Comp 311
Functional Programming

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Functional Programming and Large Scale Data Analytics

Large Scale Data Analytics

- Many trends have resulted in a dramatic rise in the amount of data available for computation:
  - e-commerce
  - social networking
  - mobile phones
  - etc.

Large Scale Data Analytics

- Significant value can be gleaned from quick processing of large datasets
  - Real-time navigation adjustments
  - Targeted online advertising
  - Customized medical diagnosis
  - Retail recommendations
  - More relevant news and social feeds

Large Scale Data Analytics

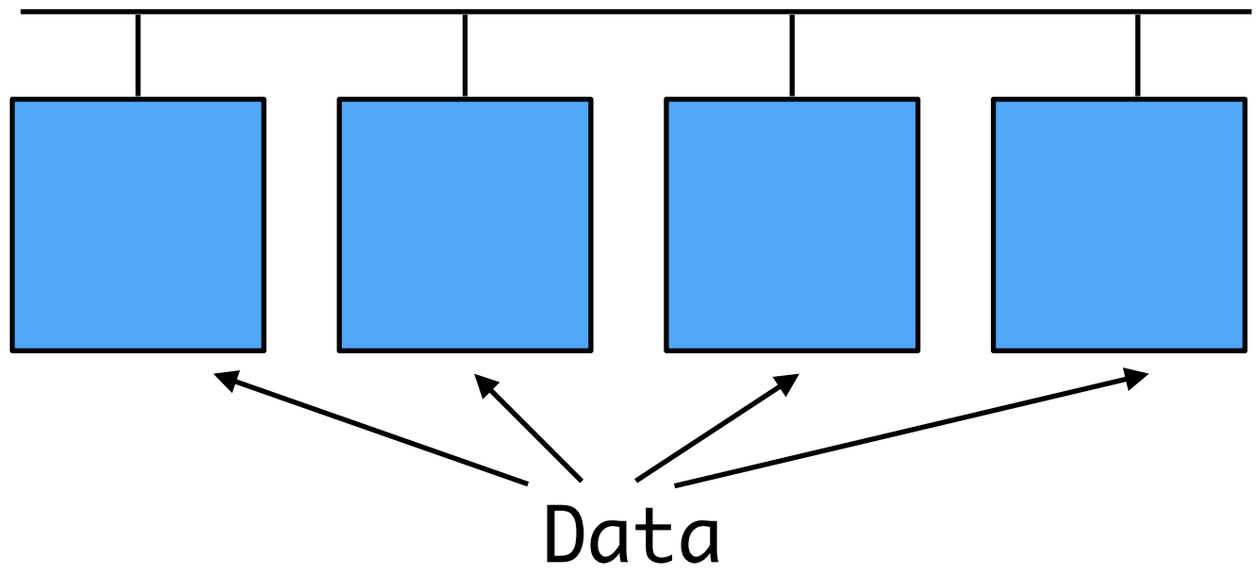
- AT&T processes roughly 30 petabytes per day through its telecommunications network
- Google processed roughly 24 petabytes per day in 2009
- Facebook, Amazon, Twitter, etc, have comparable throughputs
- Two Sigma maintains over 100 teraflops of private computing power continuously computing over 11 petabytes of quantitative data
- By comparison, the IBM Watson knowledge base stored roughly 4 terabytes of data when winning at Jeopardy

Challenges in Computing Large-Scale Streaming Data

- Continuously streaming data needs to be processed at least as fast as it is accumulated, or we will never catch up

- The bottleneck in processing very large data sets has been dominated for many years by the speed of disk access

- More processors accessing more disks enables faster processing



Cloud Computing

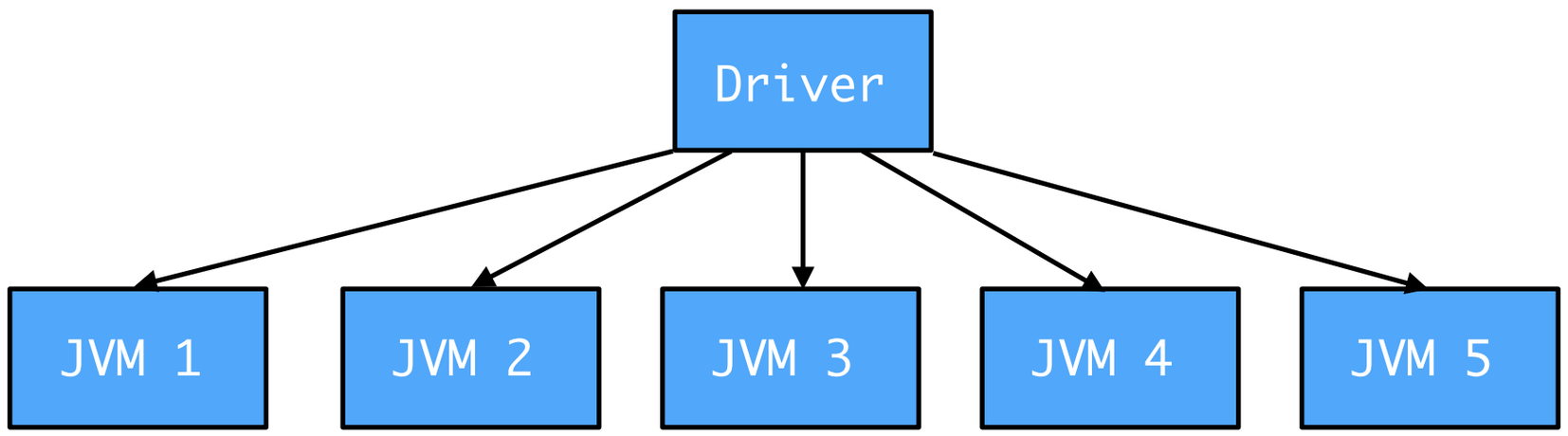
- Computing, storage, and communication at pennies per hour
- No premium to scale:
  - 1000 computers @ 1 hour = 1 computer @ 1000 hours
- Provides the illusion of infinite scalability to cloud user
  - Use as many computers as you can afford
- Leading examples: Amazon Web Services (AWS), Google App Engine, Microsoft Azure

Cloud Computing

- Economies of scale have pushed down datacenter costs by factors of 3-8
    - Traditional datacenters utilized 10% - 20% of their machines
    - Cloud computing services are far more economical
- But how do we extract portable and scalable parallelism from our programs?
    - One solution: Take advantage of functional programming to express simple parallelism easily

Cluster Computing Frameworks

- Enabled writing of parallel computations using functional operators, without worrying about distribution and fault tolerance



MapReduce

- Load a large data set from disk on to multiple machines
- Map a function over that data to return key value pairs
- Shuffle results so that pairs with the same keys are brought together
- Reduce to one value for each key
- Write result to disk

MapReduce

- Computations that involve a sequence of iterations of map/reduce operations pay a heavy price:

  Each iteration must read from and write to disk

Iterative Map/Reduce Schedulers

- Users started to realize that a much larger class of algorithms could be expressed as an iteration of MapReduce operations
    - Many machine learning algorithms fall here
- Tools started to emerge to enable easy expression of map/reduce operations along with smart scheduling

Apache Spark

- Cache results of map/reduce operations so they can be used on subsequent iterations

- 10-100X faster than MapReduce for many applications

Resilient Distributed Datasets

- Fault-Tolerant parallel data structures
- Enable users to:
  - Persist intermediate results in memory
  - Control partitioning to optimize data placement
  - Manipulate data with many available operators

Resilient Distributed Datasets

- Immutable
- Operators are *coarse-grained:* map, filter, join, etc.
    - Allows for efficient fault tolerance by logging the operations applied to build a dataset rather than the actual dataset

Resilient Distributed Datasets

- Partitioned across the many machines of a cluster
- Created by:
  - Reading data from storage
  - Performing transformations on other RDDs

Resilient Distributed Datasets

- Stores information as to how it was derived from other datasets
- Able to compute its partitions from data on disk
- Impossible to reference an RDD that cannot be reconstructed after a failure

Resilient Distributed Datasets

- Persistence
- A program:
  - Indicates which RDDs will be reused
  - Chooses a storage strategy for each RDD

Resilient Distributed Datasets

- Partitioning
  - A program:
    - Asks that RDDs are partitioned across machines based on a key in each record
    - Useful for ensuring that two datasets can be joined efficiently

The RDD API

- RDDs defined through *transformations* on data on disk
  - map, flatMap, filter, etc.
- RDDs are used in *actions:*
  - Operations that return a value or export data to disk
    - count, collect, save
    - No work is done until an action forces it

http://spark.apache.org/docs/latest/api/scala

The RDD API

- RDDs have a `persist` method
  - Indicates that an RDD will be used in subsequent operations
- Implementation attempts to keep persisted RDDs in memory of the machines in a cluster
  - Spills to disk gracefully

Creating an RDD

```
val lines = sparkContext.textFile(“hdfs://…”)
val errors = lines.filter(_.startsWith(“ERROR”))
errors.persist()
```

No work has been done yet on the cluster.

Creating an RDD

```
val lines = sparkContext.textFile(“hdfs://…”)
val errors = lines.filter(_.startsWith(“ERROR”))
errors.persist()
```

The RDD records the transformations performed to compute it from disk, enabling recomputation after a failure.

Performing an Action on an RDD

```
errors.count()
```

An action will force computation of the RDD.

Performing an Action on an RDD

```
errors.count()
```

Because errors is now stored in memory, subsequent computations involving errors will be much faster.

Performing an Action on an RDD

```
errors.count()
```

Note that the lines RDD is never stored in memory.
(Why is this behavior desirable?)

Performing an Action on an RDD

```
errors.filter(_.contains(“MySQL”))
```

New RDDs can be computed via transformations on existing RDDs.

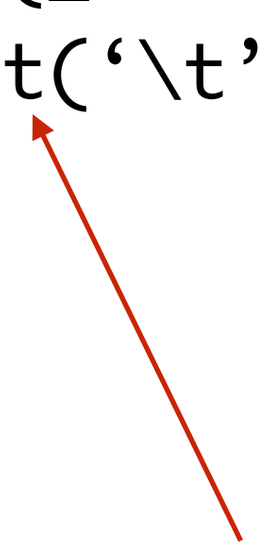
Performing an Action on an RDD

```
errors.filter(_.contains(“MySQL”)).count()
```

Again, computation is not performed until an action forces it.

Performing an Action on an RDD

```
errors.filter(_.contains(“HDFS”))
.map(_.split(‘\t’)(3))
.collect()
```



Splits a line into an array of elements, according to occurrences of the tab character.

Performing an Action on an RDD

```
errors.filter(_.contains(“HDFS”))
.map(_.split(‘\t’)(3))
.collect()
```

Accesses the fourth element of each array.
(In this case, let’s say that the fourth element of the log lines stores time.)

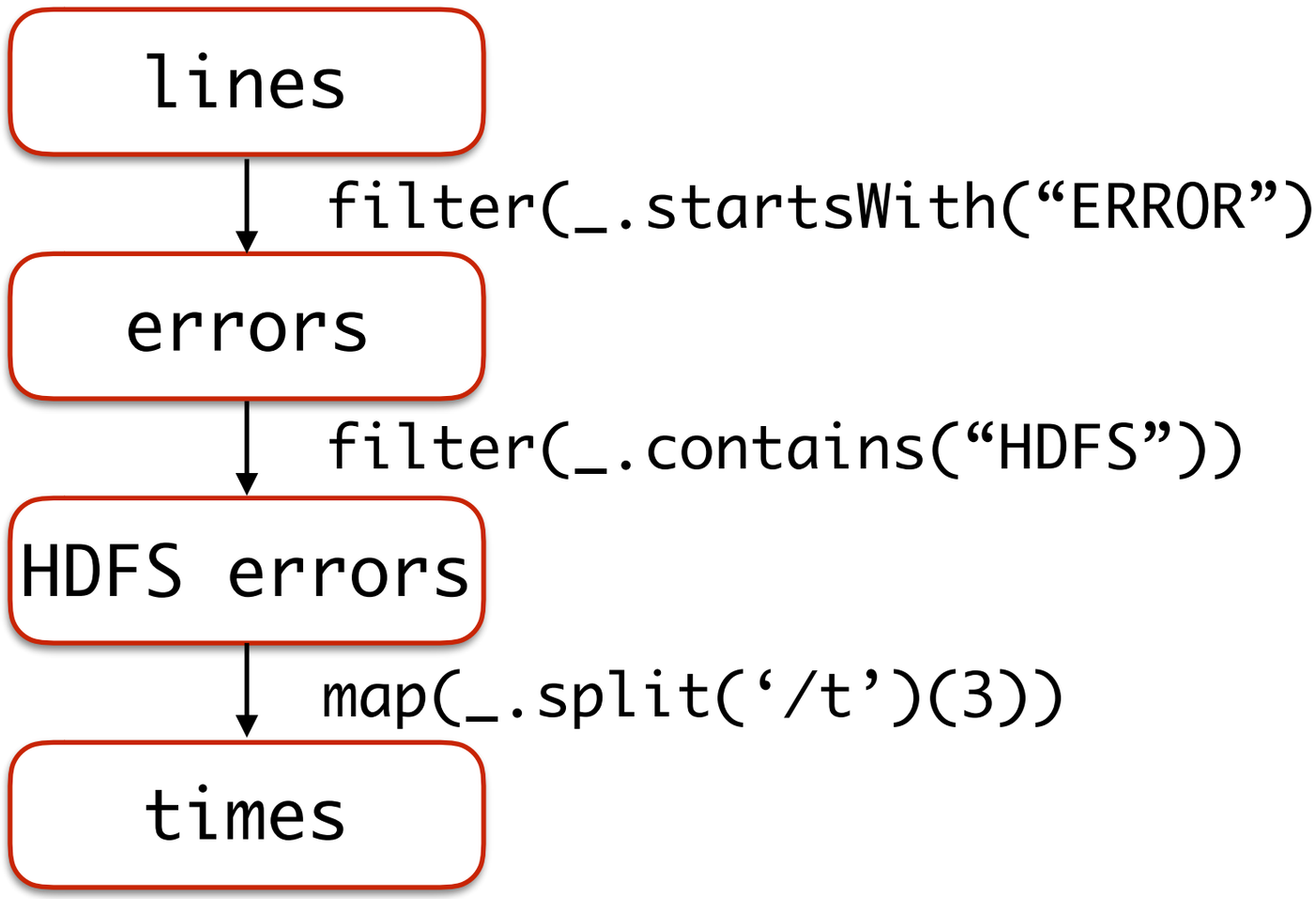
Performing an Action on an RDD

```
val times =
  for (x <- errors if x contains “HDFS”)
  yield x.split(‘\t’)(3)

times.collect()
```

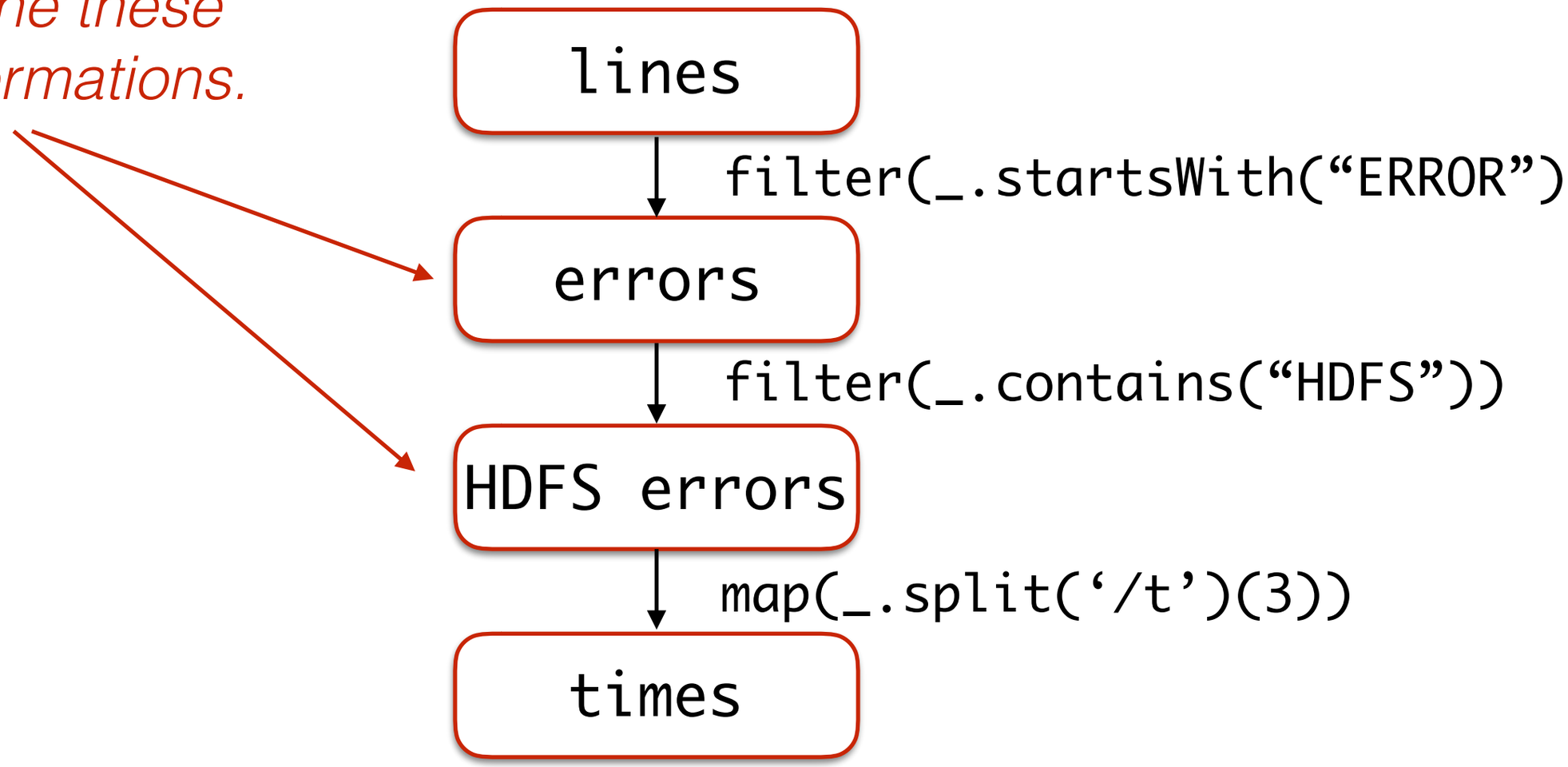
Alternative syntax using for- expressions.

Lineage Graph For times RDD



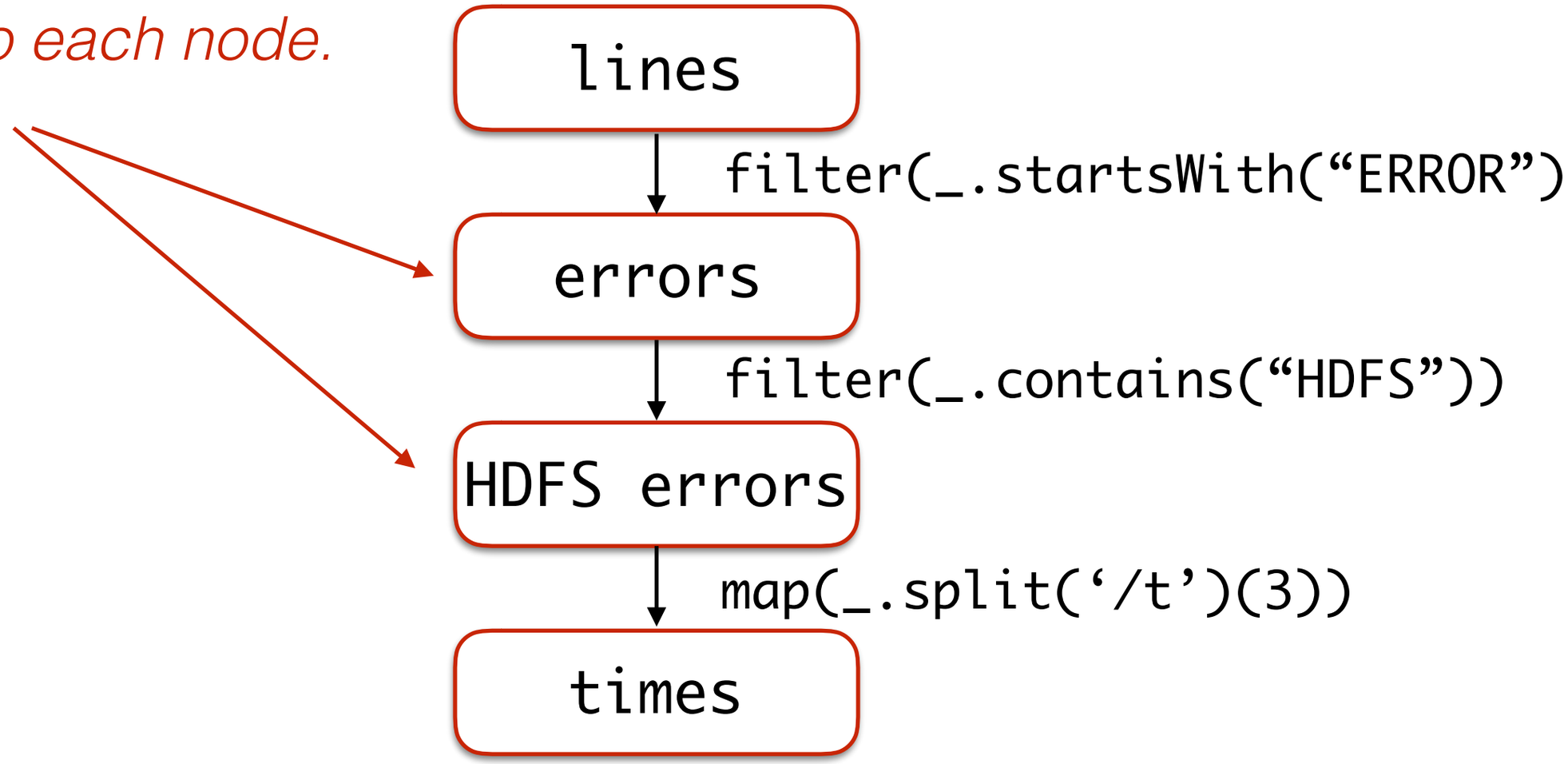
Lineage Graph For times RDD

The Spark scheduler will pipeline these transformations.



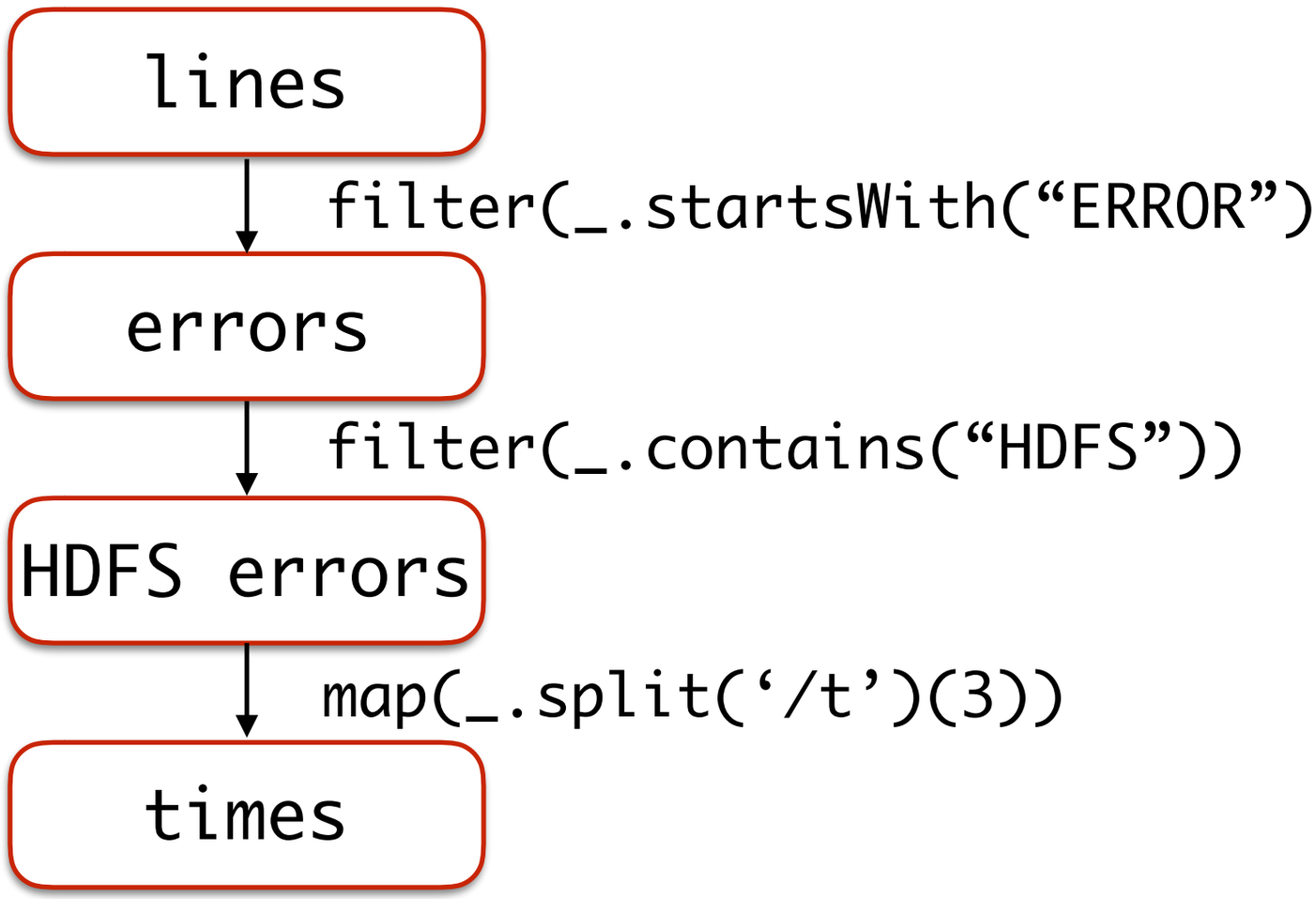
Lineage Graph For times RDD

Tasks for transformations are sent to each node.



Lineage Graph For times RDD

If a partition of errors is lost, Spark rebuilds it by recomputing from the corresponding partition of lines.



Transformations Available on RDDs

- `map(f: T => U): RDD[T] => RDD[U]`
- `filter(f: T => Boolean): RDD[T] => RDD[T]`
- `flatMap(f: T => Iterable[U]): RDD[T] => RDD[U]`
- `sample(fraction: Float): RDD[T] => RDD[T]`
- `union(RDD[T], RDD[T]): RDD[T]`

Transformations Available On RDDs of Key/Value Pairs

```
groupByKey(): RDD[(K,V)] => RDD[(K,Iterable[V])]

reduceByKey(f: (V,V) => V): RDD[(K,V)] => RDD[(K,V)]

join(): (RDD[(K,V)], RDD[(K,W)]) => RDD[K,(V,W)]
```

Transformations Available On RDDs of Key/Value Pairs

cogroup:

```
(RDD[(K,V)],RDD[(K,W)]) =>
    RDD[K (Iterable[V],Iterable[W])]
```

cartesian:

```
(RDD[T],RDD[U]) => RDD[(T,U)]
```

Transformations Available On RDDs of Key/Value Pairs

```
mapValues(f: V => W): RDD[(K,V)] => RDD[(K,W)]
```

Preserves partitioning.

Transformations Available On RDDs of Key/Value Pairs

```
partitionBy(p: Partitioner[K]): RDD[(K,V)] => RDD[(K,V)]
```

Actions Available on RDDs

```
count(): RDD[T] => Long
collect(): RDD[T] => Iterable[T]
reduce(f: (T,T) => T): RDD[T] => T
lookup(k: K): RDD[(K,V)] => Iterable[V]
save(path: String): ()
```

WordCount in Spark

```
val file = sparkContext.textFile(“hdfs://...")

val counts = file.flatMap(line => line.split(" "))
                 .map(word => (word, 1))
                 .reduceByKey((x,y) => x + y)

counts.saveAsTextFile("hdfs://...")
```

WordCount in Spark

```
val file = sparkContext.textFile(“hdfs://...")
val words = for (line <- file,
                 word <- line.split(" “))
            yield (word, 1)

val counts = words.reduceByKey(_ + _)

counts.saveAsTextFile("hdfs://...")
```

```
("this", "is", "a", "line", "this", "is",
 "another", "line", "this", "is", "yet",
 "another", "line")
.map(word => (word, 1))
```

```
(("this",1), ("is",1), ("a",1), ("line",1),
 ("this",1), ("is",1), ("another",1),
("line",1), ("this",1), ("is",1),
("yet",1),("another",1), ("line",1))
```

```
x.reduceByKey(f)
```

is semantically equivalent to

```
x.groupByKey().map(xs => xs.reduce(f))
```

```
(("this",1), ("is",1), ("a",1), ("line",1),
 ("this",1), ("is",1), ("another",1),
 ("line",1), ("this",1), ("is",1),
 ("yet",1),("another",1), ("line",1))
.groupByKey().map(xs => xs.reduce(_ + _))
```

```
(("this", (1,1,1),
 ("is", (1,1,1),
 ("a", (1)),
 ("line", (1,1,1)),
 ("another", (1,1)),
 ("yet", (1))).map(xs => xs.reduce(_ + _))
```

```
(("this", (1,1,1)).reduce(_ + _),
 ("is", (1,1,1)).reduce(_ + _),
 ("a", (1)).reduce(_ + _),
("line", (1,1,1)).reduce(_ + _),
("another", (1,1)).reduce(_ + _),
("yet", (1)).reduce(_ + _))
```

```
(("this", 3), ("is", 3), ("a", 1),
("line", 3), ("another", 2), ("yet", 1))
```

Machine Learning With Spark

- Given a collection of examples with various attributes and a label, we wish to predict the labels for new examples:

```
<height, weight, age, systolic bp, diastolic bp>: medicine?

  <170 cm, 72 kg, 52, 120, 80>: YES

  <150 cm, 60 kg, 34 years, 130, 70> : NO

  …
```

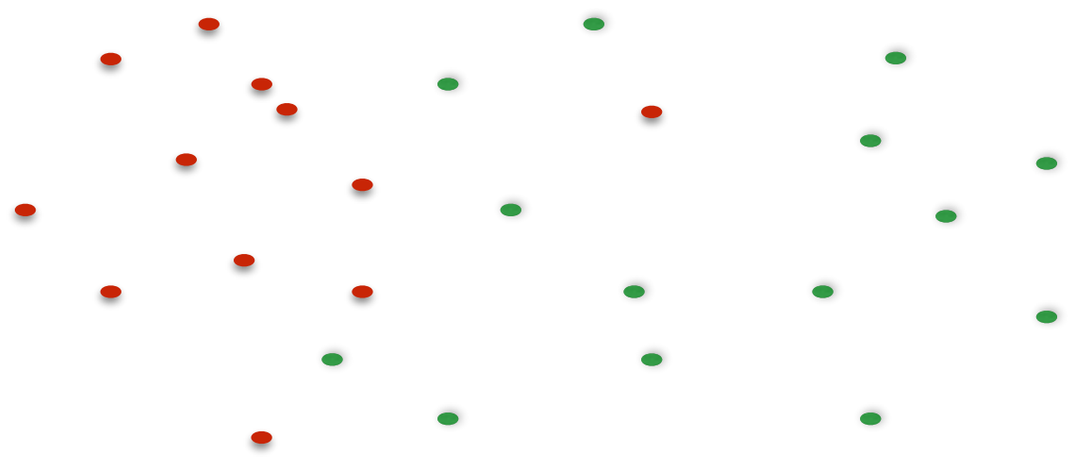
http://spark.apache.org/mllib/

Machine Learning With Spark

- We can view the examples as vectors in a high-dimensional vector space

- The problem of labeling yes/no can be solved by finding the best hyperplane that divides the given examples according to their labels

- This new hyperplane can be used to predict labels for new examples



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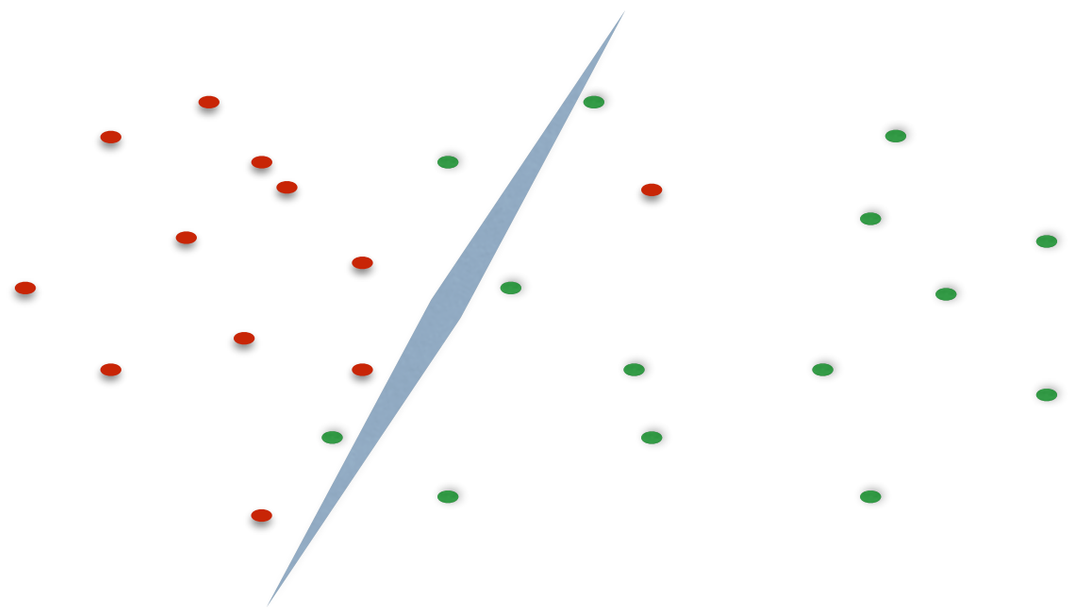


Logistic Regression With Spark

```
val points = spark.textFile(…).map(parsePoint).cache()

var w = Vector.random(D) // current separating plane
for (i <- 1 to ITERATIONS) {
  val gradient = points.map(p =>
    (1 / (1 + exp(-p.y*(w dot p.x))) - 1) * p.y * p.x
  ).reduce(_ + _)

  w -= gradient
}

println("Final separating plane: " + w)
```

Machine Learning With Spark

- Given a collection of examples with various attributes and a label, we wish to predict the labels for new examples:

<height, weight, age, systolic bp, diastolic bp>: medicine?

<170 cm, 72 kg, 52, 120, 80>: YES

<150 cm, 60 kg, 34 years, 130, 70> : NO

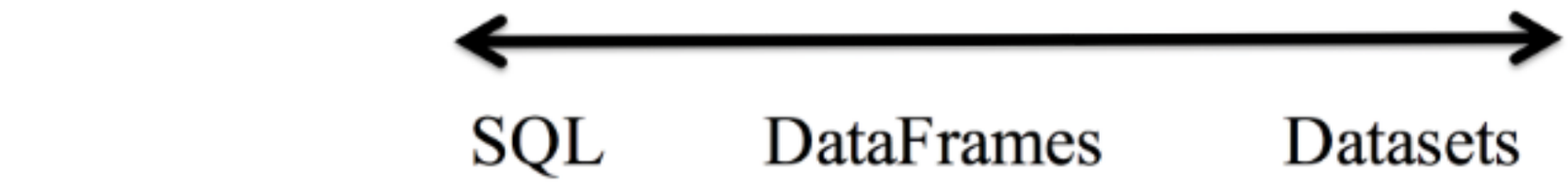
…

DataFrames

- Flavor of RDDs inspired by R, Python, RDBMS
- sql-like and sql interface
- RDDs of Rows
- Enables optimizations like a RDBMS

DataSets

- New RDD extension for Spark 2.0



	SQL	DataFrames	Datasets
Syntax Errors	Runtime	Compile Time	Compile Time
Analysis Errors	Runtime	Runtime	Compile Time

https://databricks.com/blog/2016/07/14/a-tale-of-three-apache-spark-apis-rdds-dataframes-and-datasets.html

stackoverflow

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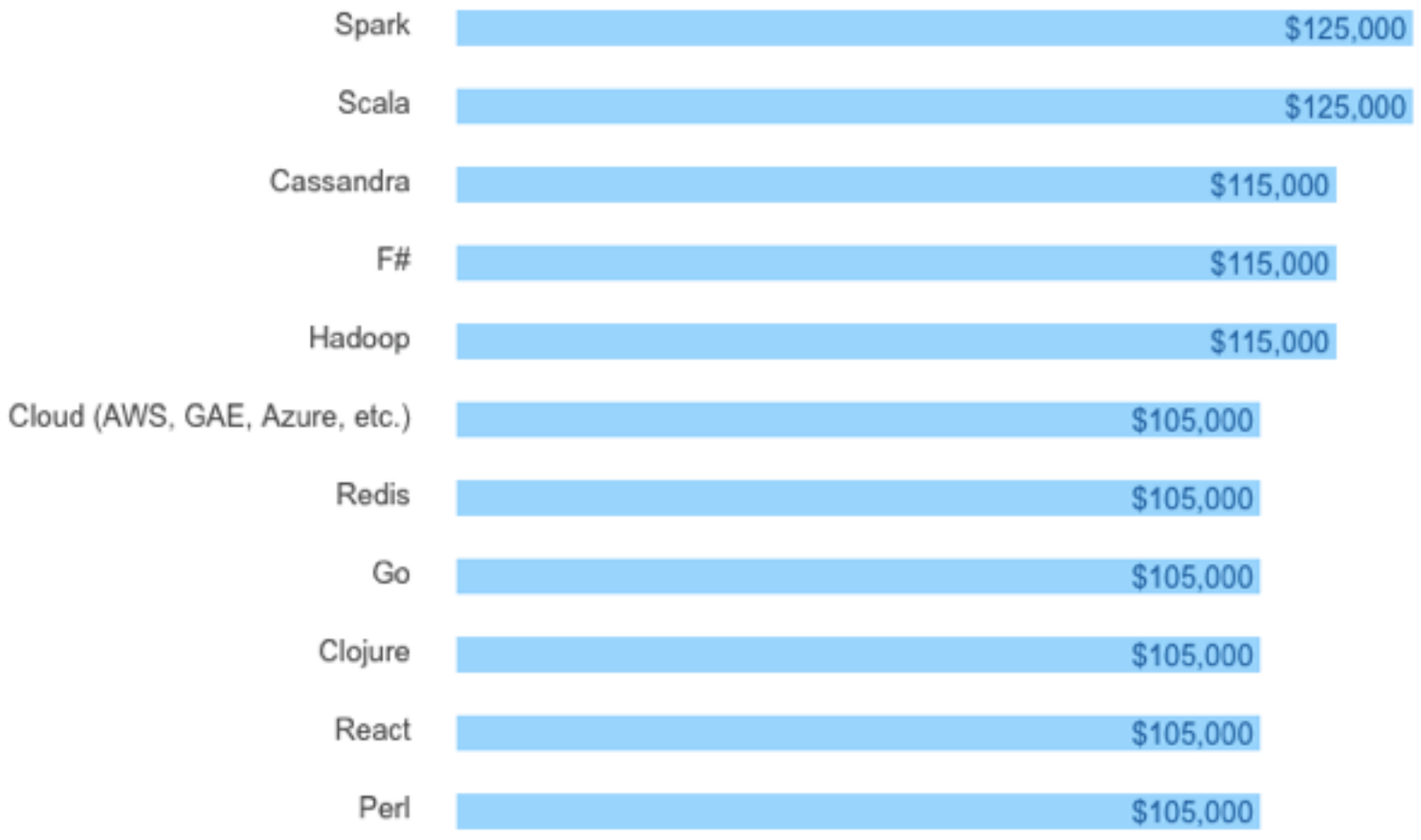
V. Top Paying Tech

Top Paying Tech in US | Top Paying Tech Worldwide



Minimum 100 responses, among all US developers

Make it rain! Cloud technology pays big bucks. So does tech frequently used in finance. Spark, Scala, Cassandra, and F# top the list of the top paying technologies. (This year's list looks a lot like last year's list.)

Have you considered looking for a Spark job?

http://stackoverflow.com/research/developer-survey-2016#technology-top-paying-tech