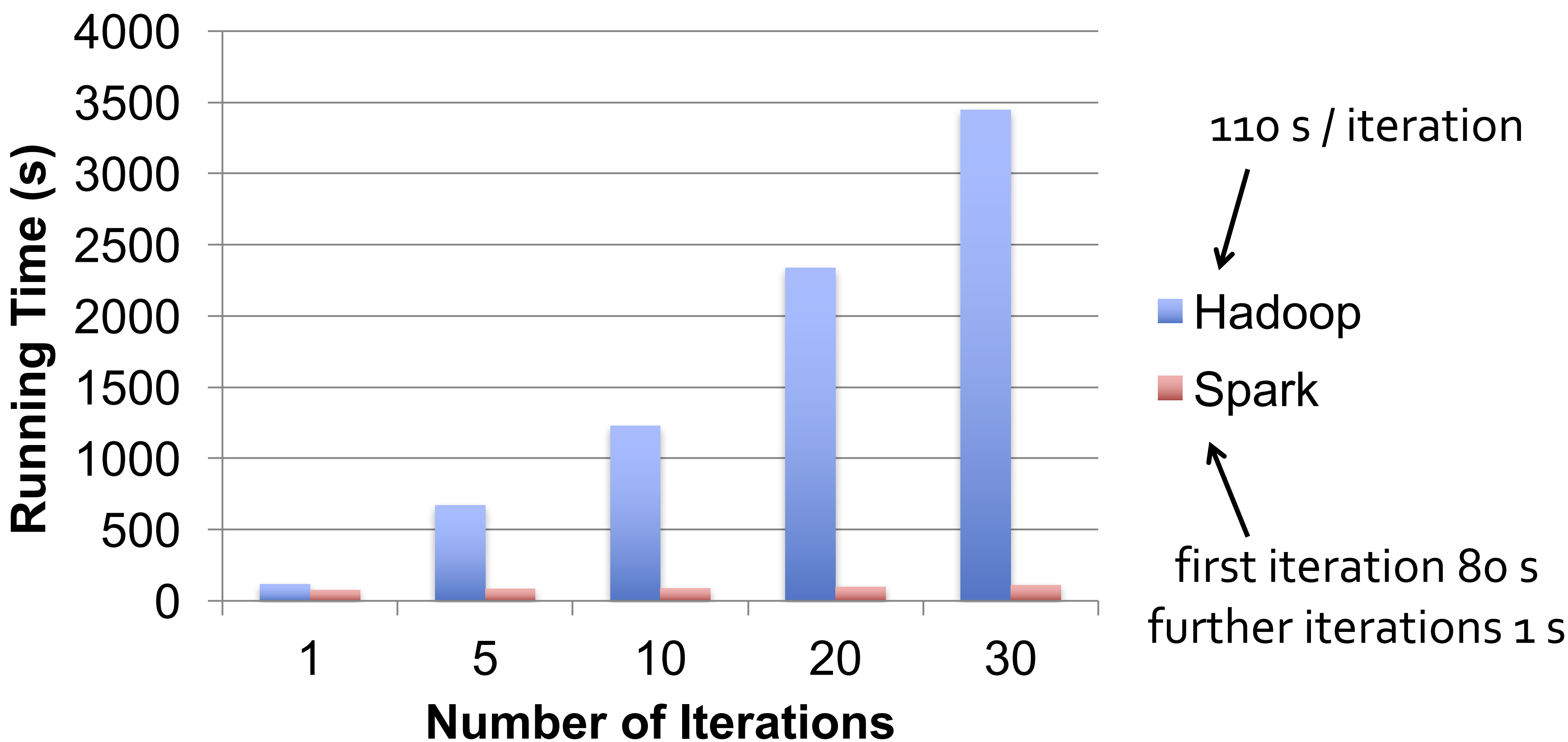
Example: Logistic Regression



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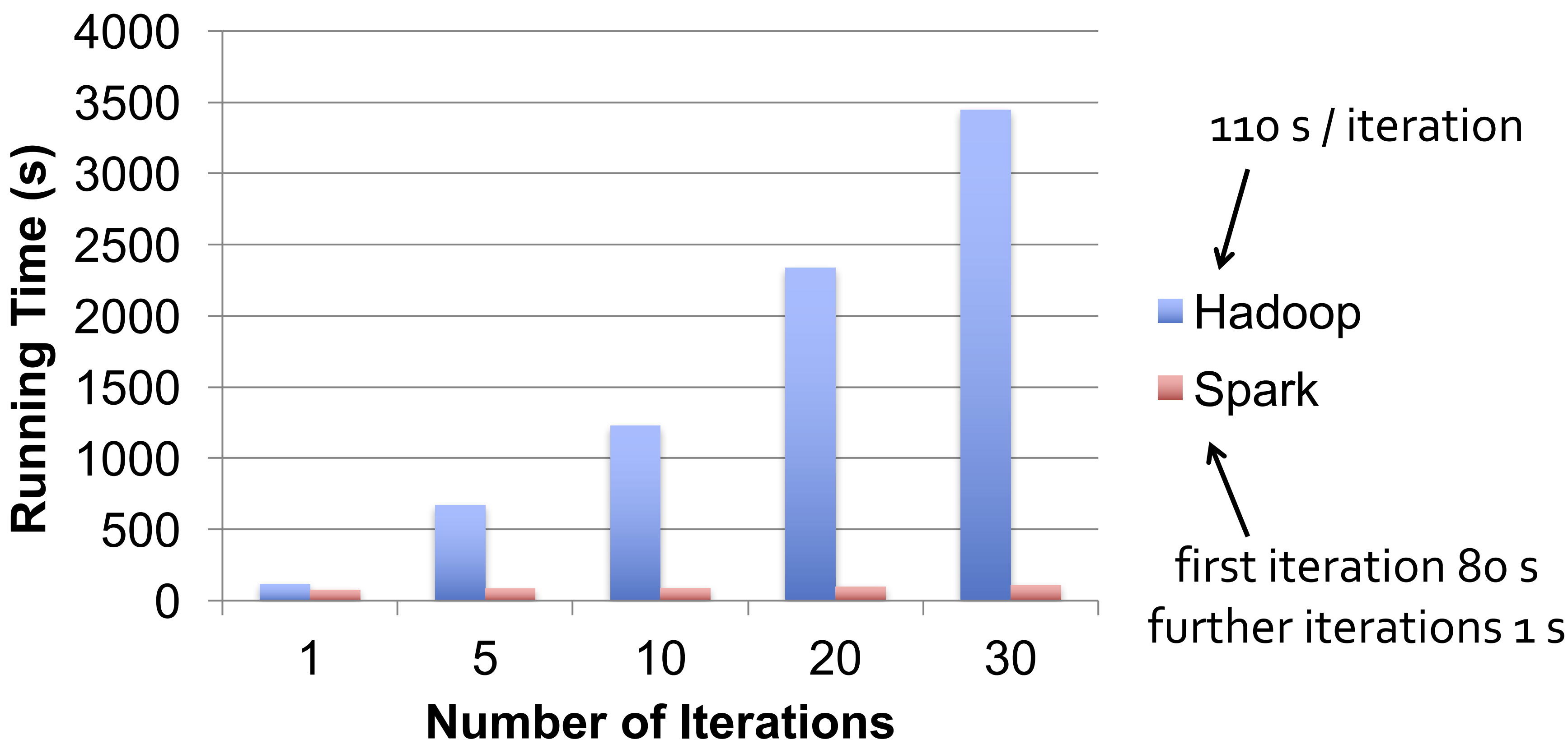
Example: Logistic Regression



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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();
```

credits:
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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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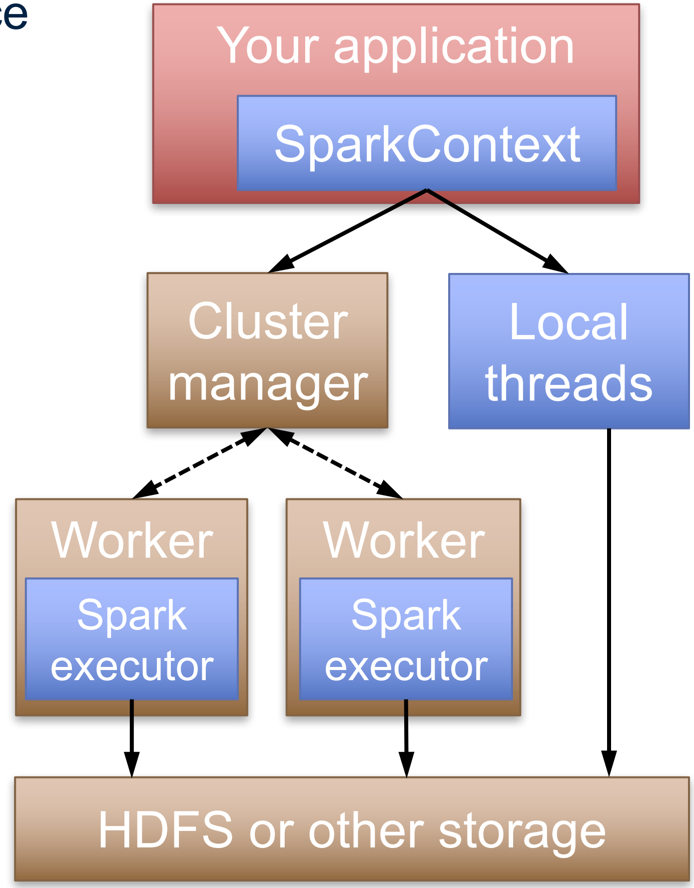
Software Components

- 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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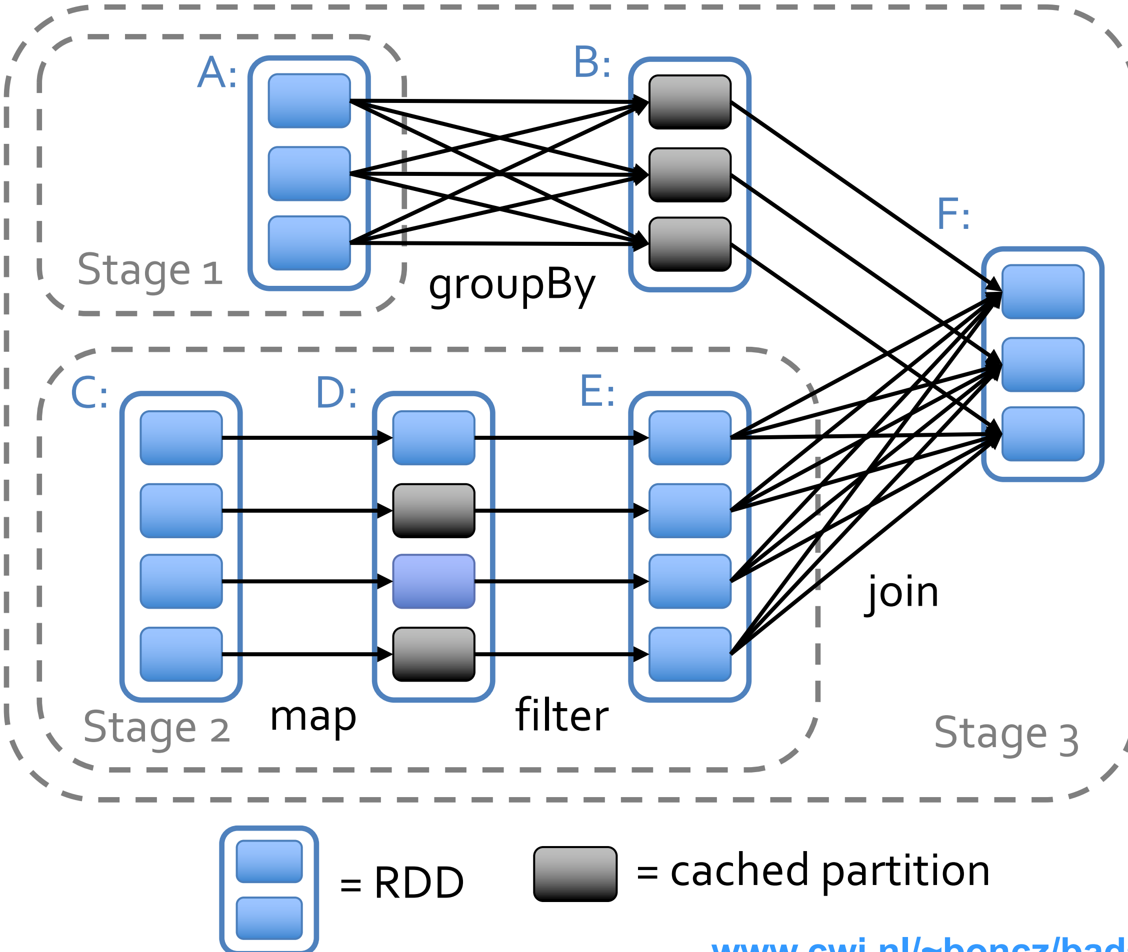
Task Scheduler

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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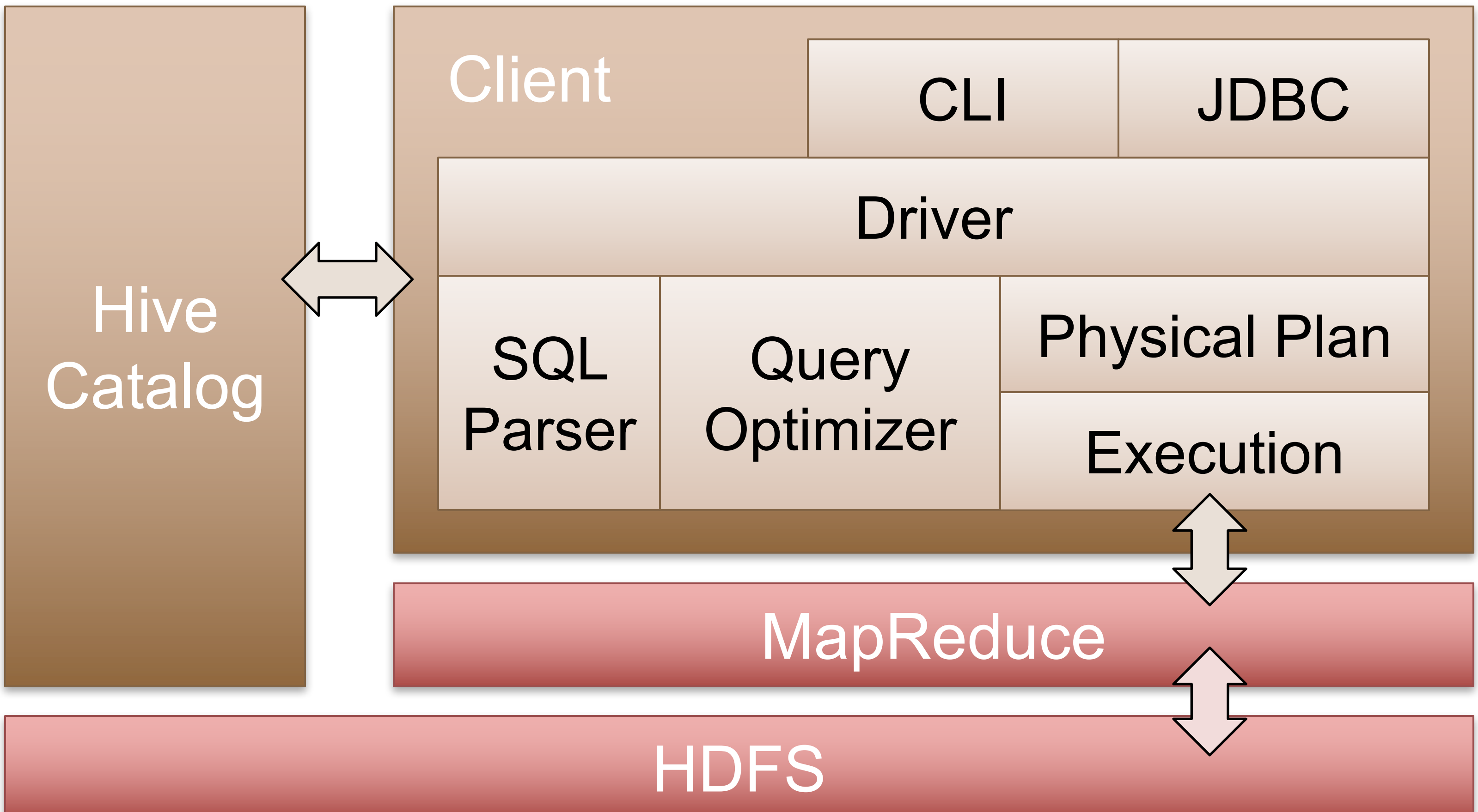
Hive Architecture



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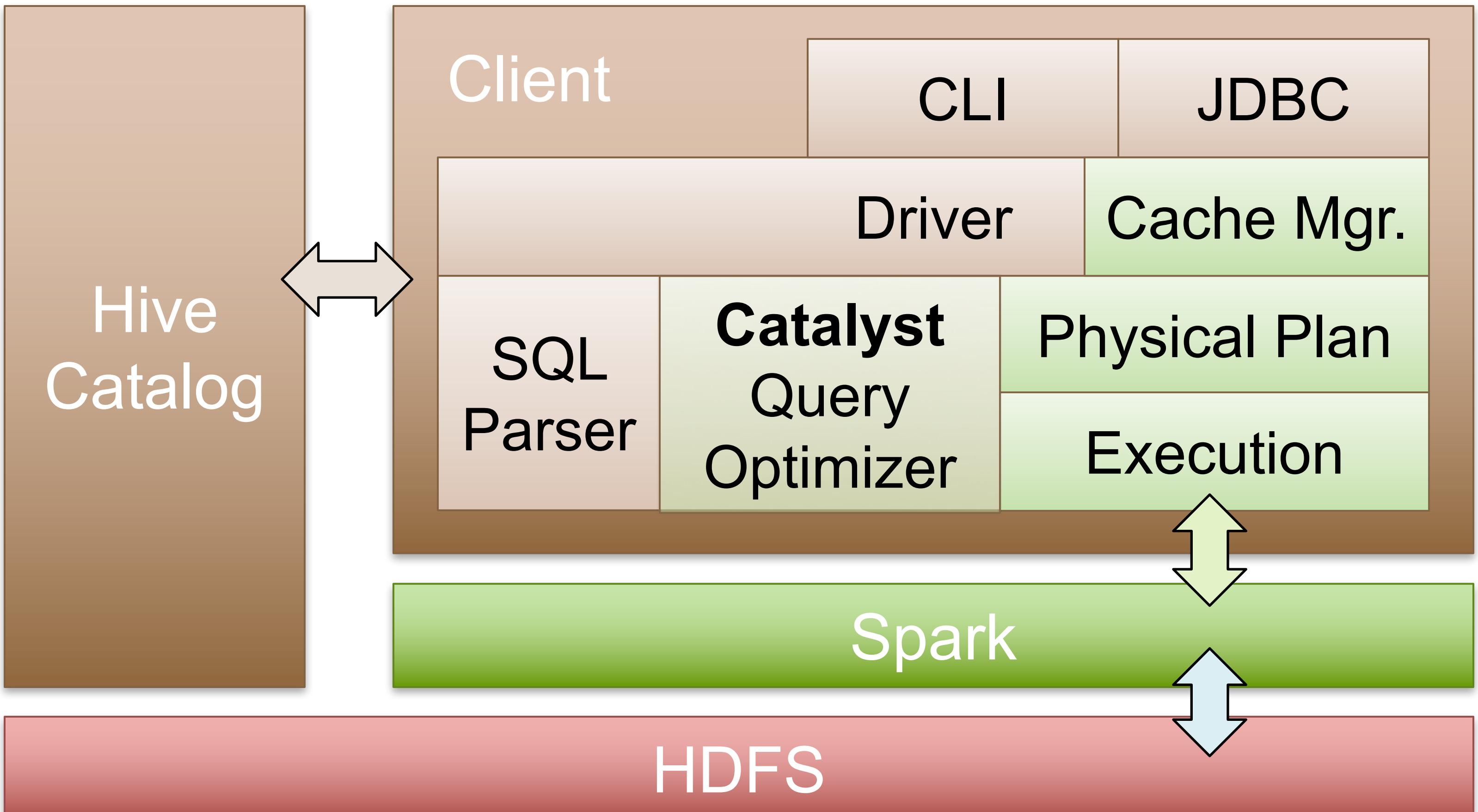
Spark SQL Architecture



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[Engle et al, SIGMOD 2012]

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From RDD to DataFrame

```
ctx = new HiveContext()
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

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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*.

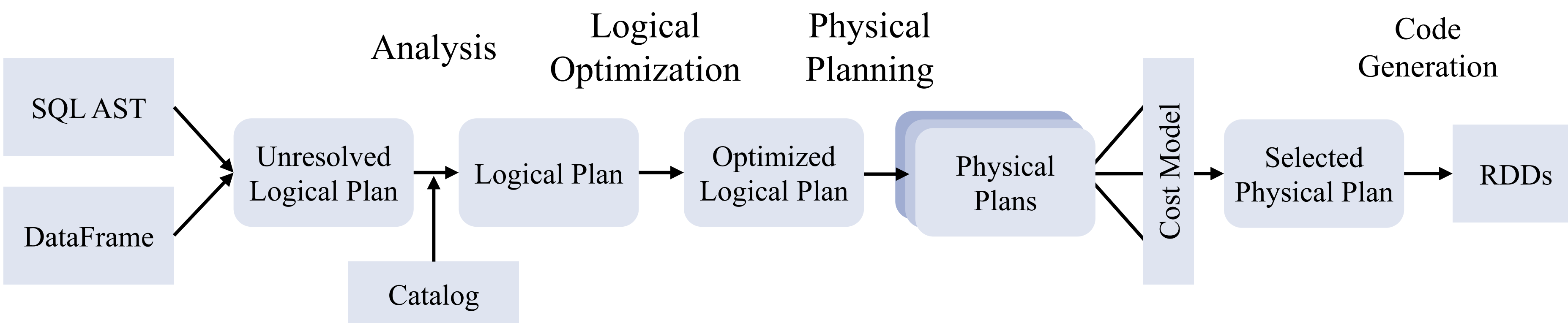
```
employees
  .join(dept, employees("deptId") === dept("id"))
  .where(employees("gender") === "female")
  .groupBy(dept("id"), dept("name"))
  .agg(count("name"))
```

- 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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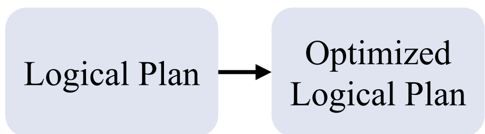
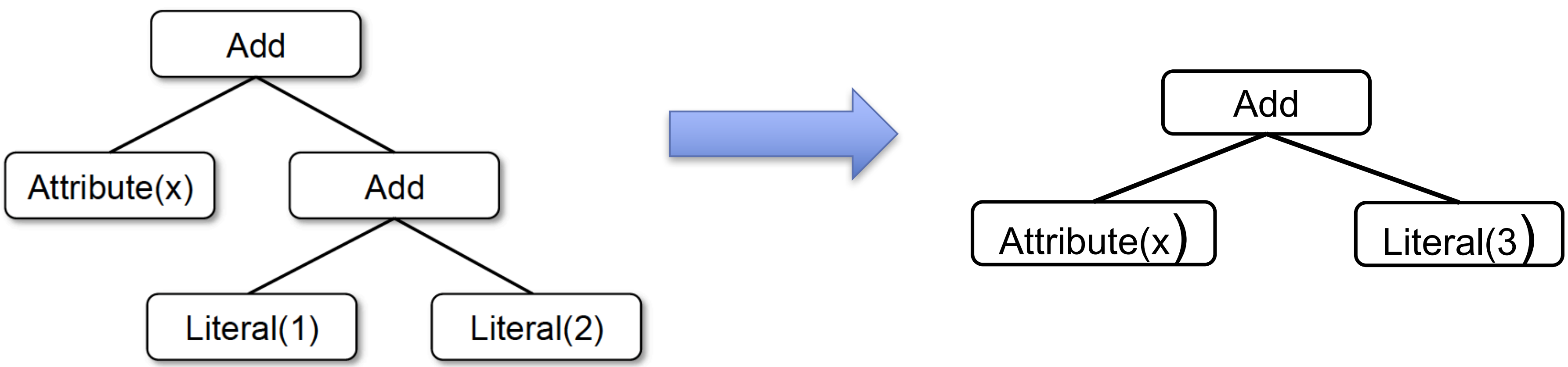
Catalyst Optimization Rules

Logical Optimization



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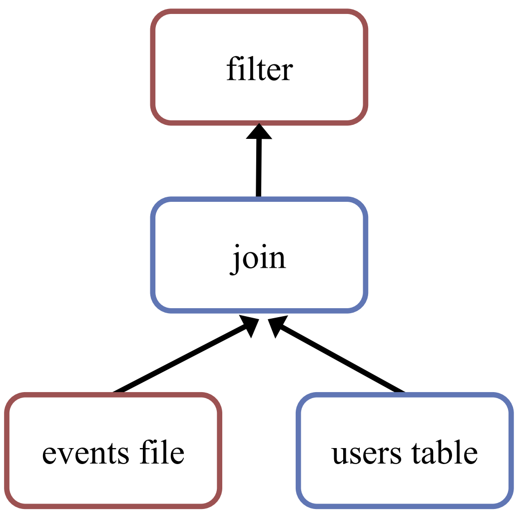
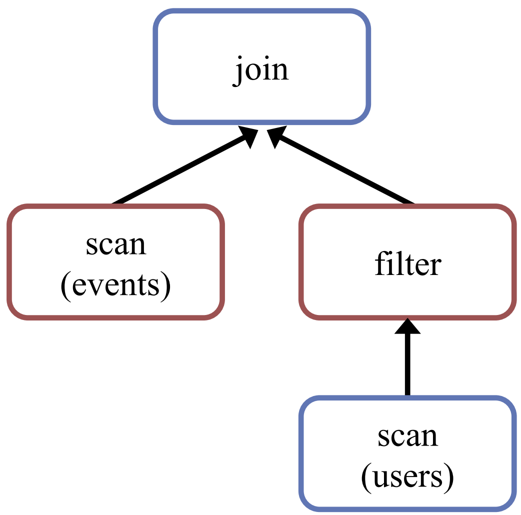
```python
def add_demographics(events):
   u = sqlCtx.table("users")                     # Load partitioned Hive table
   events \
     .join(u, events.user_id == u.user_id) \     # Join on user_id
     .withColumn("city", zipToCity(df.zip))      # Run udf to add city column
events = add_demographics(sqlCtx.load("/data/events",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

Logical Plan

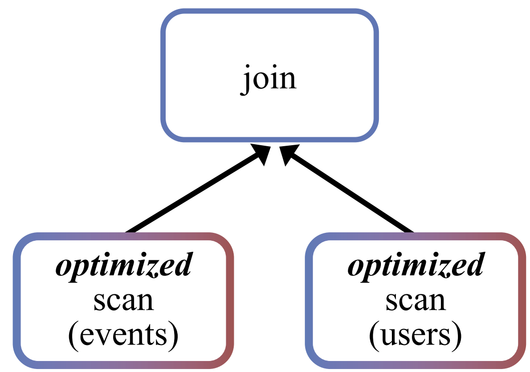


Physical Plan



Physical Plan

with Predicate Pushdown
and Column Pruning



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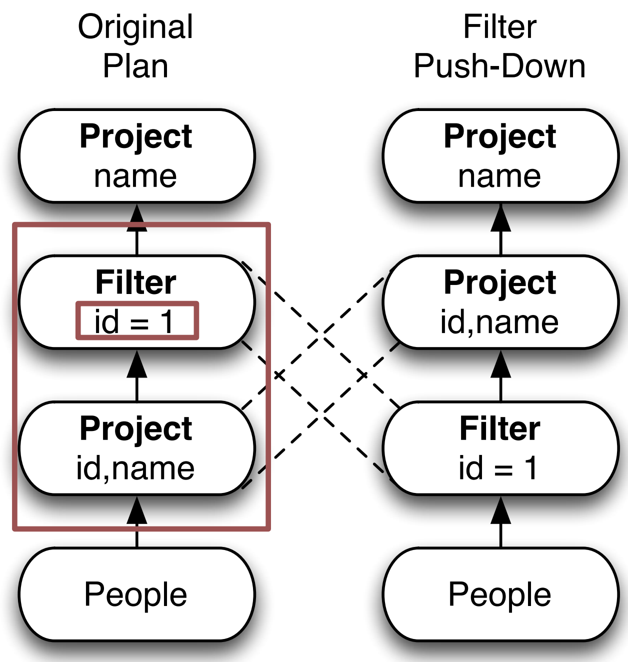
An Example Catalyst Transformation

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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    ```

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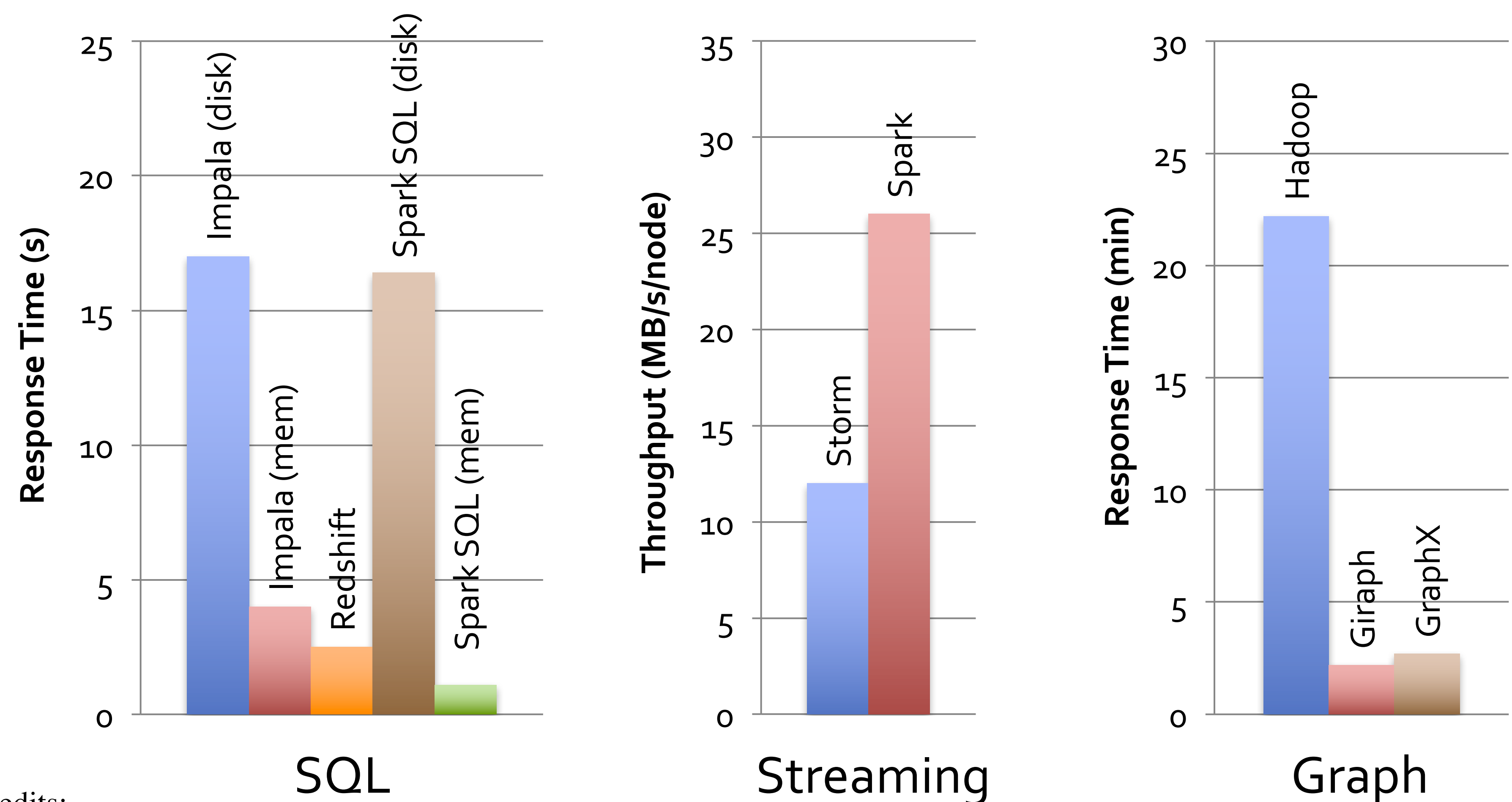
Performance



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THINK AS A VERTEX: GRAPH PROGRAMMING

PREGEL, GIRAPH, GRAPHX

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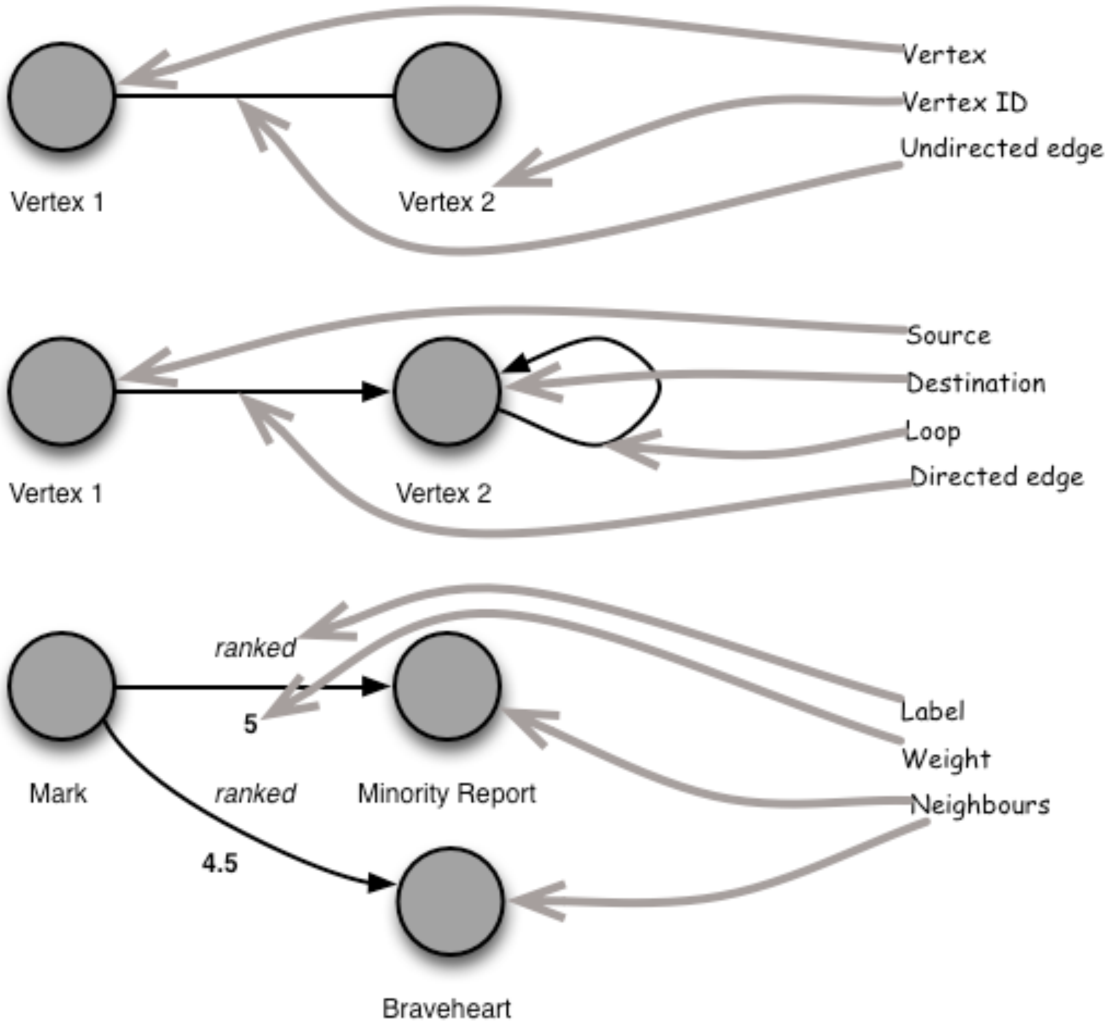
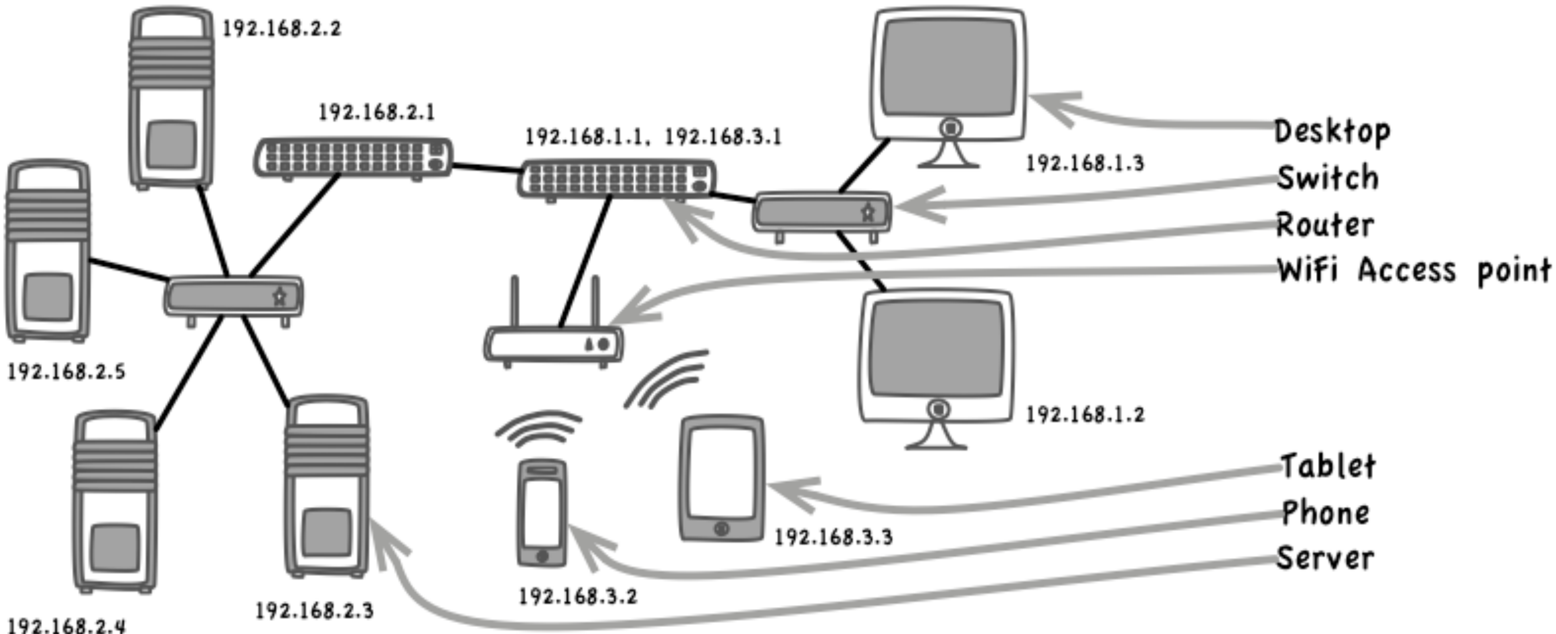
Graphs are Simple

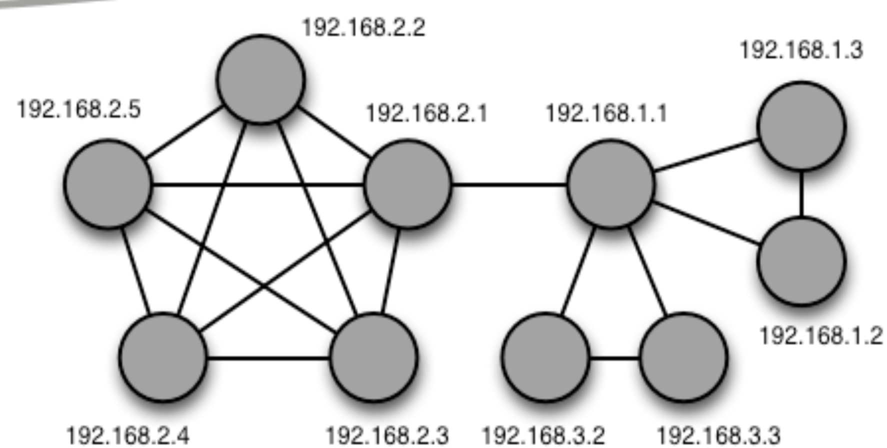


A Computer Network

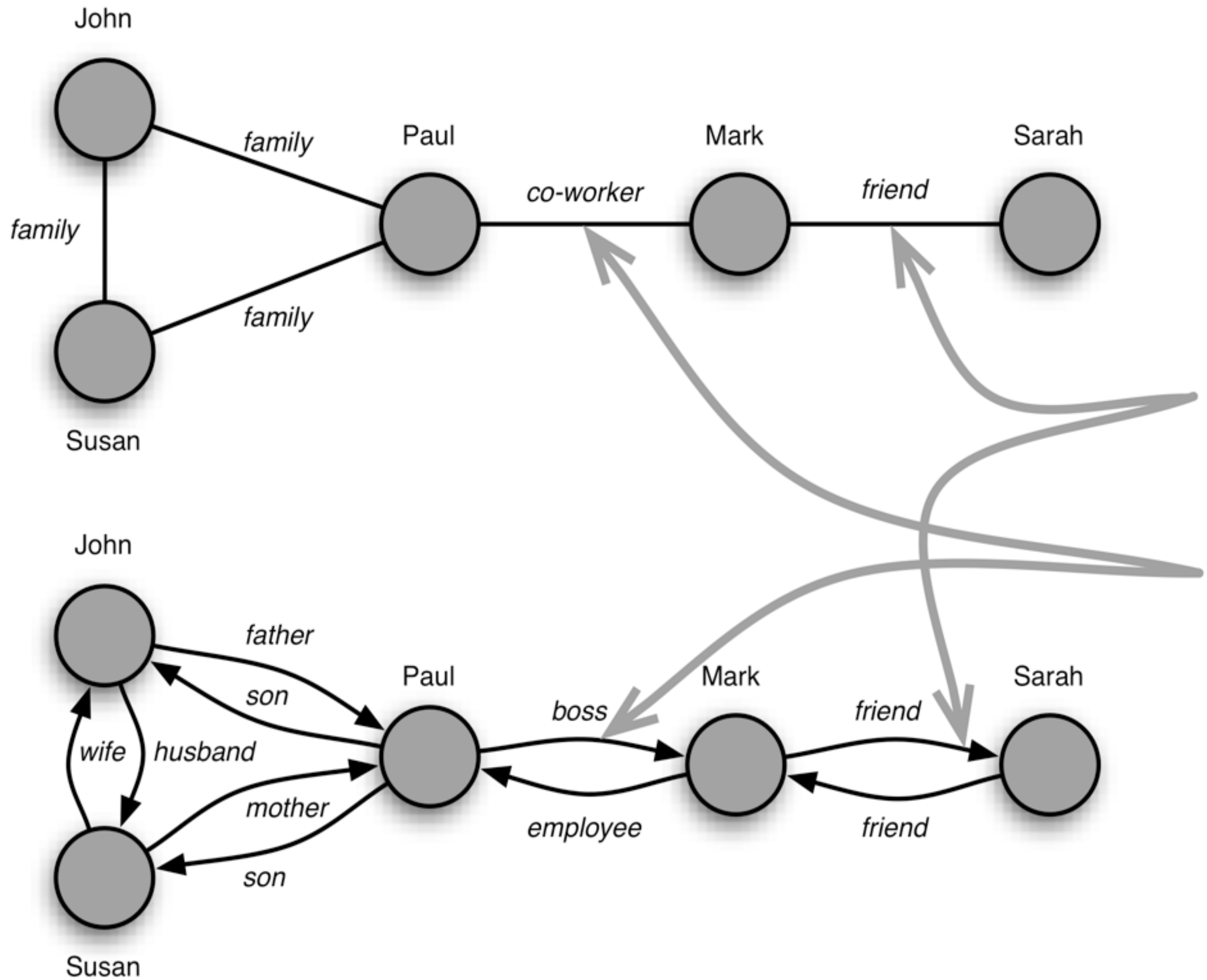


Note

1. There are three networks: servers, desktops and mobile.
2. They are connected through two routers/firewalls.
3. We ignored the switches and the access point in the graph.
4. Router 192.168.1.1 has two interfaces but we used one as vertex ID.



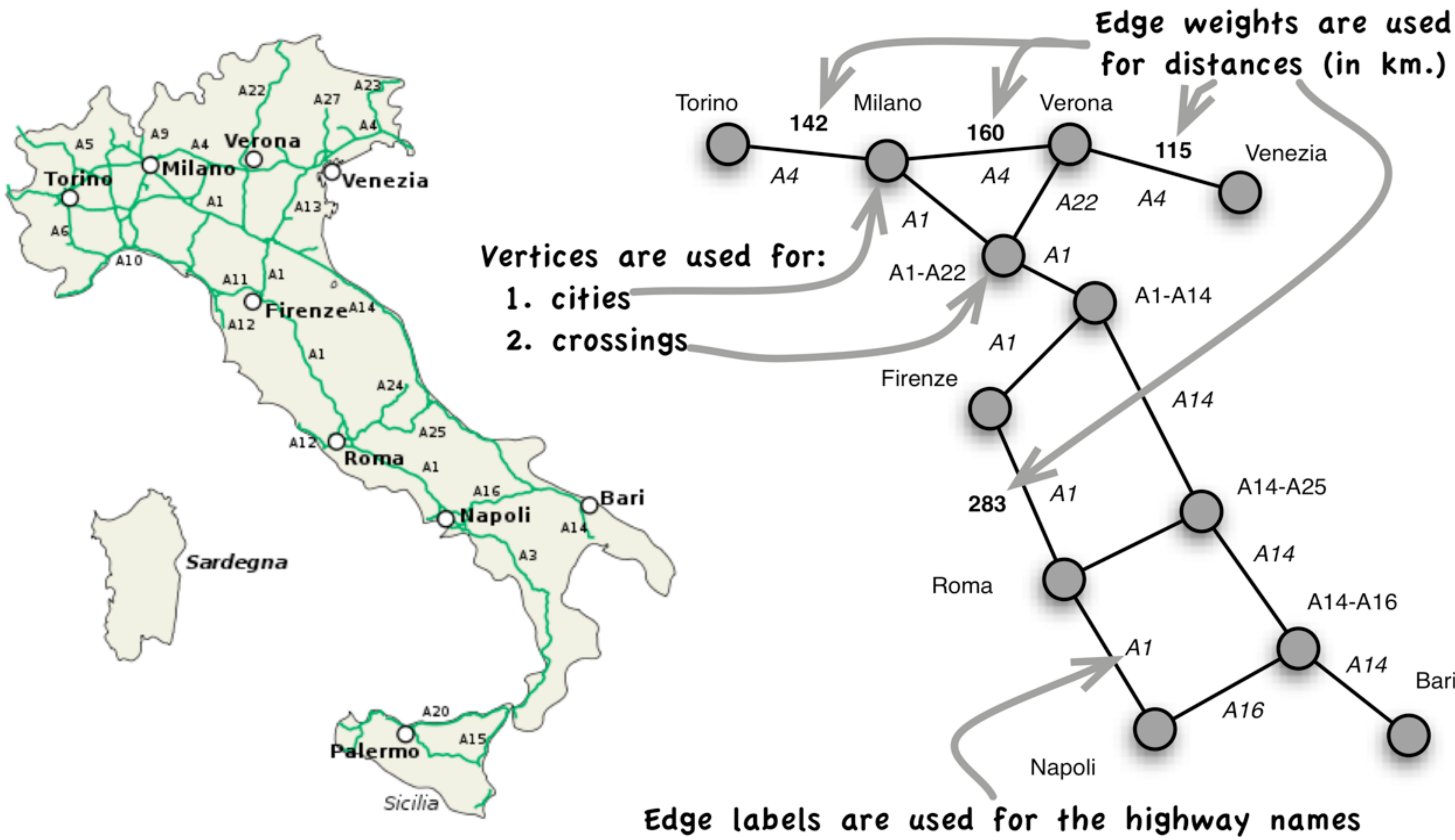
A Social Network



Note

1. A symmetric relationship is substituted by two directed edges.
2. A relationship does not have to be substituted by two edges, but e.g. by a more specific one.

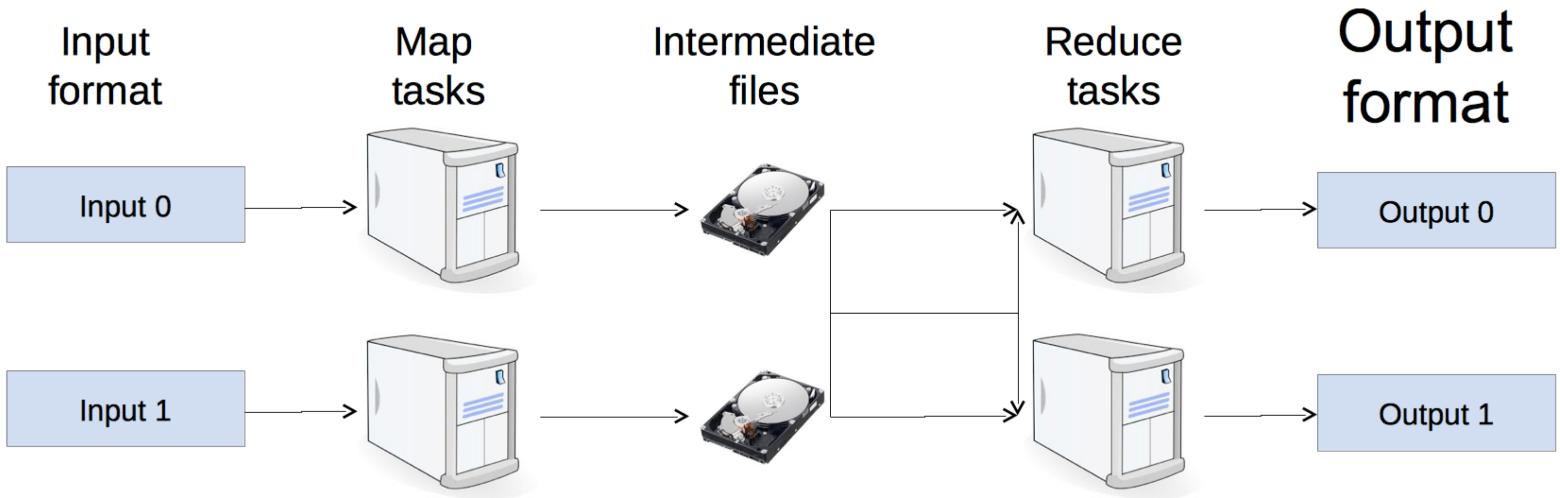
Maps are Graphs as well



PageRank in MapReduce

- Record: < v_i, pr, [v_j, ..., v_k] >
- Mapper: emits < v_j, pr / #neighbours >
- Reducer: sums the partial values

MapReduce DataFlow



- Each job is executed N times
- Job bootstrap
- Mappers send PR values and structure
- Extensive IO at input, shuffle & sort, output

Pregel: computational model

- Based on Bulk Synchronous Parallel (BSP)
  - Computational units encoded in a directed graph
  - Computation proceeds in a series of supersteps
  - Message passing architecture
- Each vertex, at each superstep:
  - Receives messages directed at it from previous superstep
  - Executes a user-defined function (modifying state)
  - Emits messages to other vertices (for the next superstep)
- Termination:
  - A vertex can choose to deactivate itself
  - Is “woken up” if new messages received
  - Computation halts when all vertices are inactive

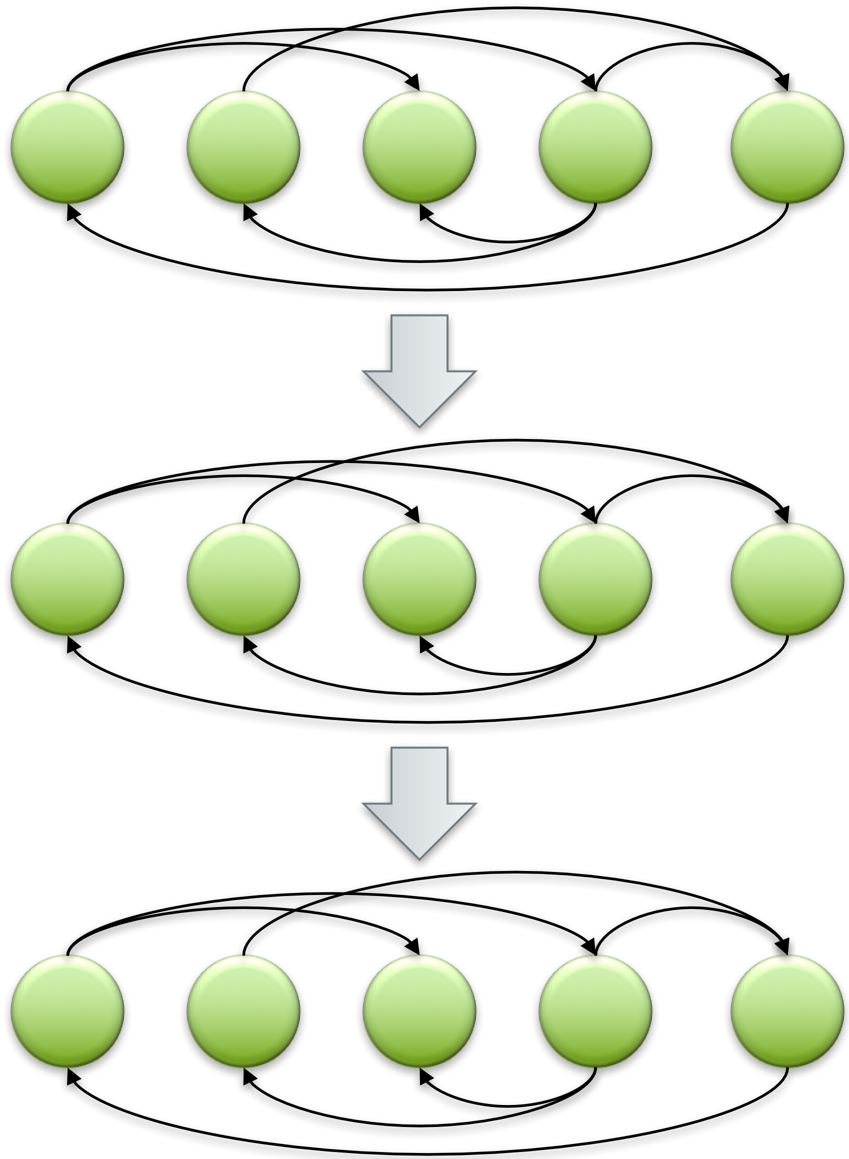
Source: Malewicz et al. (2010) Pregel: A System for Large-Scale Graph Processing. SIGMOD.

Pregel

superstep *t*

superstep *t+1*

superstep *t+2*



Source: Malewicz et al. (2010) Pregel: A System for Large-Scale Graph Processing. SIGMOD.

Pregel: implementation

- Master-Slave architecture
  - Vertices are hash partitioned (by default) and assigned to workers
  - Everything happens in memory
- Processing cycle
  - Master tells all workers to advance a single superstep
  - Worker delivers messages from previous superstep, executing vertex computation
  - Messages sent asynchronously (in batches)
  - Worker notifies master of number of active vertices
- Fault tolerance
  - Checkpointing
  - Heartbeat/revert

Source: Malewicz et al. (2010) Pregel: A System for Large-Scale Graph Processing. SIGMOD.

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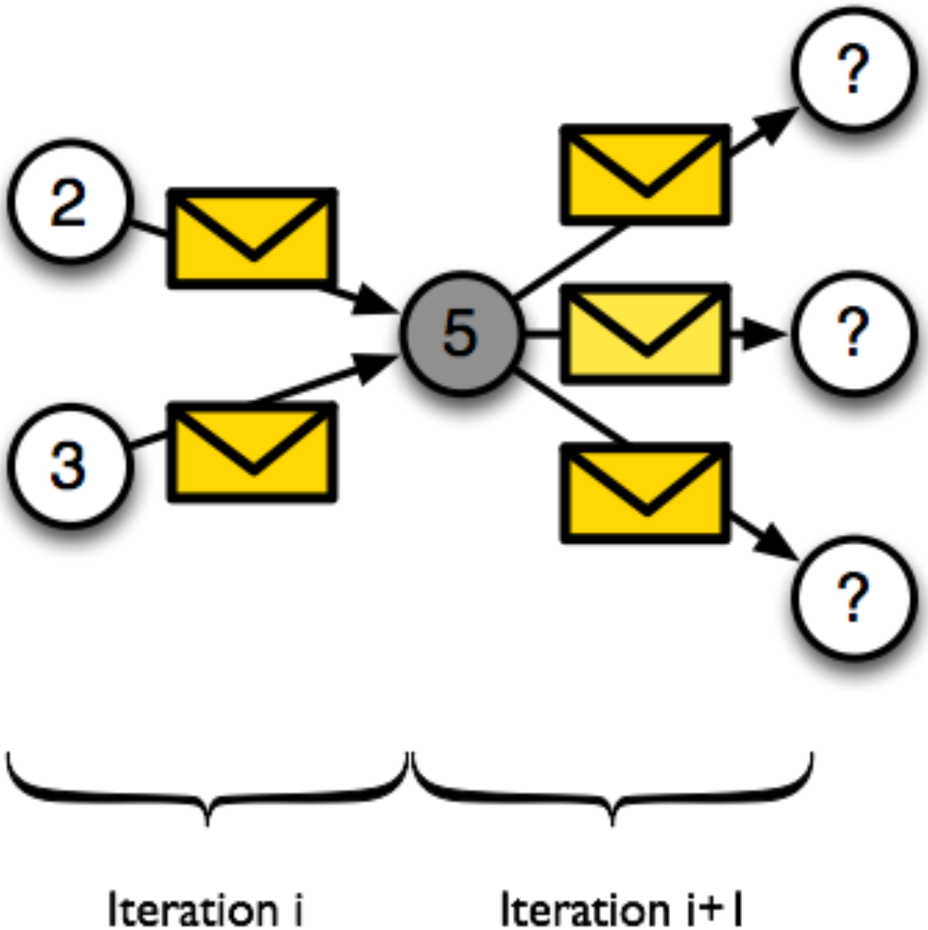
Vertex-centric API



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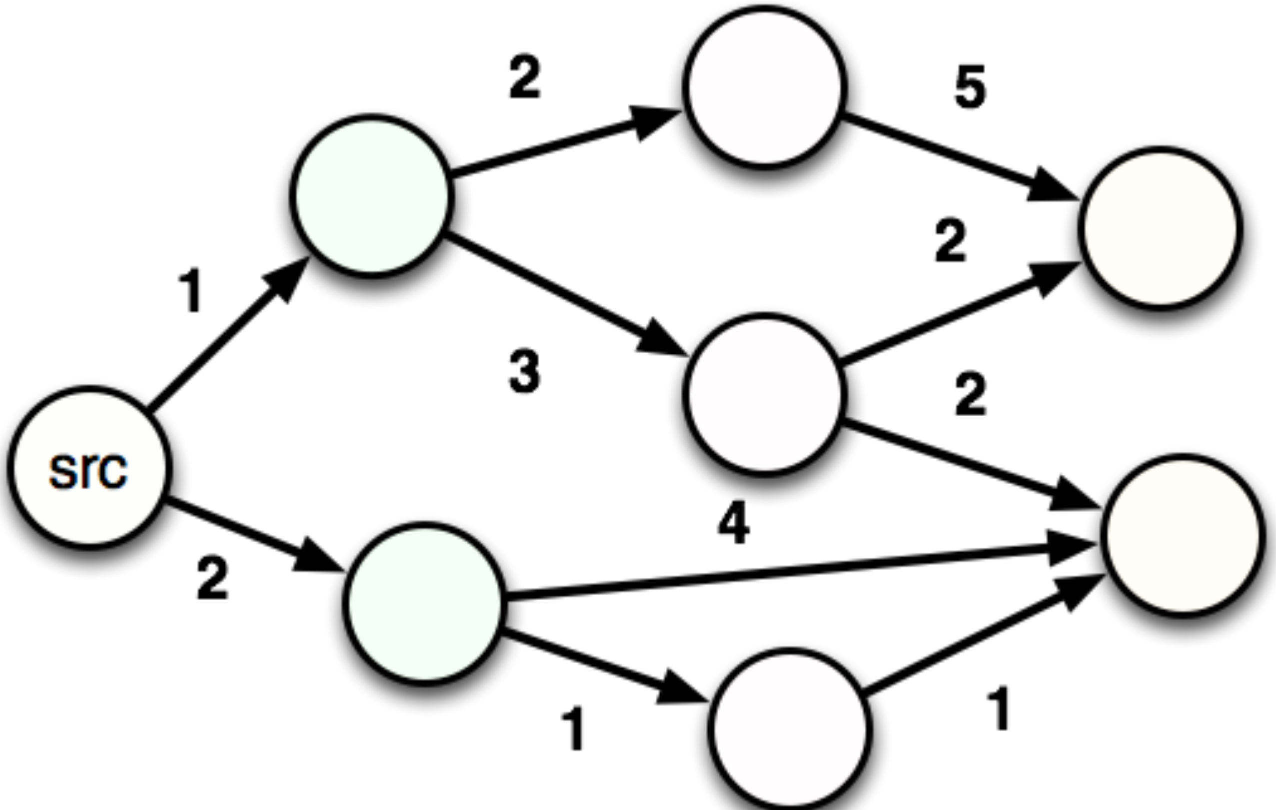
Shortest Paths



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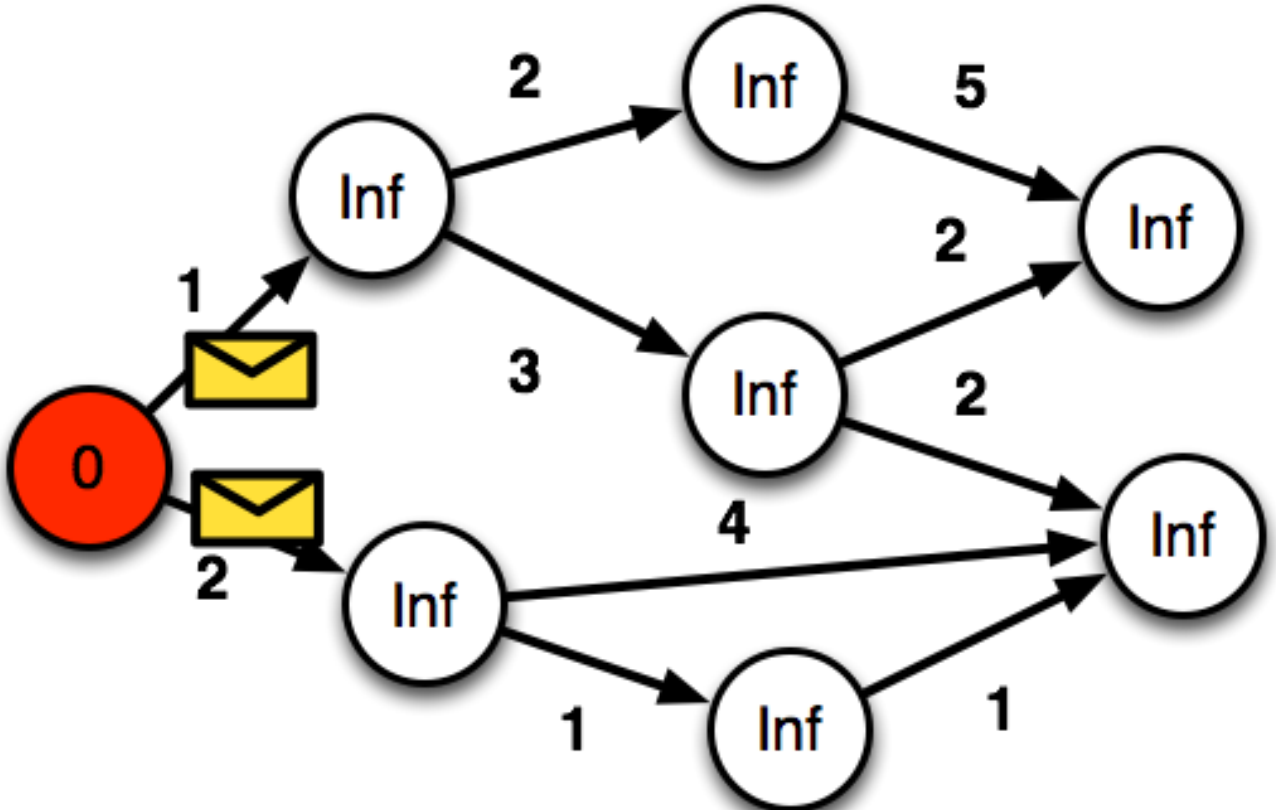
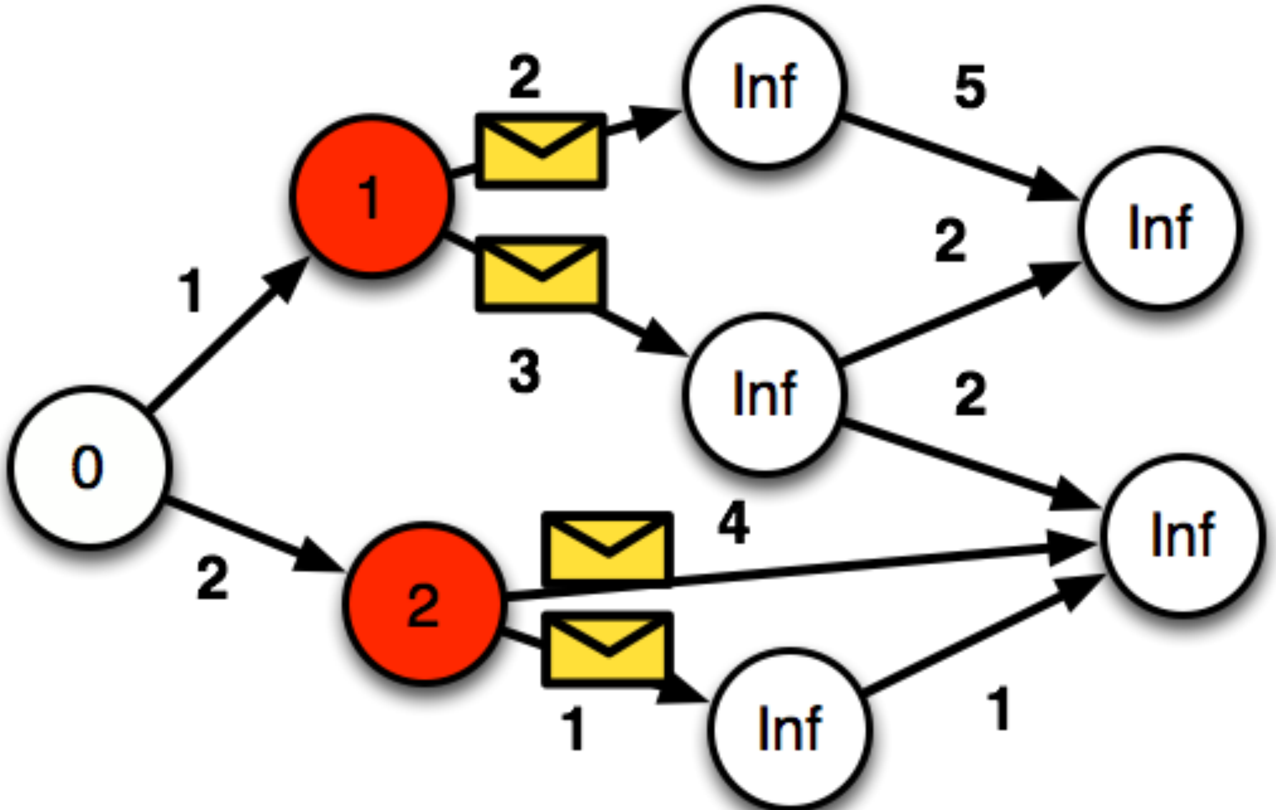
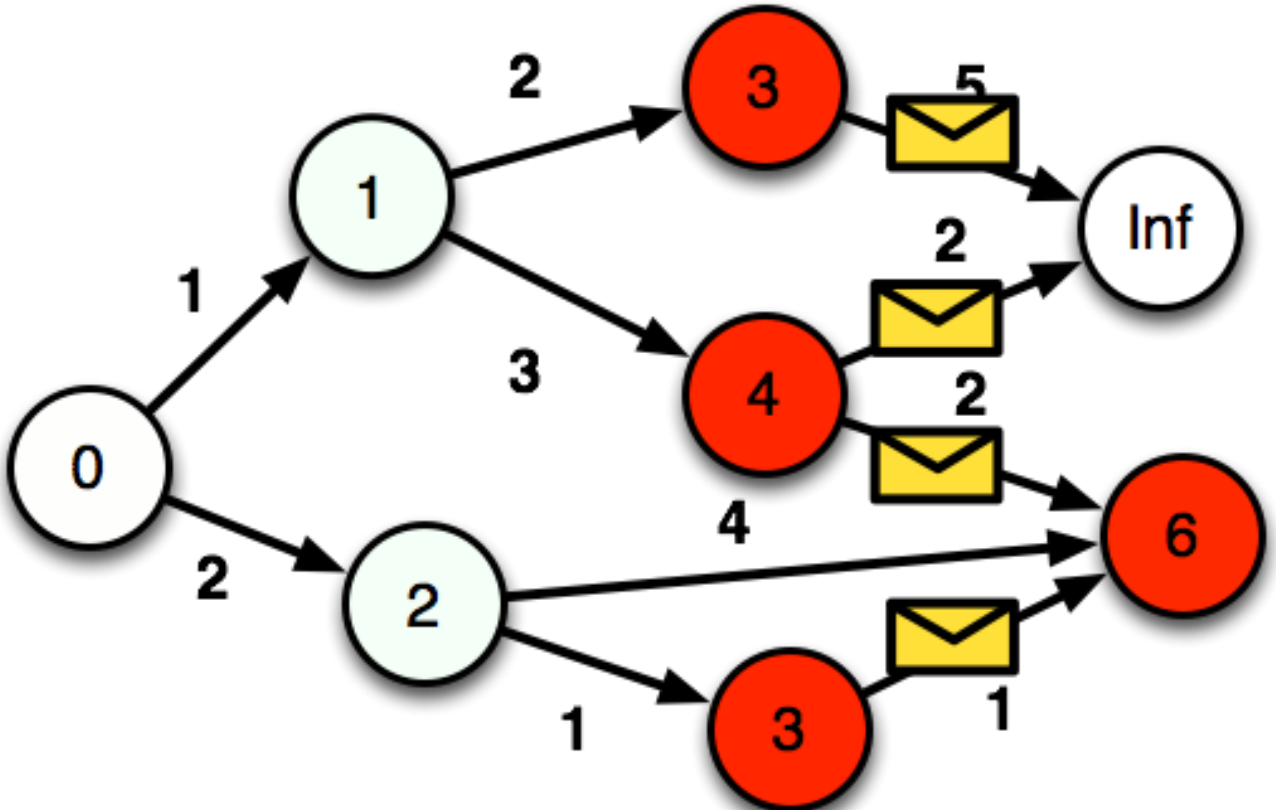
Shortest Paths



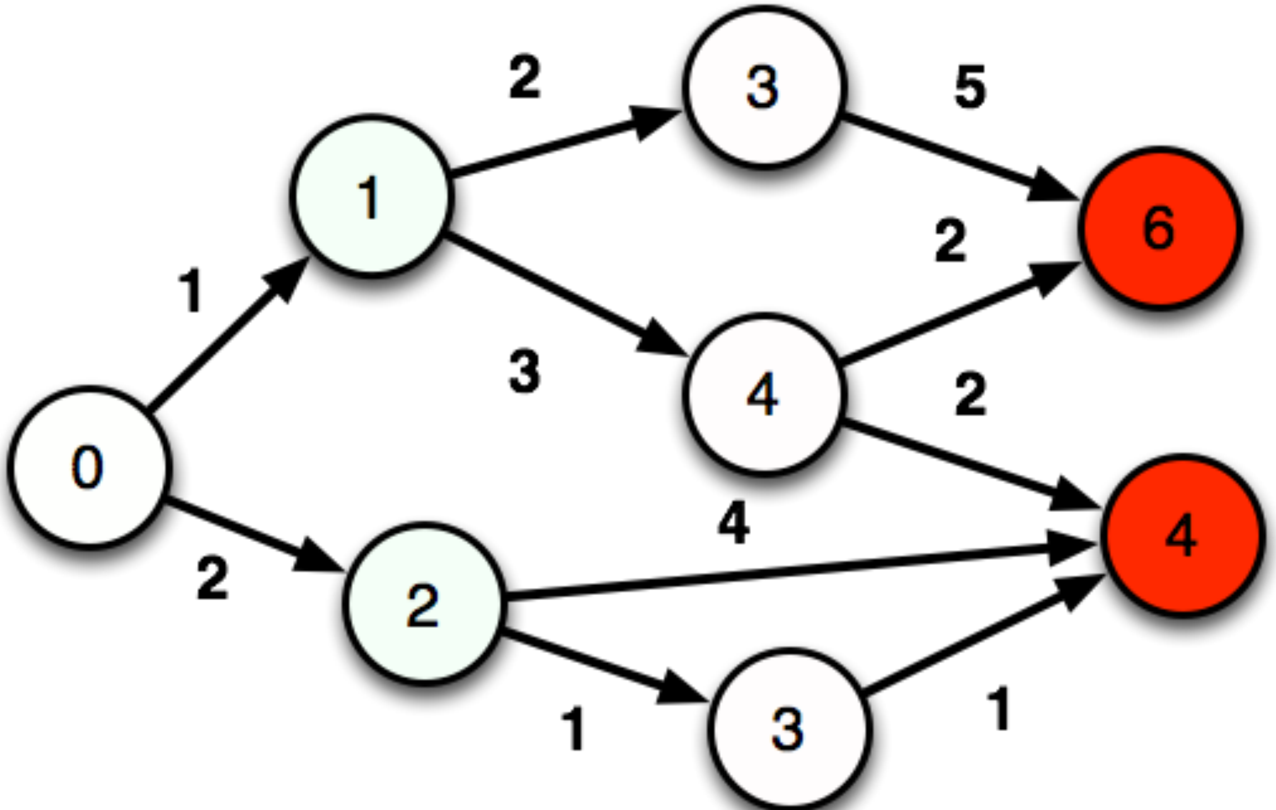
Shortest Paths



Shortest Paths



Shortest Paths



Shortest Paths

```
def compute(vertex, messages):
    minValue = Inf    # float('Inf')
    for m in messages:
        minValue = min(minValue, m)
    if minValue < vertex.getValue():
        vertex.setValue(minValue)
        for edge in vertex.getEdges():
            message = minValue + edge.getValue()
            sendMessage(edge.getTargetId(), message)
    vertex.voteToHalt()
```

Graph Programming Frameworks

- Google Pregel
  - Non open-source, probably not used much anymore
- Apache Giraph
  - Developed and used by Facebook
- Apache Flink
  - Gelly API
- Apache Spark
  - GraphX API

  +

  - DataFrames API

Source: Malewicz et al. (2010) Pregel: A System for Large-Scale Graph Processing. SIGMOD.

SPARK MLLIB

credits:
Matei Zaharia & Xiangrui Meng

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

credits:
Matei Zaharia & Xiangrui Meng

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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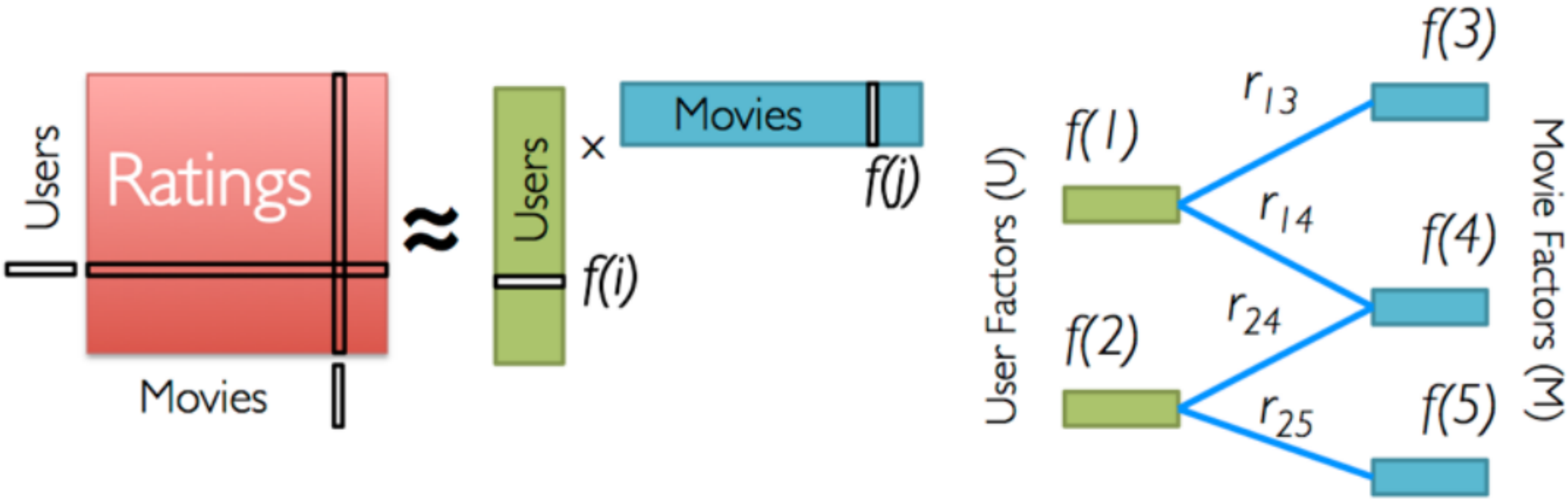
Alternating Least Squares (ALS)



Iterate:

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

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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]))
```

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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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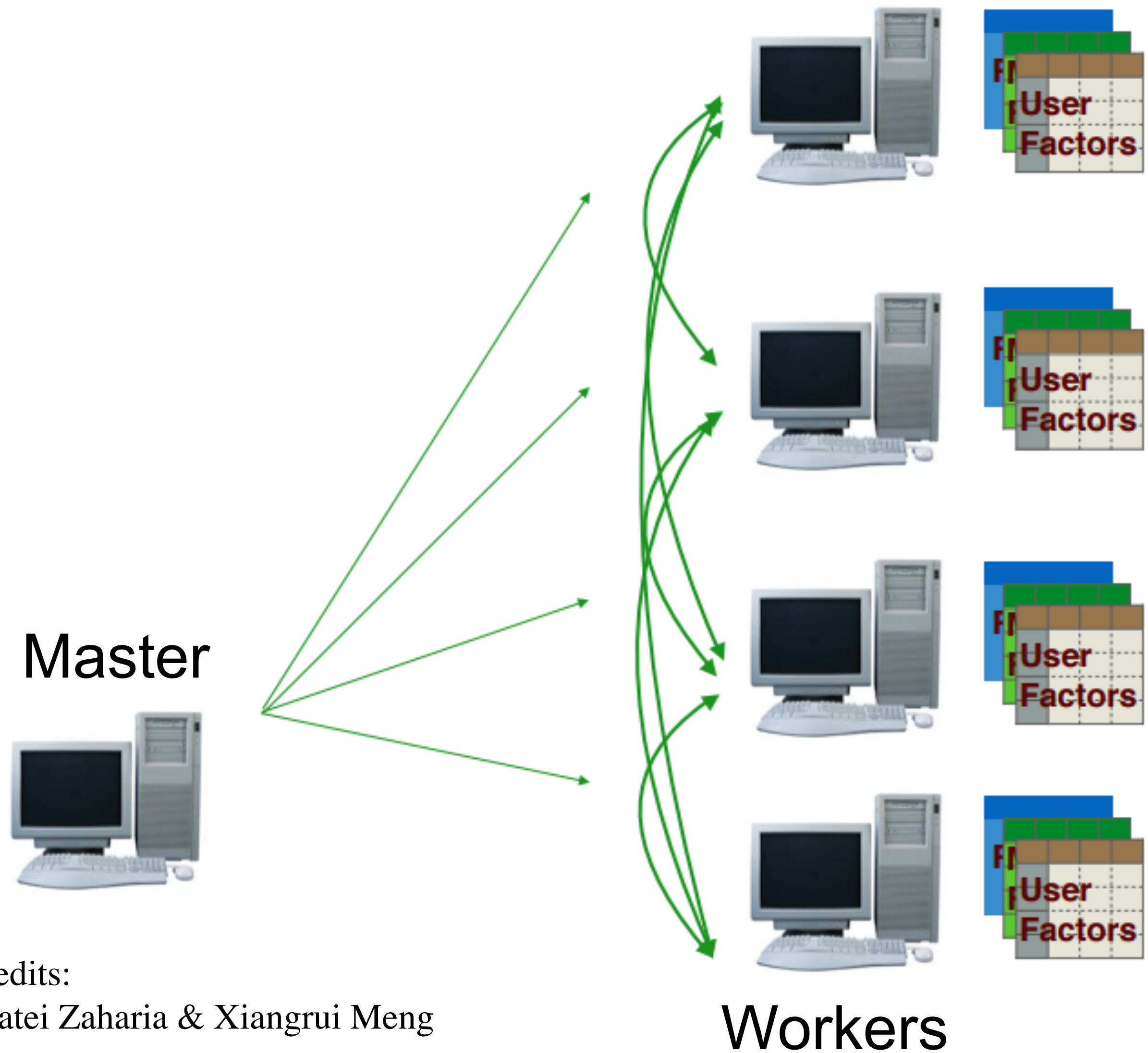
Spark Implementation of ALS



- 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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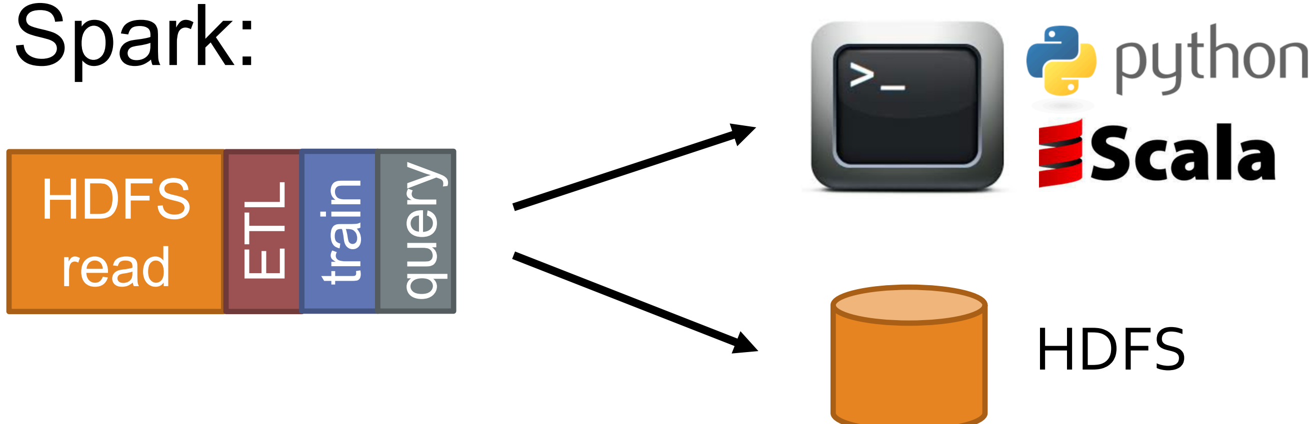
What it Means for Users

- 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, ..
    - RDDs ➔ DataFrames
- 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

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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

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