Query Optimization 2

Instructor: Matei Zaharia

cs245.stanford.edu

Recap: Data Statistics

Information about tuples in a table that we can use to estimate costs

» Must be *approximated* for intermediate tables

We saw one way to do this for 4 statistics:

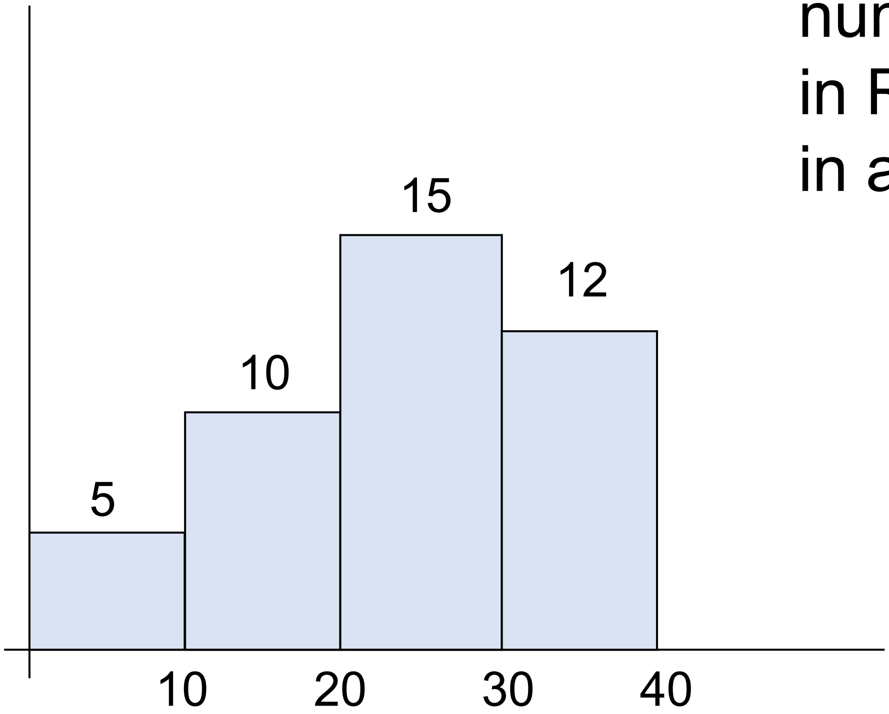
» T(R) = # of tuples in R

» S(R) = average size of tuples in R

» B(R) = # of blocks to hold R's tuples

» V(R, A) = # distinct values of attribute A in R

Another Type of Data Stats: Histograms



number of tuples in R with A value in a given range

$\sigma_{A \geq a}(R) = ?$

Outline

What can we optimize?

Rule-based optimization

Data statistics

Cost models

Cost-based plan selection

Spark SQL

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Cost Models

How do we measure a query plan's cost?

Many possible metrics:

» Number of disk I/Os — We'll focus on this

» Number of compute cycles

» Combined time metric

» Memory usage

» Bytes sent on network

» …

Example: Index vs Table Scan

Our query: $\sigma_p(R)$ for some predicate p

s = p's selectivity (fraction tuples passing)

Table scan:

block size

R has $B(R) = T(R) \times S(R)/b$ blocks on disk

Cost: B(R) I/Os

Index search:

Index lookup for p takes L I/Os

We then have to read part of R;
Pr[read block i]

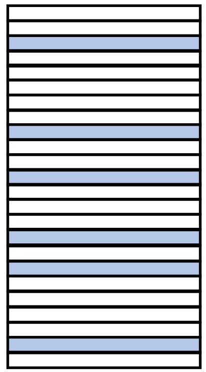
$\approx 1 - \Pr[\text{no match}]^{\text{records in block}}$

$= 1 - (1-s)^{b\,/\,S(R)}$

Cost: $L + (1-(1-s)^{b/S(R)})\ B(R)$

What If Results Were Clustered?

Unclustered: records that match p are spread out uniformly



Clustered: records that match p are close together in R's file

We'd need to change our estimate of C_{index}:

$$C_{index} = L + \underbrace{s\ B(R)}_{\text{Fraction of R's blocks read}}$$

Less than C_{index} for unclustered data

Join Operators

Join **orders** and **algorithms** are often the choices that affect performance the most

For a multi-way join $R \bowtie S \bowtie T \bowtie \ldots$, each join is selective and order matters a lot

» Try to eliminate lots of records early

Even for one join $R \bowtie S$, algorithm matters

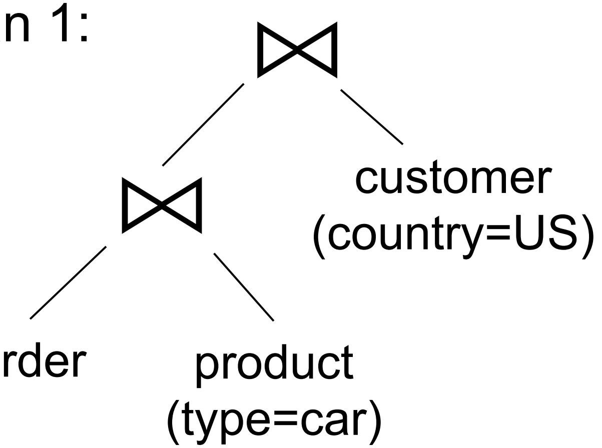
Example

```
SELECT order.date, product.price, customer.name
  FROM order, product, customer
 WHERE order.product_id = product.product_id
   AND order.cust_id = customer.cust_id
   AND product.type = "car"
   AND customer.country = "US"
```

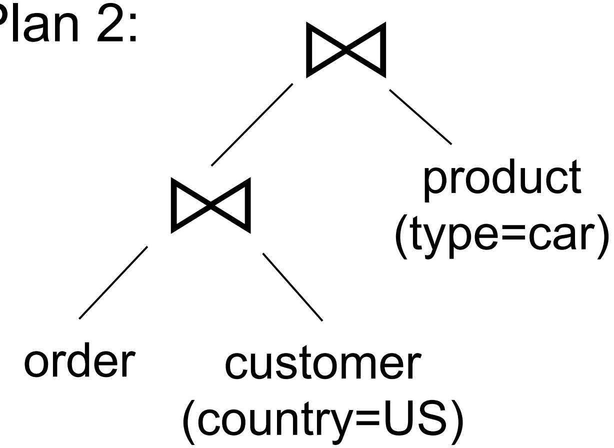
join conditions

selection predicates

Plan 1:



Plan 2:



When is each plan better?

Common Join Algorithms

Iteration (nested loops) join

Merge join

Join with index

Hash join

Iteration Join

```
for each r∈R1:
  for each s∈R2:
    if r.C == s.C then output (r, s)
```

I/Os: one scan of R_1 and $T(R_1)$ scans of R_2, so cost = $B(R_1) + T(R_1)\ B(R_2)$ reads

Improvement: read M **blocks** of R_1 in RAM at a time then read R_2: $B(R_1) + B(R_1)\ B(R_2) / M$

Note: cost of writes is always $B(R_1 \bowtie R_2)$

Merge Join

```
if R₁ and R₂ not sorted by C then sort them
i, j = 1
while i ≤ T(R₁) && j ≤ T(R₂):
   if R₁[i].C = R₂[j].C then outputTuples
   else if R₁[i].C > R₂[j].C then j += 1
   else if R₁[i].C < R₂[j].C then i += 1
```

Merge Join

```
procedure outputTuples:
   while R_1[i].C == R_2[j].C && i ≤ T(R_1):
      jj = j
      while R_1[i].C == R_2[jj].C && jj ≤ T(R_2):
         output (R_1[i], R_2[jj])
         jj += 1
      i += i+1
```

Example

i	$R_1[i].C$	$R_2[j].C$	j
1	10	5	1
2	20	20	2
3	20	20	3
4	30	30	4
5	40	30	5
		50	6
		52	7

Cost of Merge Join

If R_1 and R_2 already sorted by C, then

cost = $B(R_1) + B(R_2)$ reads

(+ write cost of $B(R_1 \bowtie R_2)$)

Cost of Merge Join

If R_i is not sorted, can sort it in 4 $B(R_i)$ I/Os:

- » Read runs of tuples into memory, sort
- » Write each sorted run to disk
- » Read from all sorted runs to merge
- » Write out results

Join with Index

```
for each r∈R₁:
  list = index_lookup(R₂, C, r.C)
  for each s∈list:
    output (r, s)
```

Read I/Os: 1 scan of R_1, $T(R_1)$ index lookups on R_2, and $T(R_1)$ data lookups

$$cost = B(R_1) + T(R_1)\,(L_{index} + L_{data})$$

Can be less when R_1 is sorted/clustered by C!

Hash Join (R_2 Fits in RAM)

```
hash = load R₂ into RAM and hash by C
for each r∈R₁:
  list = hash_lookup(hash, r.C)
  for each s∈list:
    output (r, s)
```

Read I/Os: $B(R_1) + B(R_2)$

Hash Join on Disk

Can be done by hashing both tables to a common set of buckets on disk

» Similar to merge sort: $4\ (B(R_1) + B(R_2))$

Trick: hash only (key, pointer to record) pairs

» Can then sort the pointers to records that match and fetch them near-sequentially

Other Concerns

Join selectivity may affect how many records we need to fetch from each relation

» If very selective, may prefer methods that join pointers or do index lookups

Summary

Join algorithms can have different performance in different situations

In general, the following are used:

» Index join if an index exists

» Merge join if at least one table is sorted

» Hash join if both tables unsorted

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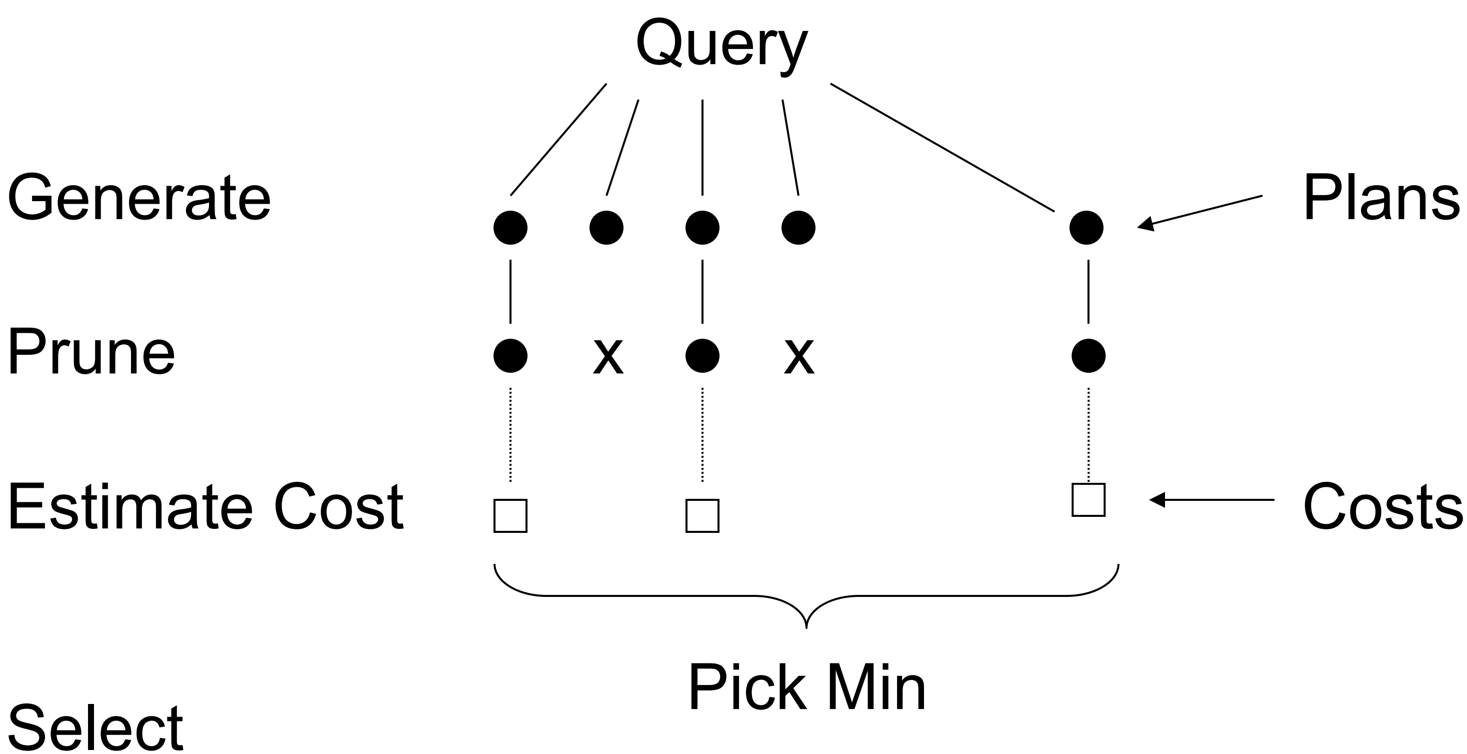
Complete CBO Process

Generate and compare possible query plans



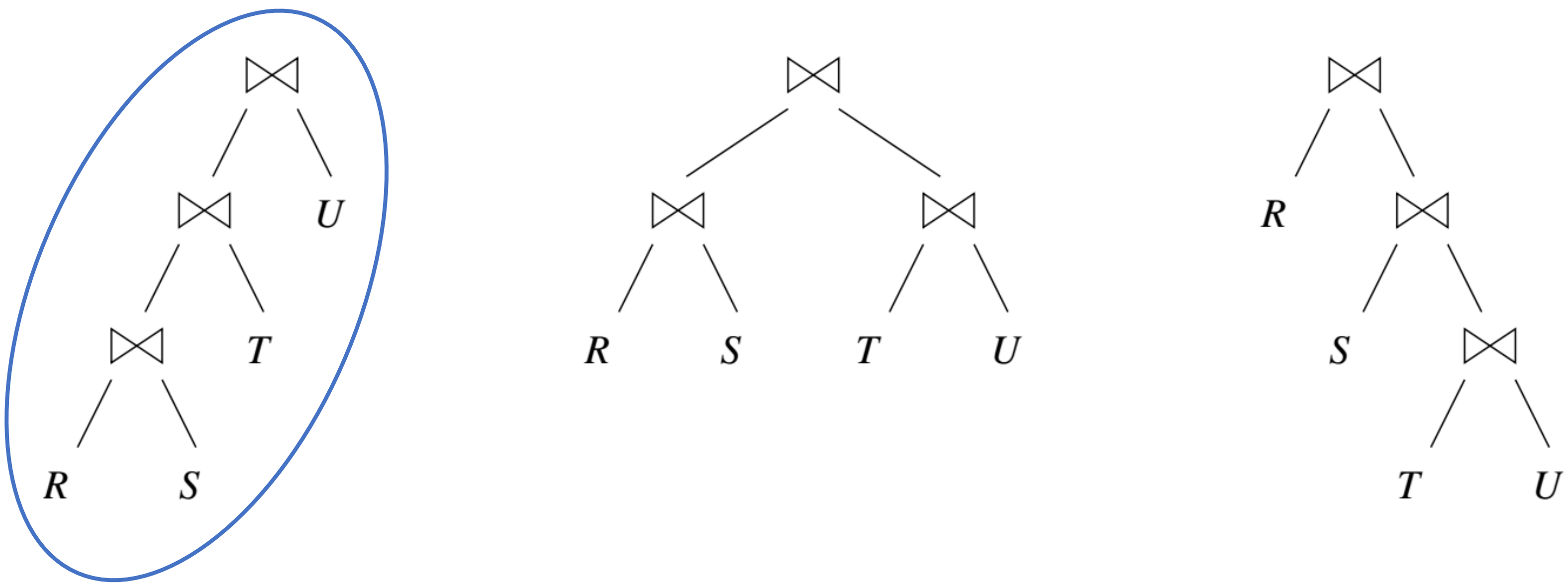
How to Generate Plans?

Simplest way: recursive search of the options for each planning choice

Access paths for table 1 × Access paths for table 2 × Algorithms for join 1 × Algorithms for join 2 × …

How to Generate Plans?

Can limit search space: e.g. many DBMSes only consider “left-deep” joins



Often interacts well with conventions for specifying join inputs in asymmetric join algorithms (e.g. assume right argument has index)

How to Generate Plans?

Can prioritize searching through the most impactful decisions first

» E.g. join order is one of the most impactful

How to Prune Plans?

While computing the cost of a plan, throw it away if it is worse than best so far

Start with a **greedy algorithm** to find an "OK" initial plan that will allow lots of pruning

Memoization and Dynamic Programming

During a search through plans, many subplans will appear repeatedly

Remember cost estimates and statistics (T(R), V(R, A), etc) for those: “memoization”

Can pick an order of subproblems to make it easy to reuse results (dynamic programming)

Resource Cost of CBO

It's possible for cost-based optimization itself to take longer than running the query!

Need to design optimizer to not take too long

» That's why we have shortcuts in stats, etc

Luckily, a few "big" decisions drive most of the query execution time (e.g. join order)

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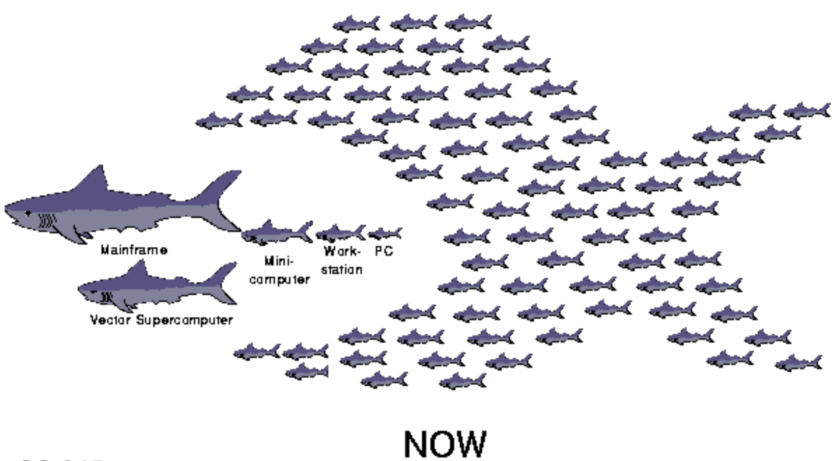
Background

2004: MapReduce published, enables writing large scale data apps on *commodity clusters*

» Cheap but unreliable "consumer" machines, so system emphasizes fault tolerance

» Focus on C++/Java programmers



Background

2006: Apache Hadoop project formed as an open source MapReduce + distributed FS

» Started in Nutch open source search engine

» Soon adopted by Yahoo & Facebook

2006: Amazon EC2 service launched as the newest attempt at "utility computing"

Background

2007: Facebook starts Hive (later Apache Hive) for SQL on Hadoop

» Other SQL-on-MapReduces existed too

» First steps toward “data lake” architecture

Background

2006-2012: Many other cluster programming frameworks proposed to bring MR's benefits to other apps

APACHE STORM™

GraphLab

APACHE GIRAPH

Google
Pregel

Google
Dremel

Impala

Microsoft
Dryad

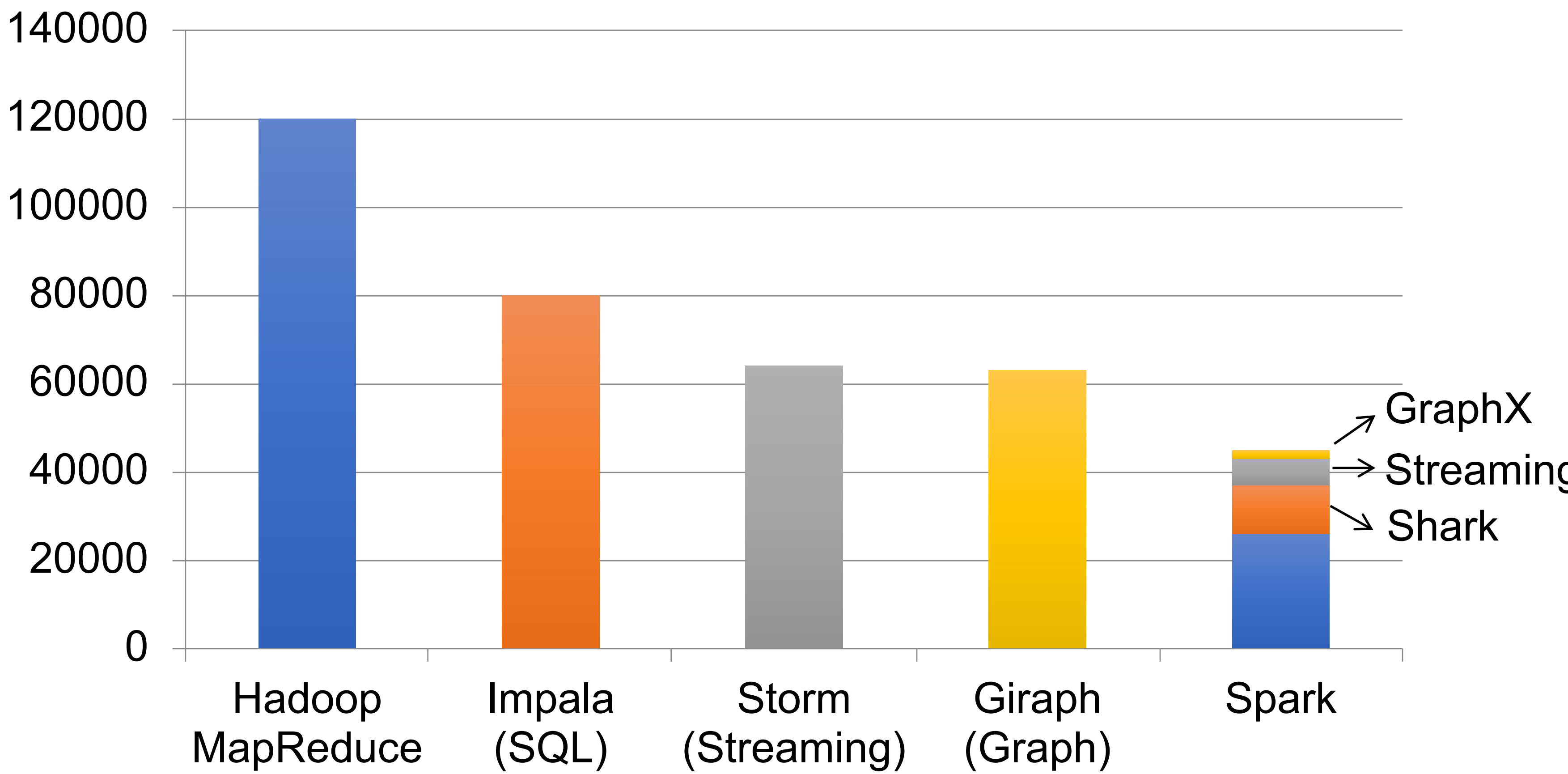
Background

2010: Spark engine released, built around MapReduce + in-memory computing

» Motivation: interactive queries + iterative algorithms such as graph analytics

Spark then moves to be a general (“unified”) engine, covering existing ones

Code Size Comparison (2013)



non-test, non-example source lines

Background

2012: Shark starts as a port of Hive on Spark

2014: Spark SQL starts as a SQL engine built directly on Spark (but interoperable w/ Hive)

» Also adds two new features: DataFrames for integrating relational ops in complex programs and extensible optimizer

Original Spark API

Resilient Distributed Datasets (RDDs)

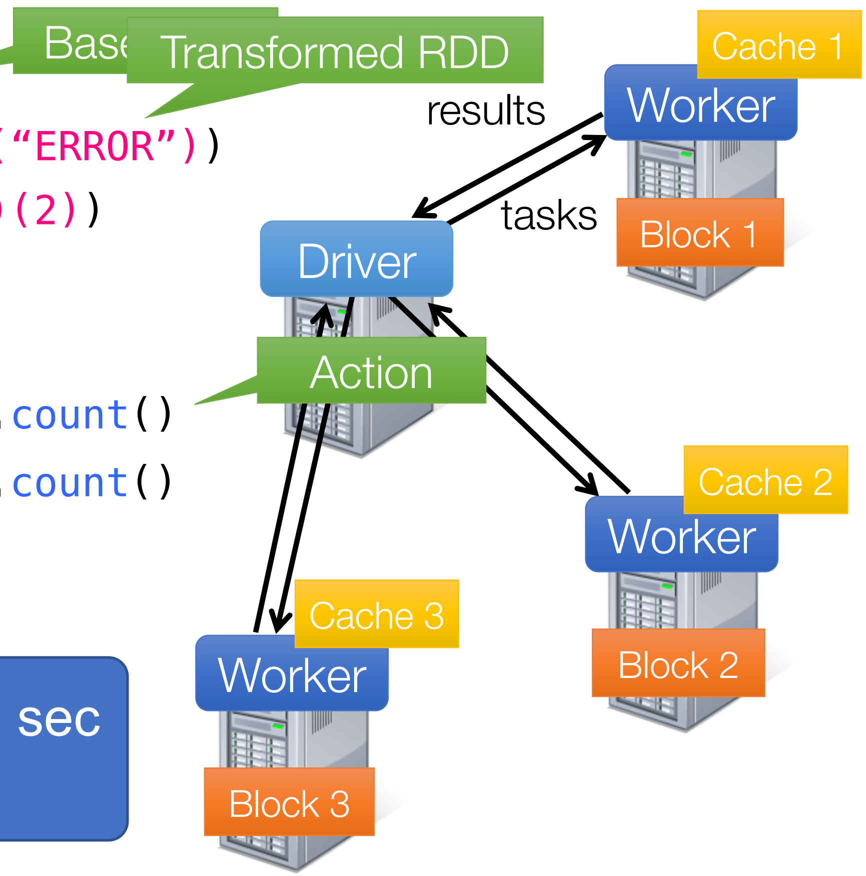
- Immutable collections of objects that can be stored in memory or disk across a cluster
- Built with parallel transformations (map, filter, …)
- Automatically rebuilt on failure

Example: Log Mining

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

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

messages.filter(s => s.contains("foo")).count()
messages.filter(s => s.contains("bar")).count()
. . .
```



Result: full-text search of Wikipedia in 1 sec (vs 40 s for on-disk data)

Challenges with Spark's Functional API

Looks high-level, but hides many semantics of computation from engine

» Functions passed in are arbitrary blocks of code

» Data stored is arbitrary Java/Python objects

Users can mix APIs in suboptimal ways

Example Problem

```
pairs = data.map(word => (word, 1))

groups = pairs.groupByKey()

groups.map((k, vs) => (k, vs.sum))
```

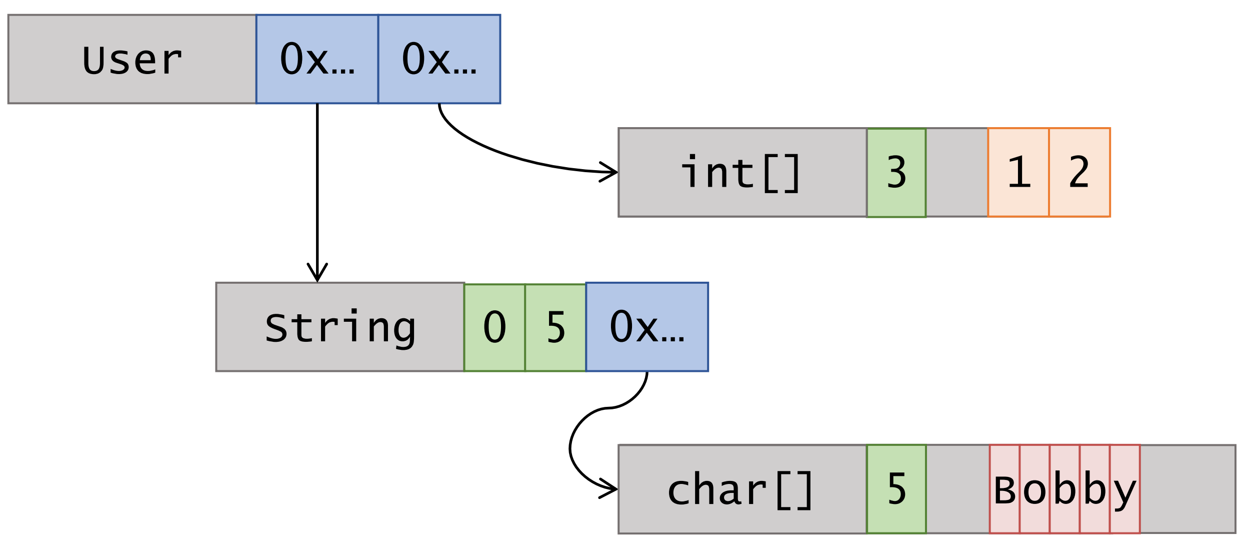
Materializes all groups as lists of integers

Then promptly aggregates them

Challenge: Data Representation

Java objects often many times larger than data

```
class User(name: String, friends: Array[Int])
User("Bobby", Array(1, 2))
```



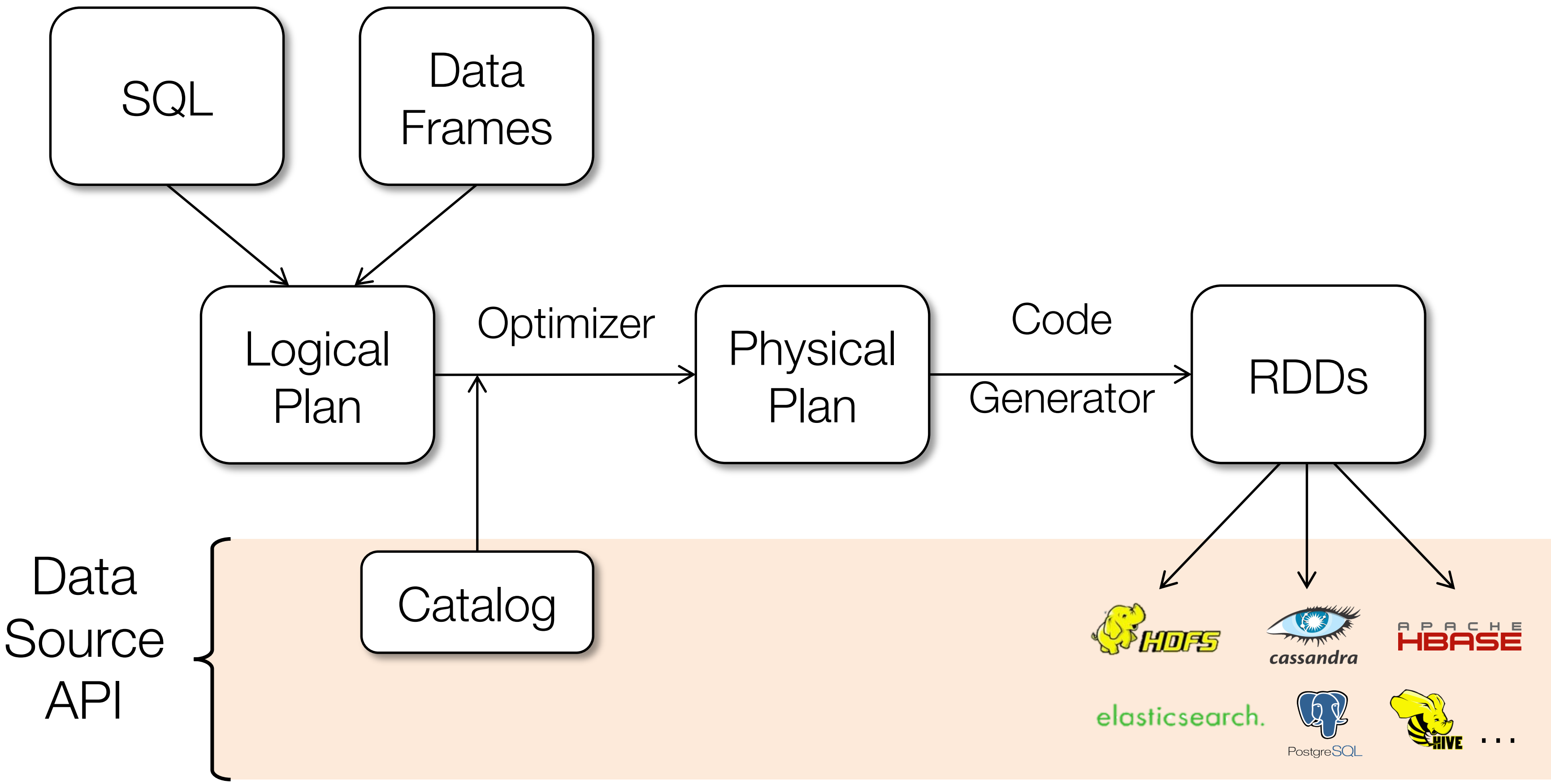
Spark SQL & DataFrames

Efficient library for working with structured data

» 2 interfaces: SQL for data analysts and external apps, DataFrames for complex programs

» Optimized computation and storage underneath

Spark SQL Architecture



DataFrame API

DataFrames hold rows with a known **schema** and offer **relational operations** through a DSL

```
c = HiveContext()
users = c.sql("select * from users")

ma_users = users[users.state == "MA"]
                      Expression AST
ma_users.count()

ma_users.groupBy("name").avg("age")

ma_users.map(lambda row: row.user.toUpper())
```

API Details

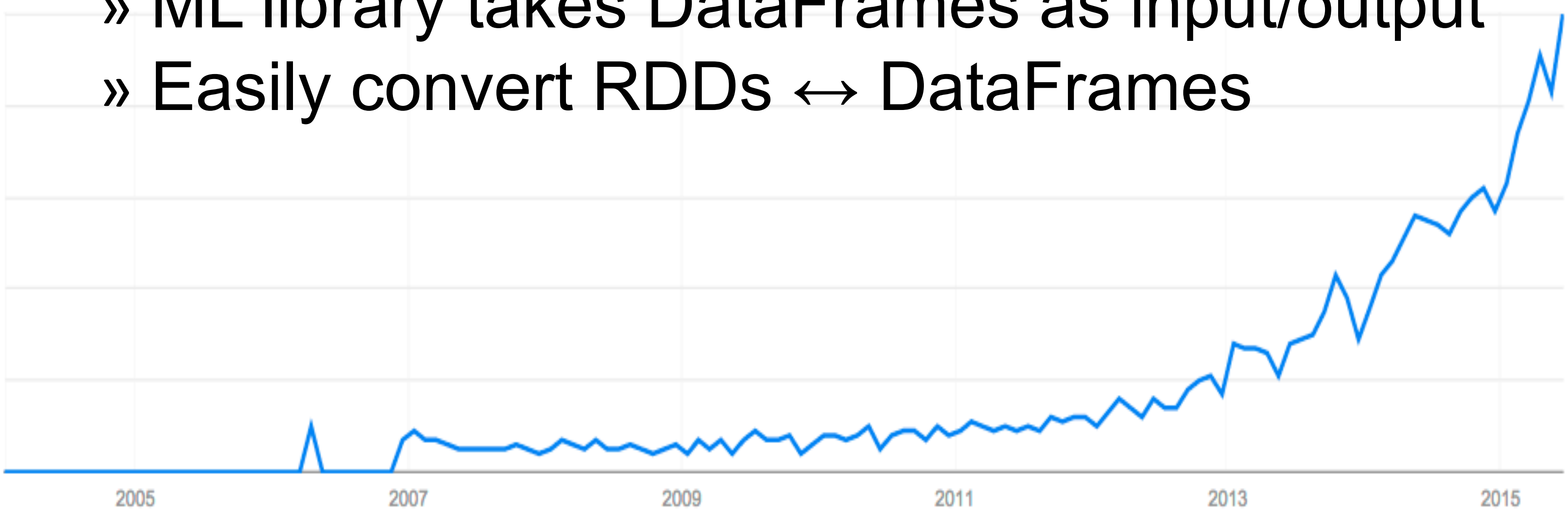
Based on data frame concept in R, Python

» Spark is the first to make this declarative

Integrated with the rest of Spark

» ML library takes DataFrames as input/output

» Easily convert RDDs ↔ DataFrames



Google trends for “data frame”

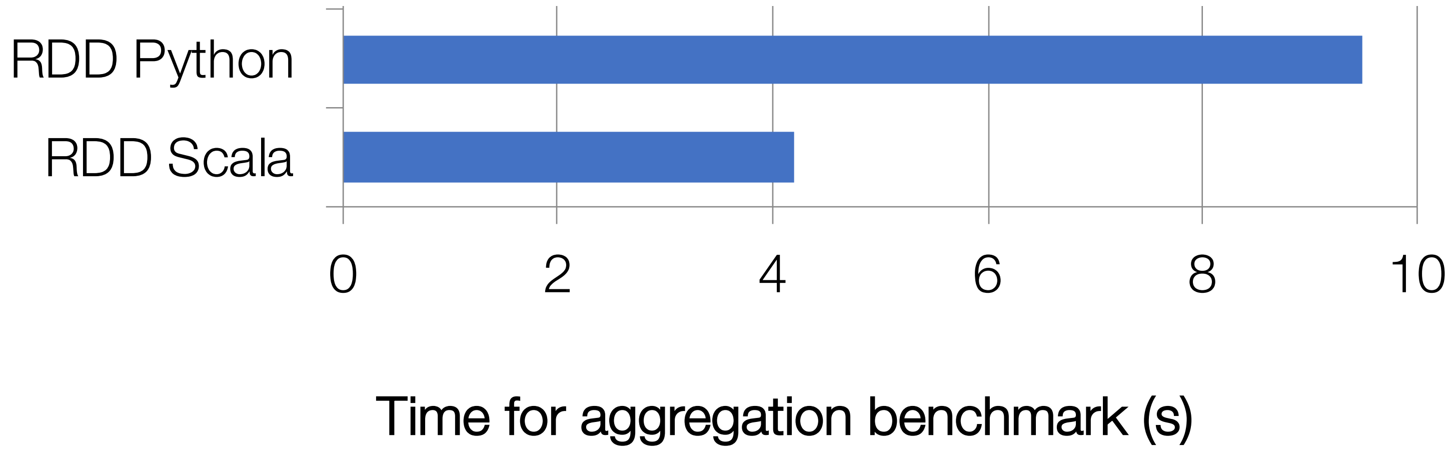
What DataFrames Enable

1. Compact binary representation
   - Columnar, compressed cache; rows for processing

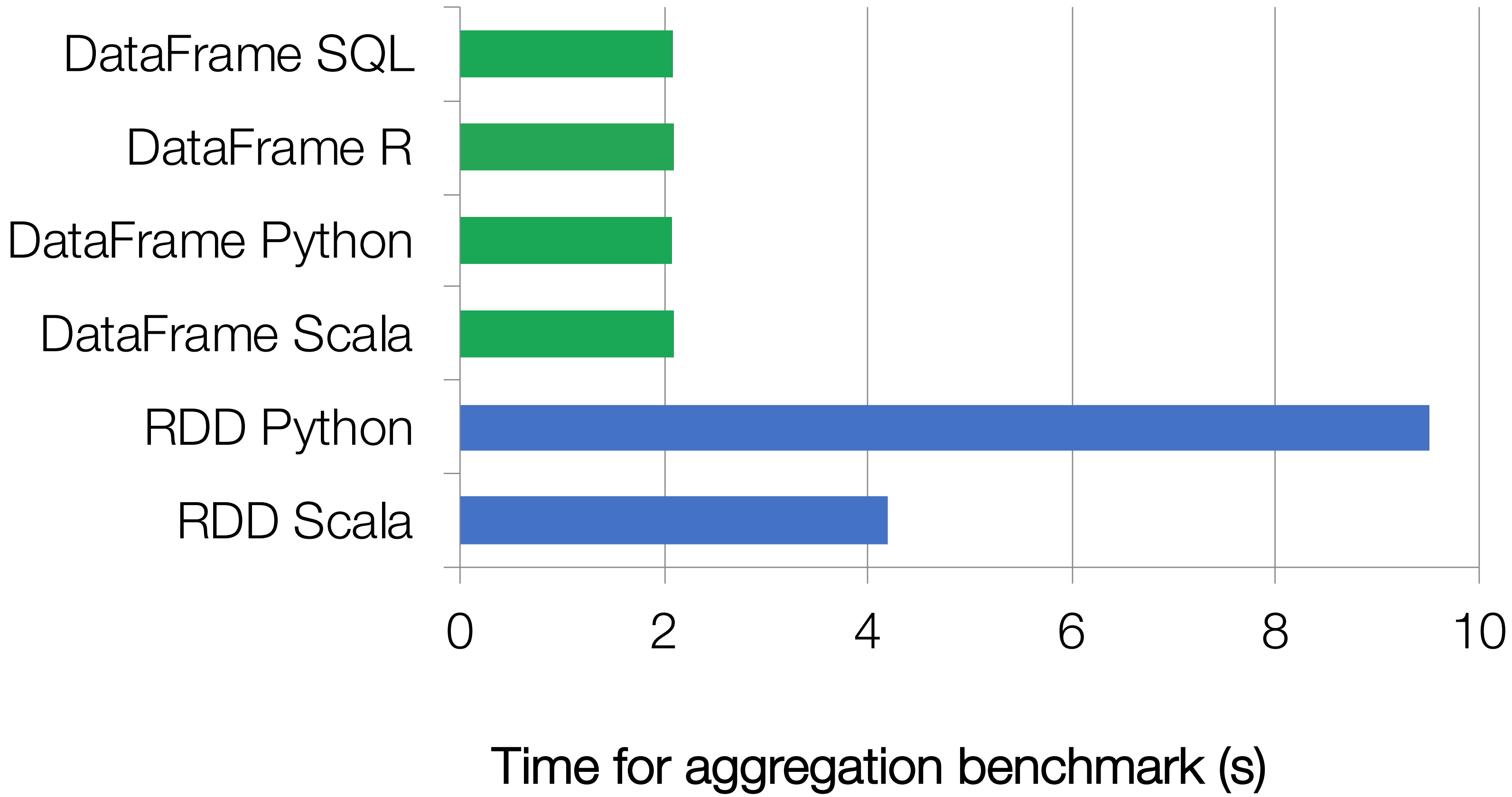
2. Optimization across operators (join reordering, predicate pushdown, etc)

3. Runtime code generation

Performance



Performance



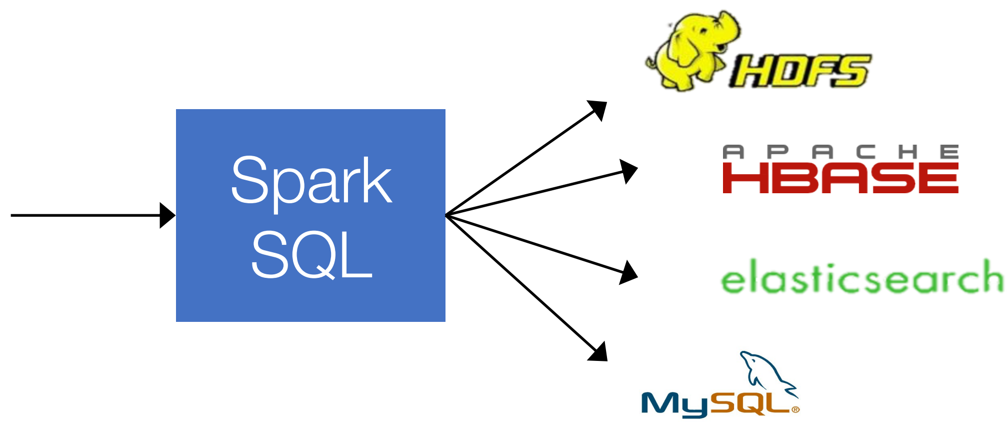
Data Sources

Uniform way to access structured data

- Apps can migrate across Hive, Cassandra, JSON, Parquet, …
- Rich semantics allows query pushdown into data sources

```
users[users.age > 20]

select * from users
```



Examples

JSON:

```
select user.id, text from tweets
```

```
{
 “text”: “hi”,
 “user”: {
   “name”: “bob”,
   “id”: 15 }
}
```

tweets.json

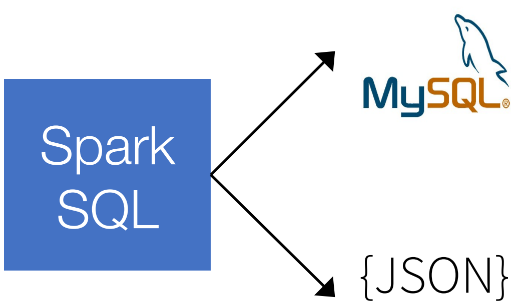
JDBC:

```
select age from users where lang = “en”
```

Together:

```
select t.text, u.age
from tweets t, users u
where t.user.id = u.id
and u.lang = “en”
```

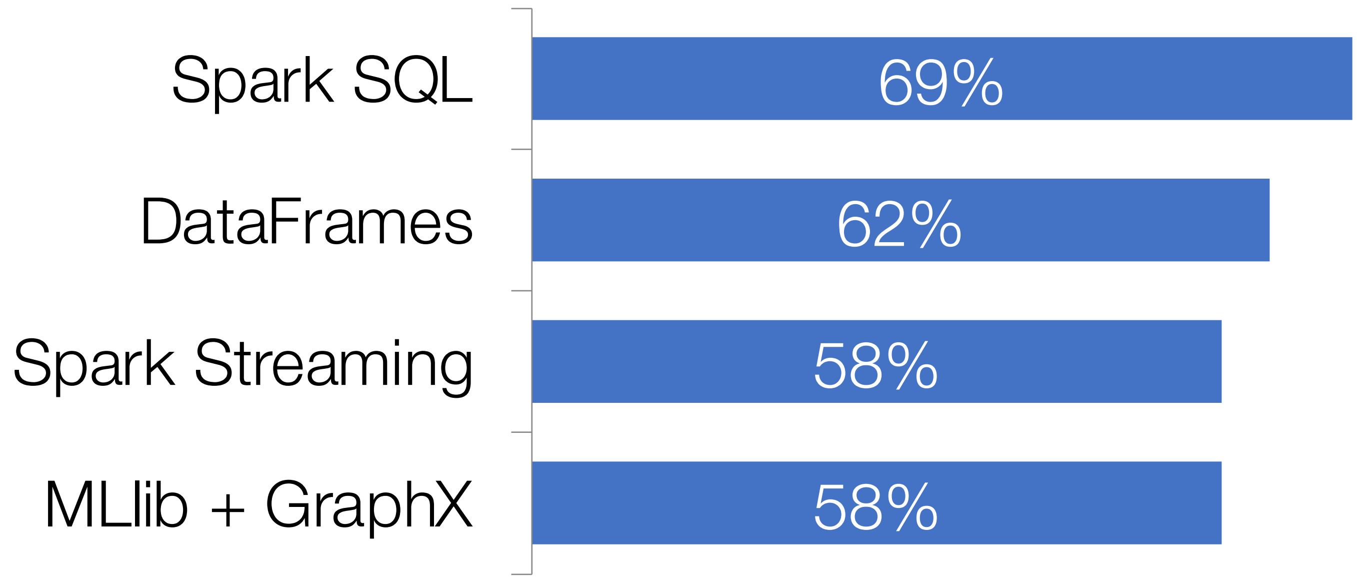
```
select id, age from
users where lang=“en”
```



Extensible Optimizer

Uses Scala pattern matching (see demo!)

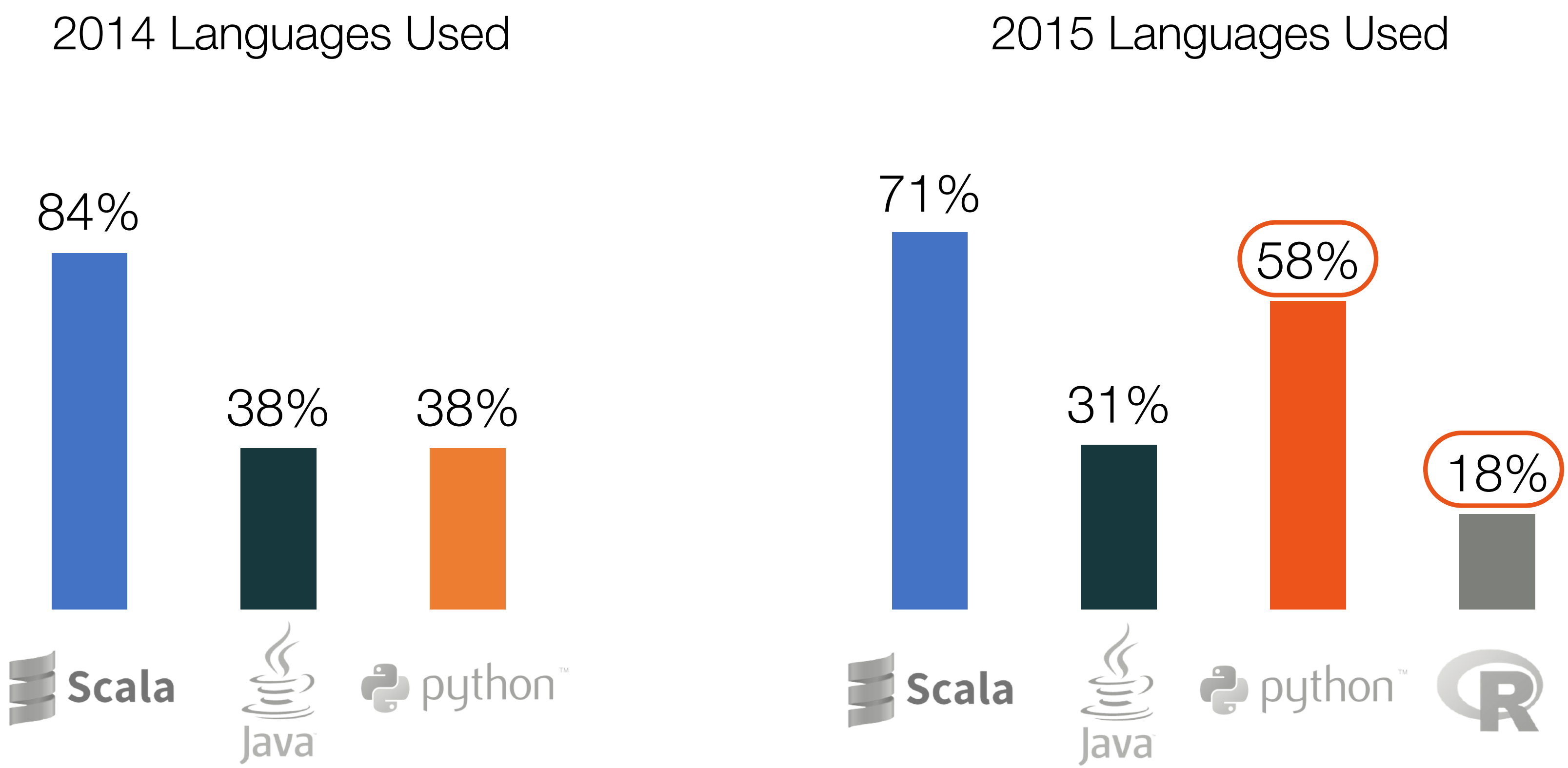
Which Spark Components Do People Use?



75% of users use 2 or more components

(2015 survey)

Which Languages Are Used?



Extensions to Spark SQL

Tens of data sources using the pushdown API

Interval queries on genomic data

Geospatial package (Magellan)

Approximate queries & other research