Tackling The Challenges of Big Data

Big Data Storage

Distributed Computing Platforms

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Introduction

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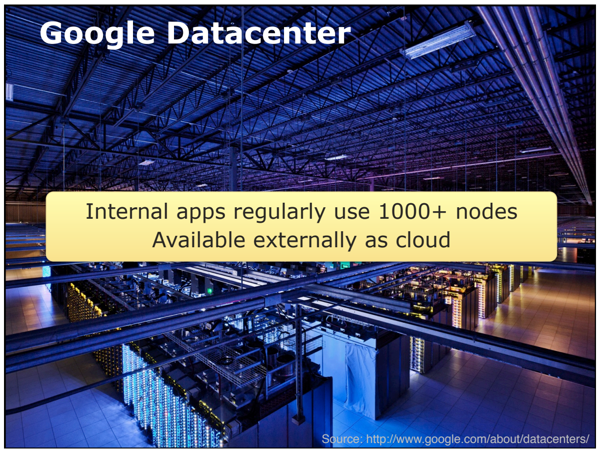
Motivation

- **Large datasets are inexpensive to collect, but require high parallelism to process**
  - 1 TB of disk space = $50
  - Reading 1 TB from disk = 6 hours
  - **Reading 1 TB from 1000 disks = 20 seconds**
- **Not only queries, but *all* computations will need to scale (data loading, complex analytics, etc)**
- **How do we program large clusters?**



Google Datacenter

Internal apps regularly use 1000+ nodes
Available externally as cloud

Source: http://www.google.com/about/datacenters/

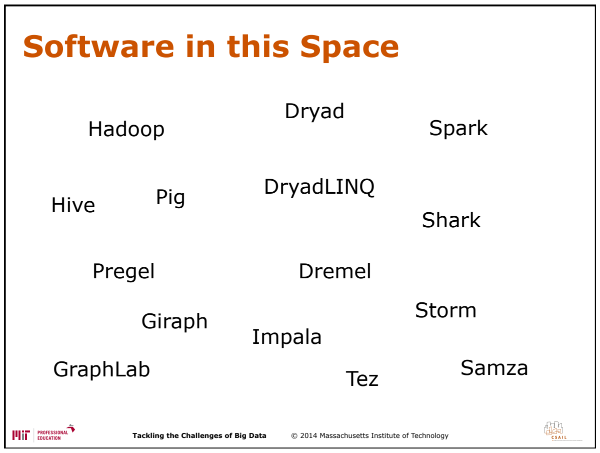
Traditional Network Programming

- **Message-passing between nodes**
- **Very difficult to use at scale:**
  - How to split problem across nodes?
    - ***Must consider network, data locality**
  - How to deal with failures?
    - ***1 server fails every 3 years => 10K nodes see 10 faults per day**
  - Even worse: stragglers (node is not failed, but slow)

Almost nobody directly uses this model!

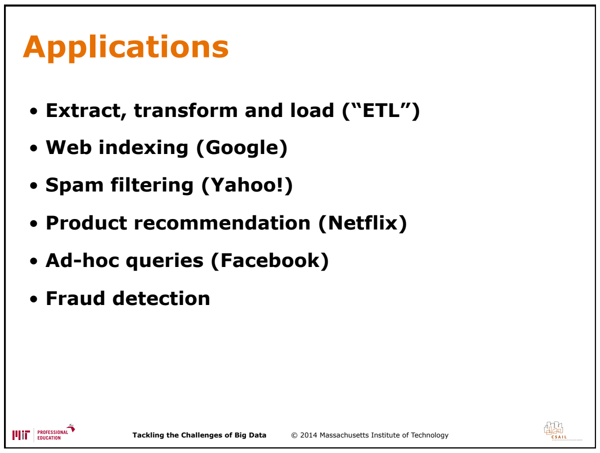
Data-Parallel Models

- **Restrict the programming interface so that the system can do more automatically**
- **"Here's an operation, run it on all of the data"**
  - I don't care *where* it runs (you schedule that)
  - In fact, feel free to run it *twice* on different nodes
- **Biggest example: MapReduce**



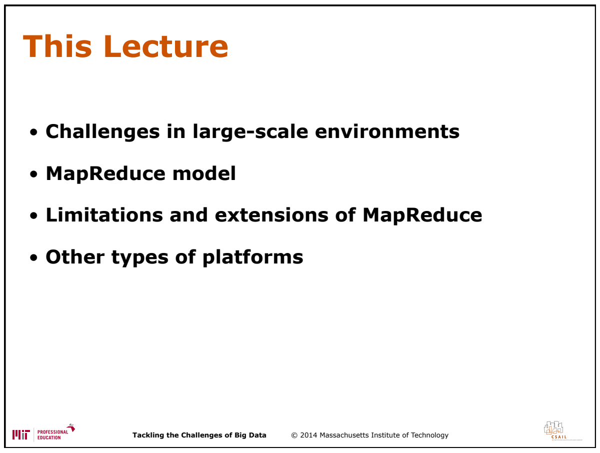
Software in this Space

Hadoop
Dryad
Spark
Hive
Pig
DryadLINQ
Shark
Pregel
Dremel
Giraph
Storm
Impala
GraphLab
Tez
Samza



Applications

- **Extract, transform and load ("ETL")**
- **Web indexing (Google)**
- **Spam filtering (Yahoo!)**
- **Product recommendation (Netflix)**
- **Ad-hoc queries (Facebook)**
- **Fraud detection**



This Lecture

- **Challenges in large-scale environments**
- **MapReduce model**
- **Limitations and extensions of MapReduce**
- **Other types of platforms**

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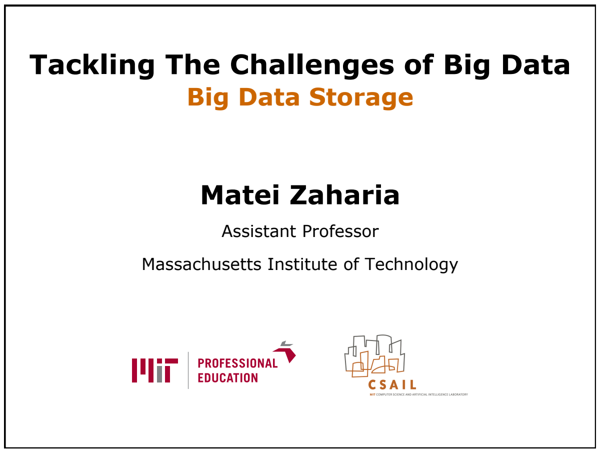

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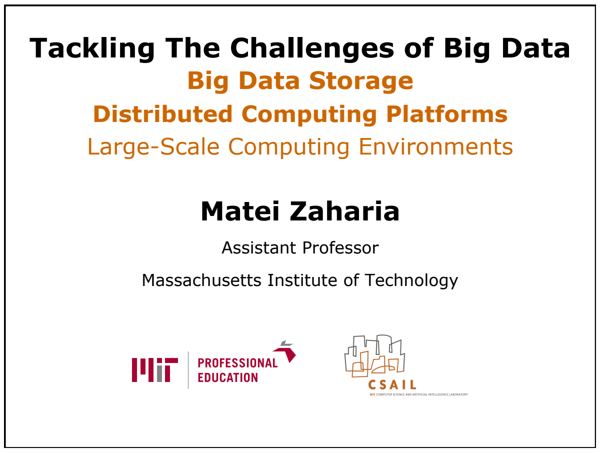

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Large-Scale Computing Environments

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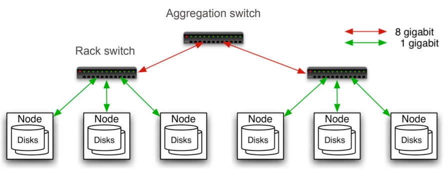
Goals of Large-Scale Data Platforms

- **Scalability in number of nodes:**
  - Parallelize I/O to quickly scan large datasets
- **Cost-efficiency:**
  - Commodity nodes (cheap, but unreliable)
  - Commodity network (low bandwidth)
  - Automatic fault-tolerance (fewer admins)
  - Easy to use (fewer programmers)

Typical Hadoop Cluster



- **40 nodes/rack, 1000-4000 nodes in cluster**
- **10 Gbps bandwidth in rack, 40 Gbps out of rack**
- **Node specs (Cloudera):**
  8-16 cores, 64-512 GB RAM, 12×2 TB disks

Typical Hadoop Cluster

Source: Yahoo!

Challenges of Cluster Environment

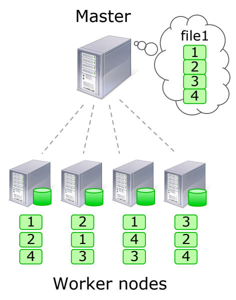
- **Cheap nodes fail, especially when you have many**
  - Mean time between failures for 1 node = 3 years
  - MTBF for 1000 nodes = 1 day
  - **Solution:** Build fault tolerance into system
- **Commodity network = low bandwidth**
  - **Solution:** Push computation to the data
- **Programming distributed systems is hard**
  - **Solution:** Data-parallel model: users write map/reduce functions, system handles work distribution and faults

Typical Software Components

- **Distributed file system (e.g. Hadoop's HDFS)**
  - Single namespace for entire cluster
  - Replicates data 3x for fault-tolerance
- **MapReduce system (e.g. Hadoop MapReduce)**
  - Runs jobs submitted by users
  - Manages work distribution & fault-tolerance
  - Colocated with file system

Hadoop Distributed File System

- **Files split into blocks**
- **Blocks replicated across several nodes (often 3)**
- **Master stores metadata (file names, locations, …)**
- **Optimized for large files, sequential reads**



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Large-Scale Computing Environments

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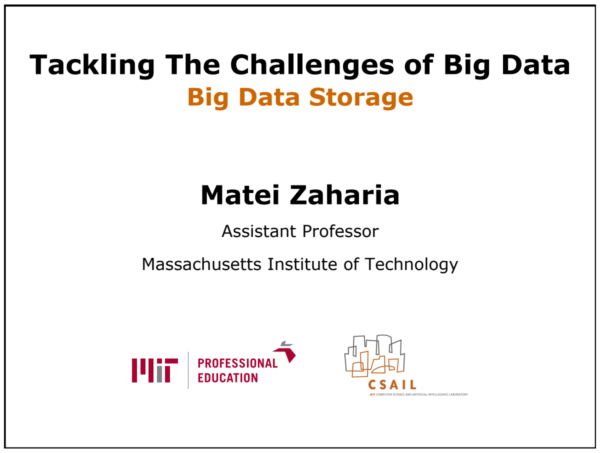

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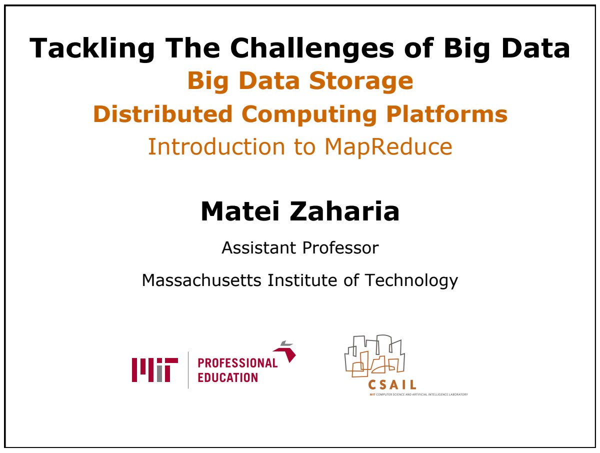

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Introduction to MapReduce

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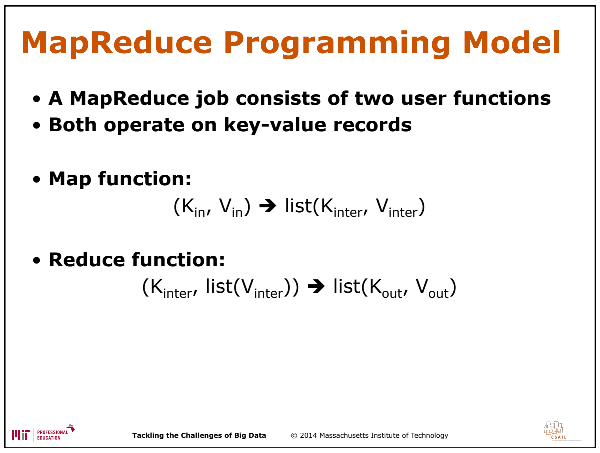


MapReduce Programming Model

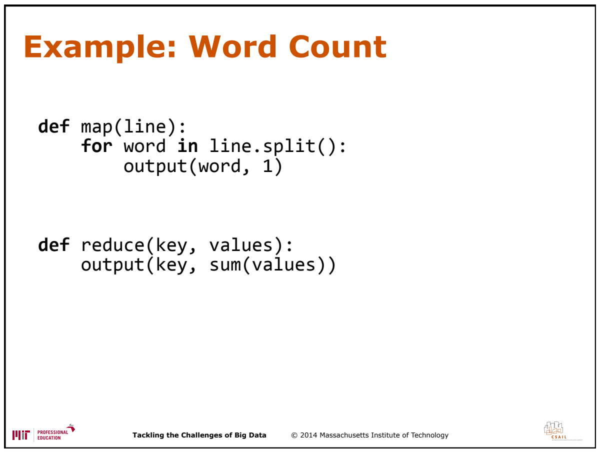
- A MapReduce job consists of two user functions
- Both operate on key-value records

- Map function:

$$(K_{in}, V_{in}) \rightarrow \text{list}(K_{inter}, V_{inter})$$

- Reduce function:

$$(K_{inter}, \text{list}(V_{inter})) \rightarrow \text{list}(K_{out}, V_{out})$$

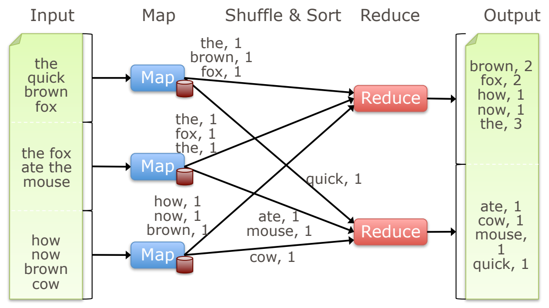


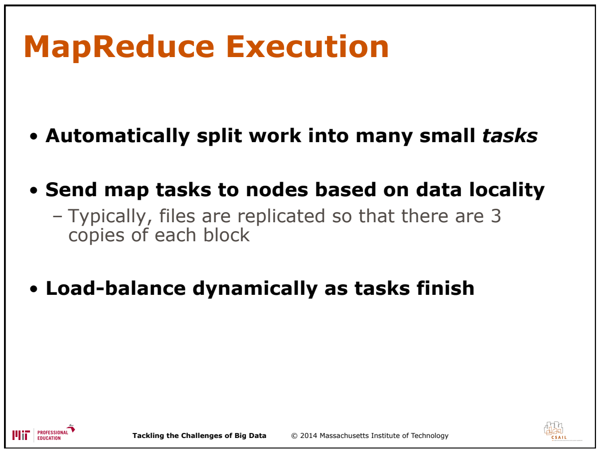
Example: Word Count

```
def map(line):
    for word in line.split():
        output(word, 1)


def reduce(key, values):
    output(key, sum(values))
```

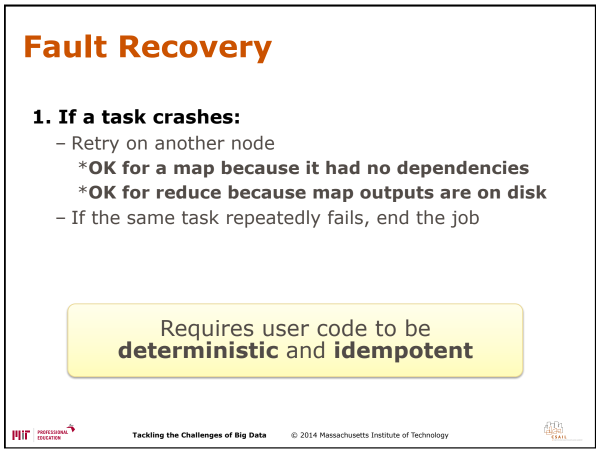
Word Count Execution





MapReduce Execution

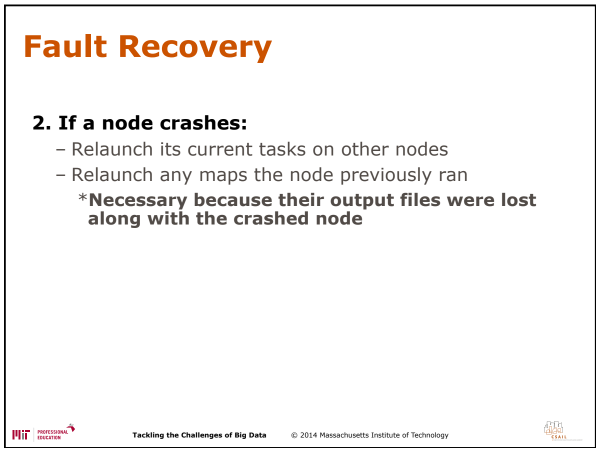
- **Automatically split work into many small *tasks***
- **Send map tasks to nodes based on data locality**
  - Typically, files are replicated so that there are 3 copies of each block
- **Load-balance dynamically as tasks finish**



Fault Recovery

1. If a task crashes:
- Retry on another node
  - ***OK for a map because it had no dependencies**
  - ***OK for reduce because map outputs are on disk**
- If the same task repeatedly fails, end the job

Requires user code to be **deterministic** and **idempotent**



Fault Recovery

2. If a node crashes:
- Relaunch its current tasks on other nodes
- Relaunch any maps the node previously ran
  - ***Necessary because their output files were lost along with the crashed node**

Fault Recovery

3. If a task is going slowly (straggler):

- Launch second copy of task on another node
- Take the output of whichever copy finishes first, and cancel the other one

By offering a data-parallel model, MapReduce can handle many distribution issues automatically

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MapReduce Examples

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1. Search

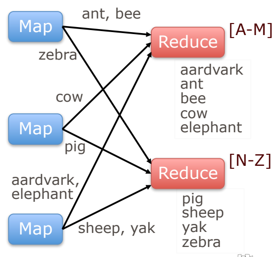
- **Input: (lineNumber, line) records**
- **Output: lines matching a given pattern**
- **Map:**

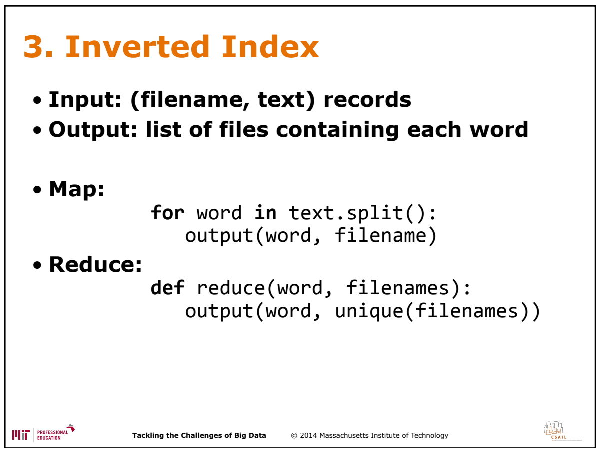
```
if (line matches pattern):
    output(line, lineNumber)
```

- **Reduce: identity function**
  - Alternative: no reducer (map-only job)

2. Sort

- **Input: (key, value) records**
- **Output: same records, sorted by key**
- **Map: identity function**
- **Reduce: identify function**
- **Pick partitioning function *p* so that $k_1 < k_2 \Rightarrow p(k_1) < p(k_2)$**





3. Inverted Index

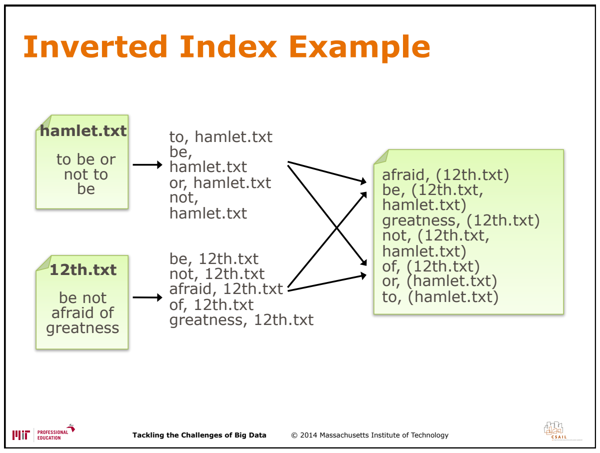
- **Input: (filename, text) records**
- **Output: list of files containing each word**

- **Map:**

```
for word in text.split():
    output(word, filename)
```

- **Reduce:**

```
def reduce(word, filenames):
    output(word, unique(filenames))
```



Inverted Index Example

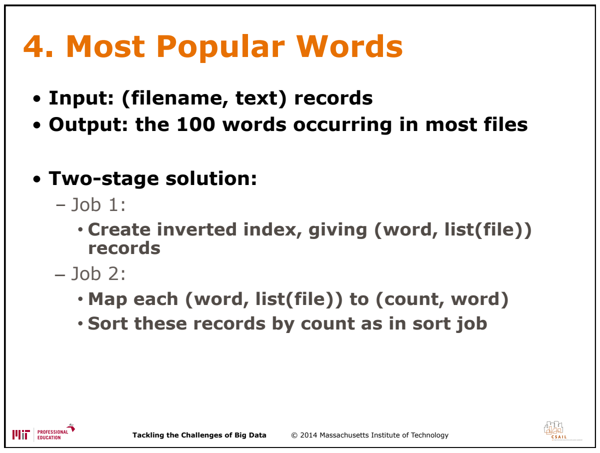
hamlet.txt
to be or not to be

to, hamlet.txt
be, hamlet.txt
or, hamlet.txt
not, hamlet.txt

12th.txt
be not afraid of greatness

be, 12th.txt
not, 12th.txt
afraid, 12th.txt
of, 12th.txt
greatness, 12th.txt

afraid, (12th.txt)
be, (12th.txt, hamlet.txt)
greatness, (12th.txt)
not, (12th.txt, hamlet.txt)
of, (12th.txt)
or, (hamlet.txt)
to, (hamlet.txt)



4. Most Popular Words

- **Input: (filename, text) records**
- **Output: the 100 words occurring in most files**

- **Two-stage solution:**
  - Job 1:
    - **Create inverted index, giving (word, list(file)) records**
  - Job 2:
    - **Map each (word, list(file)) to (count, word)**
    - **Sort these records by count as in sort job**

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MapReduce Examples

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Models Built on MapReduce

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Limitations of MapReduce

- **MapReduce is great at single-pass analysis, but most applications require multiple MR steps**
- **Examples:**
  - Google indexing pipeline: 21 steps
  - Analytics queries (e.g. sessions, top K): 2-5 steps
  - Iterative algorithms (e.g. PageRank): 10's of steps
- **Two problems: programmability & performance**

Programmability

- **Multi-step jobs lead to convoluted code**
  - 21 MR steps -> 21 mapper and reducer functions
- **Repeated code for common patterns**

Performance

- **MR only provides one pass of computation**
  - Must write out data to file system in-between jobs
- **Expensive for apps that need to *reuse* data**
  - Multi-pass algorithms (e.g. PageRank)
  - Interactive data mining (many queries on same data)

Reactions

- **Higher-level interfaces over MapReduce**
  - Translate a higher-level language into MR steps
  - May merge steps to optimize performance
  - Examples: Hive, Pig
- **Generalizations of the model**
  - Examples: Dryad, Spark

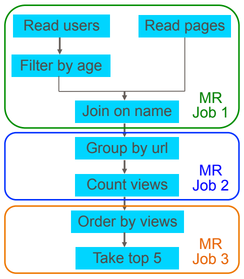
Hive

- **Relational data warehouse over Hadoop**
  - Maintains a catalog of tables with schemas
  - Runs queries in a subset of SQL
  - Supports traditional query optimization, as well as complex data types and MapReduce scripts
- **Developed at Facebook**
- **Used for most of Facebook's MR jobs**

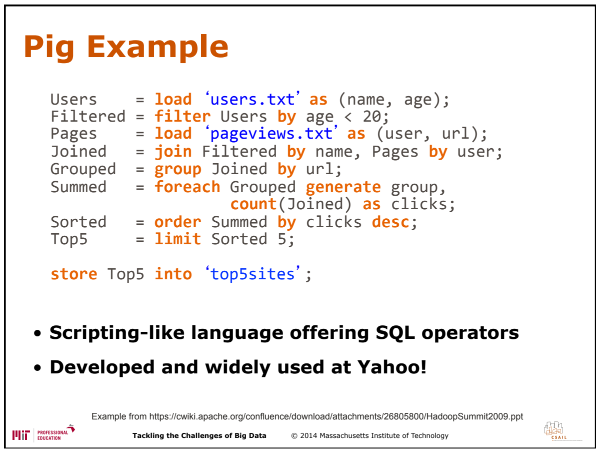
Hive Example

- **Given a tables of page views and user info, find top 5 pages visited by users under 20**

```
SELECT url, COUNT(*) AS views
FROM users u, pageviews v
WHERE u.name = v.username
AND u.age < 20
ORDER BY views DESC
LIMIT 5
```



Example from https://cwiki.apache.org/confluence/download/attachments/26805800/HadoopSummit2009.ppt



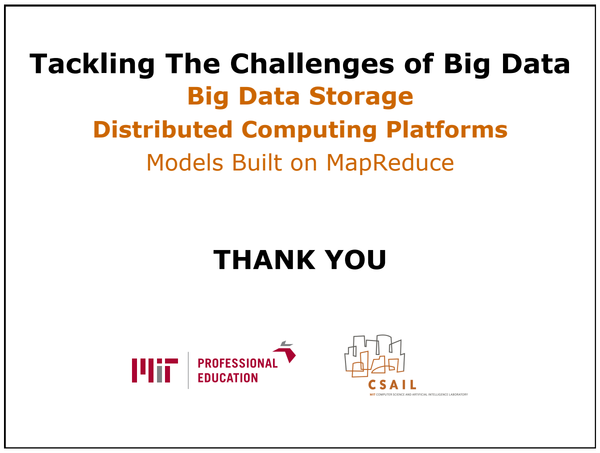
Pig Example

```
Users    = load 'users.txt' as (name, age);
Filtered = filter Users by age < 20;
Pages    = load 'pageviews.txt' as (user, url);
Joined   = join Filtered by name, Pages by user;
Grouped  = group Joined by url;
Summed   = foreach Grouped generate group,
                count(Joined) as clicks;
Sorted   = order Summed by clicks desc;
Top5     = limit Sorted 5;

store Top5 into 'top5sites';
```

- **Scripting-like language offering SQL operators**
- **Developed and widely used at Yahoo!**

Example from https://cwiki.apache.org/confluence/download/attachments/26805800/HadoopSummit2009.ppt



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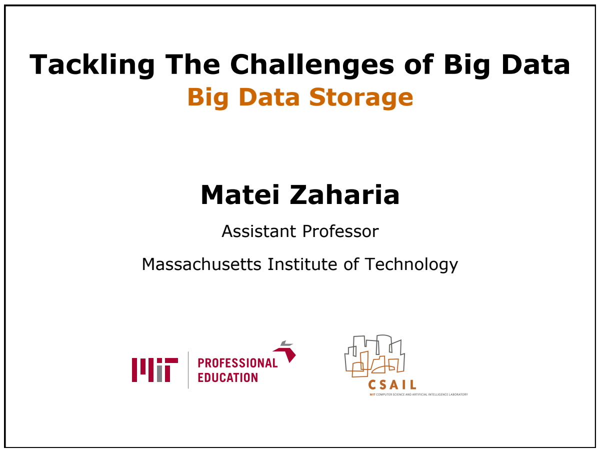

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Generalizations of MapReduce

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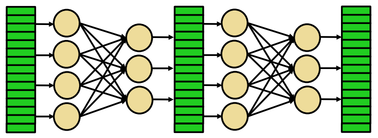
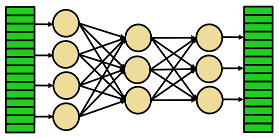
Motivation

- **Compiling high-level operators to MapReduce helps, but multi-step apps still have limitations**
  - Sharing data *between* MapReduce jobs is slow (requires writing to replicated file system)
  - Some apps need to do multiple passes over *same* data
- **E.g., word count + sort:**



Dryad Model

- **General graphs of tasks instead of two-level MapReduce graph**

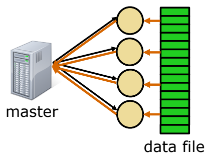


- **Similar recovery mechanisms (replay parent tasks in graph to recover, replicate slow tasks)**

[Isard et al, EuroSys 2007]

Spark Model

- **Dryad supports richer operator graphs, but data flow is still acyclic**
- **Many applications need to efficiently *reuse* data**
  - Interactive data mining: run multiple user queries (not known in advance) on same subset of data
  - Iterative algorithms: make multiple passes over data



Spark Model

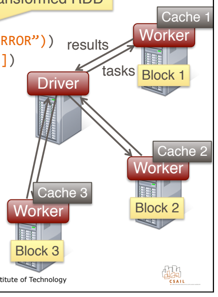
- **Let users explicitly build and persist distributed datasets**
- **Key idea: Resilient Distributed Datasets (RDDs)**
  - Collections of objects partitioned across cluster that can be stored on disk or in memory
  - Built through graphs of parallel transformations (e.g. *map*, *reduce*, *group-by*)
  - Automatically rebuilt on failure
- **High-level APIs in Java, Scala, Python**

Example: Log Mining

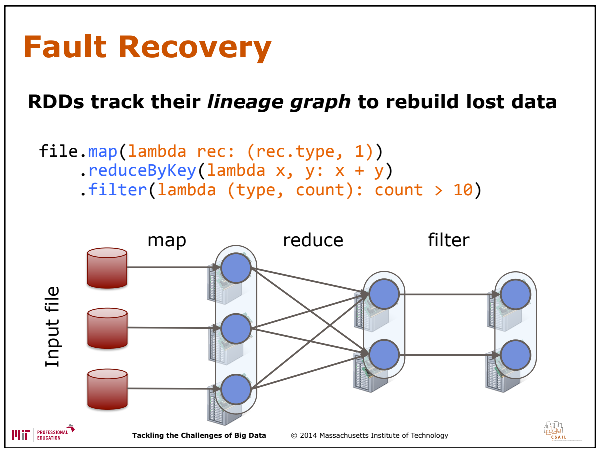
Load error messages from a log file in memory, then interactively search for various patterns

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

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



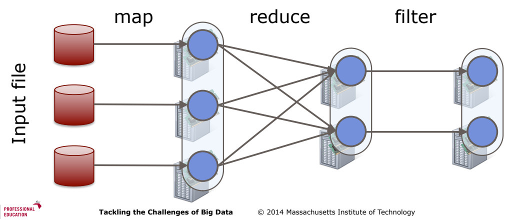
Result: full-text search of Wikipedia in 1 sec (vs 30 sec for on-disk data)

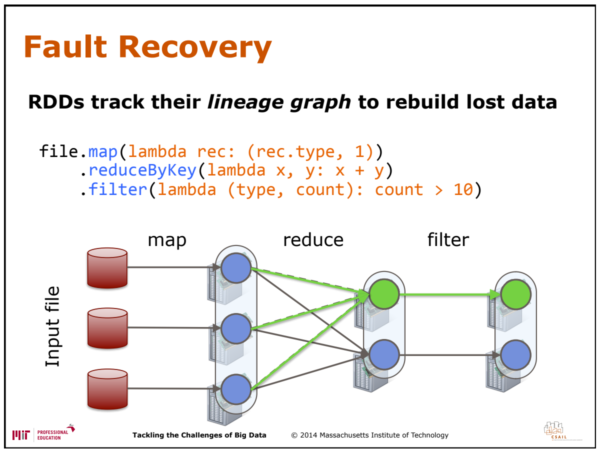


Fault Recovery

RDDs track their *lineage graph* 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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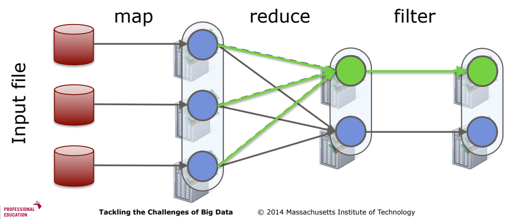
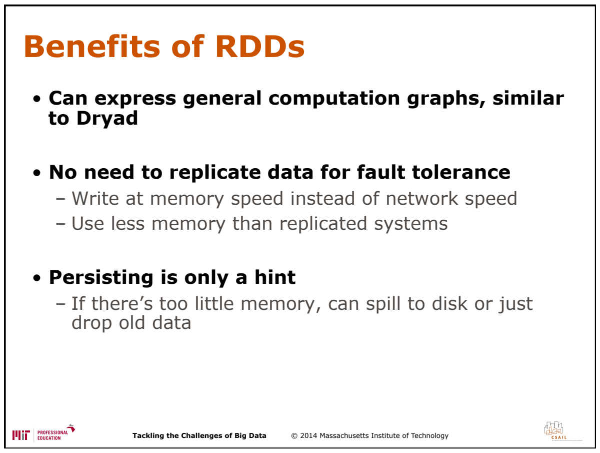
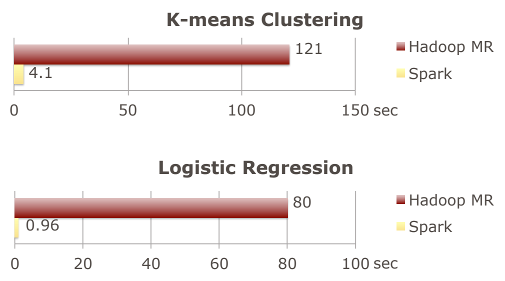




Benefits of RDDs

- **Can express general computation graphs, similar to Dryad**
- **No need to replicate data for fault tolerance**
  - Write at memory speed instead of network speed
  - Use less memory than replicated systems
- **Persisting is only a hint**
  - If there's too little memory, can spill to disk or just drop old data

Iterative Algorithms



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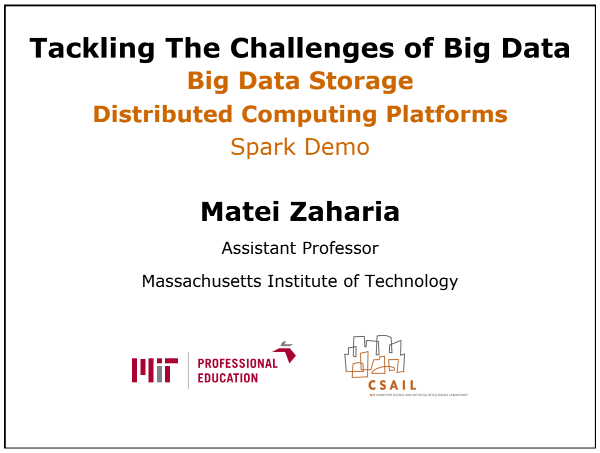

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Spark Demo

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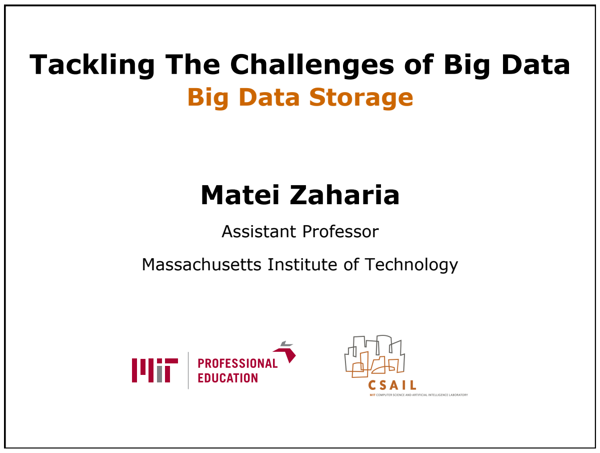

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Tackling The Challenges of Big Data

Big Data Storage

Distributed Computing Platforms

Other Platforms

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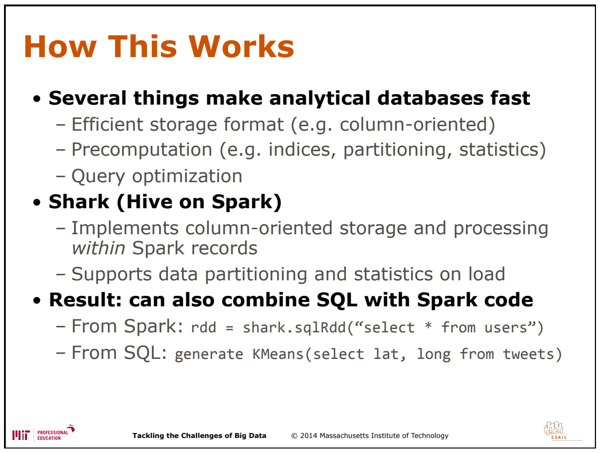
Introduction

- **We've covered MapReduce and its extensions, which are the most popular models today**
- **This area is still seeing rapid change & innovation**
- **We'll briefly sketch some related questions:**
  - How do these efforts relate to databases and SQL?
  - What are some very different models from MapReduce?
    - ***Asynchronous computation, streaming**

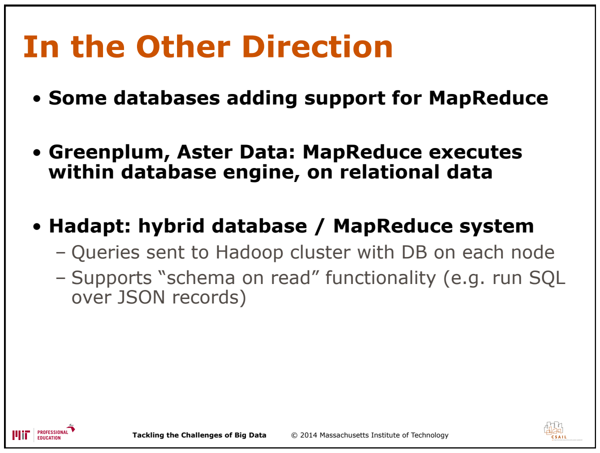
1. Convergence with SQL

- **One of the first things users wanted to run in MapReduce clusters was SQL!**
- **Some systems build SQL engines over MapReduce cluster architectures**
  - Google Dremel, Cloudera Impala, Apache Drill & Tez
  - Usually lack fault tolerance but target short queries
- **Others implement many of the optimizations in database engines on MapReduce-like runtimes**
  - Google Tenzing, Shark (Hive on Spark)



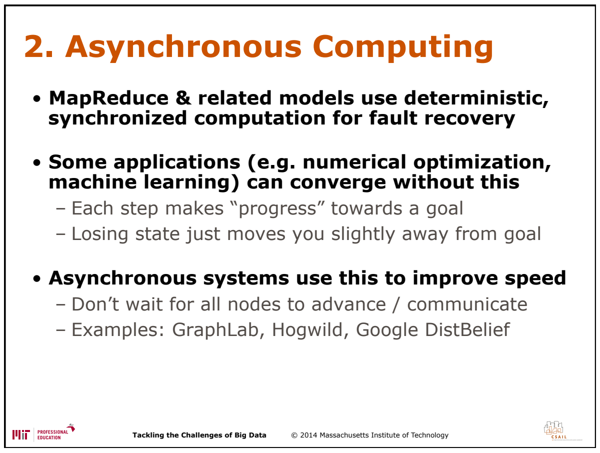
How This Works

- **Several things make analytical databases fast**
  - Efficient storage format (e.g. column-oriented)
  - Precomputation (e.g. indices, partitioning, statistics)
  - Query optimization
- **Shark (Hive on Spark)**
  - Implements column-oriented storage and processing *within* Spark records
  - Supports data partitioning and statistics on load
- **Result: can also combine SQL with Spark code**
  - From Spark: `rdd = shark.sqlRdd("select * from users")`
  - From SQL: `generate KMeans(select lat, long from tweets)`



In the Other Direction

- **Some databases adding support for MapReduce**
- **Greenplum, Aster Data: MapReduce executes within database engine, on relational data**
- **Hadapt: hybrid database / MapReduce system**
  - Queries sent to Hadoop cluster with DB on each node
  - Supports "schema on read" functionality (e.g. run SQL over JSON records)



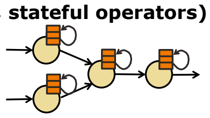
2. Asynchronous Computing

- **MapReduce & related models use deterministic, synchronized computation for fault recovery**
- **Some applications (e.g. numerical optimization, machine learning) can converge without this**
  - Each step makes "progress" towards a goal
  - Losing state just moves you slightly away from goal
- **Asynchronous systems use this to improve speed**
  - Don't wait for all nodes to advance / communicate
  - Examples: GraphLab, Hogwild, Google DistBelief

Asynchronous System Example

3. Stream Processing

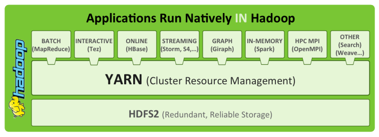
- **Processing data in real-time can require very different designs**
- **Example: Storm (continuous, stateful operators)**
  - Build graph of operators
  - System plays each record through at least once in case of failures



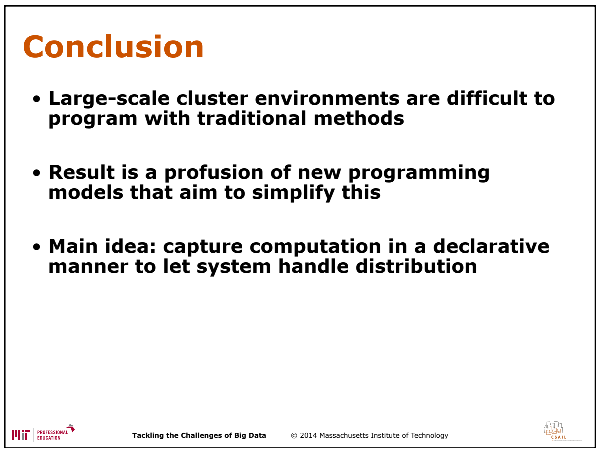
- **Several options for determinism on failures**
  - Transactional storage (Trident)
  - Run as sequence of batch jobs (Spark Streaming)

Resource Sharing

- **Given all these programming models, how do we get them to coexist**
- **Cross-framework *resource managers* allow dynamically sharing a cluster between them**
  - Let applications launch work through common API
  - Hadoop YARN, Apache Mesos

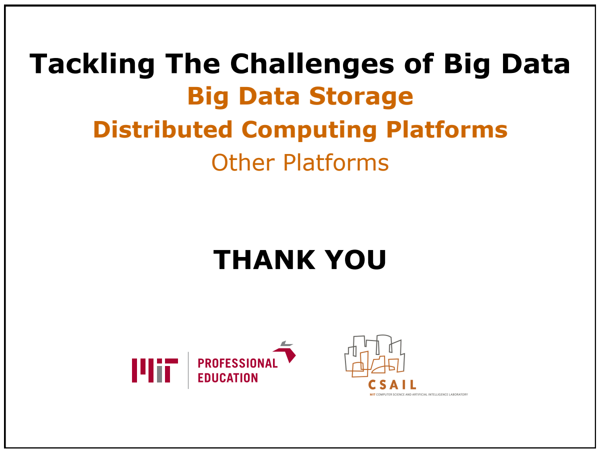

Applications Run Natively IN Hadoop
BATCH (MapReduce)
INTERACTIVE (Tez)
ONLINE (HBase)
STREAMING (Storm, S4,...)
GRAPH (Giraph)
IN-MEMORY (Spark)
HPC MPI (OpenMPI)
OTHER (Search) (Weave...)
YARN (Cluster Resource Management)
HDFS2 (Redundant, Reliable Storage)
hadoop

Source: Hortonworks (http://hortonworks.com/hadoop/yarn/)



Conclusion

- Large-scale cluster environments are difficult to program with traditional methods
- Result is a profusion of new programming models that aim to simplify this
- Main idea: capture computation in a declarative manner to let system handle distribution



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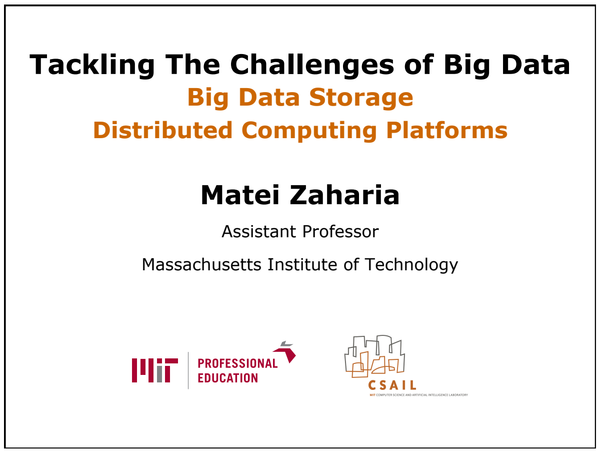
THANK YOU



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