Query Optimization 2

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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:

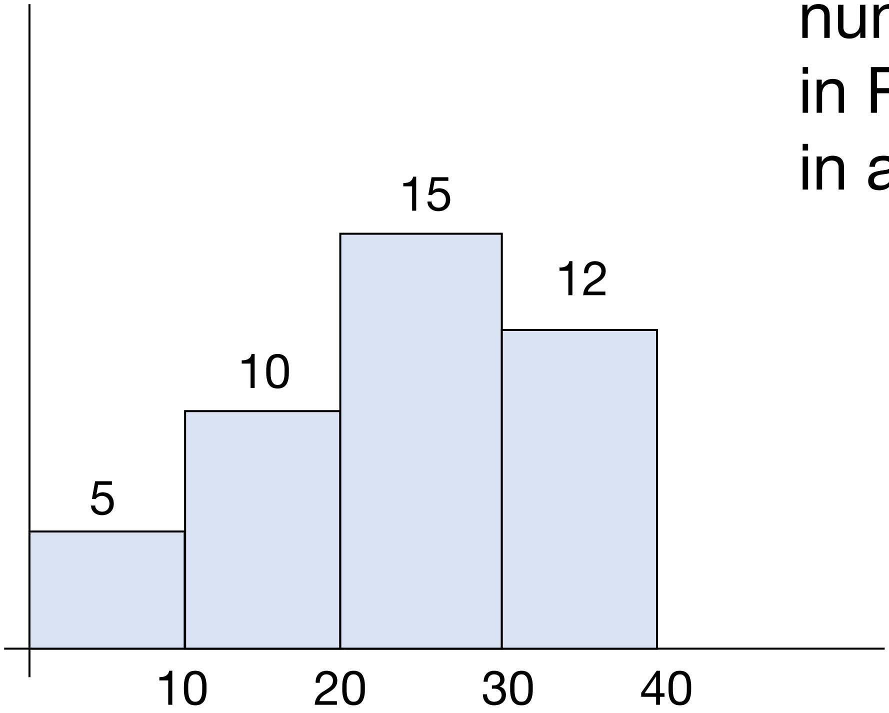
» T(R) = # of tuples in R

» 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:

- » $\boxed{\text{Number of disk I/Os}}$ ← 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]

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

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

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}:

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

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

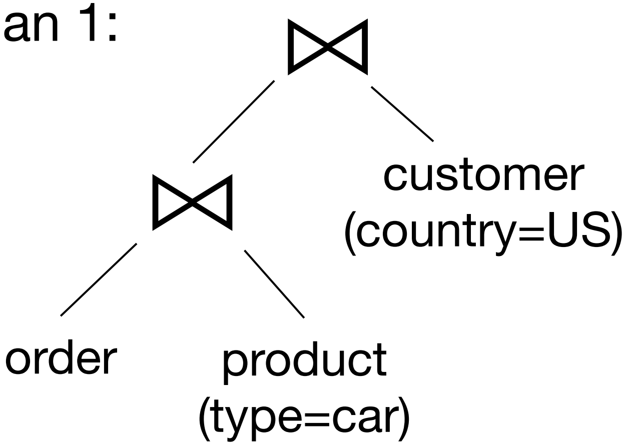
Example

```
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”
```

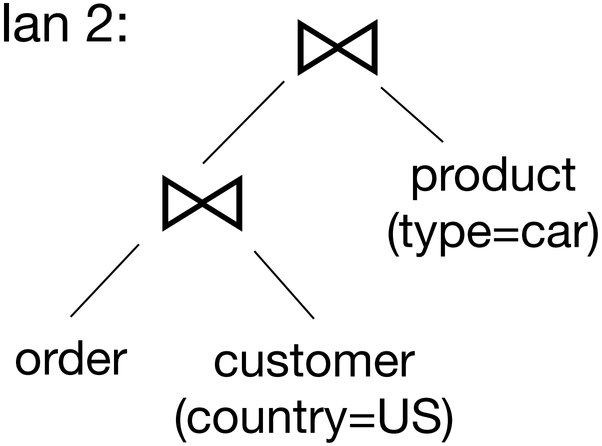
join conditions

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 R₁[i].C == R₂[j].C && i ≤ T(R₁):
      jj = j
      while R₁[i].C == R₂[jj].C && jj ≤ T(R₂):
         output (R₁[i], R₂[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

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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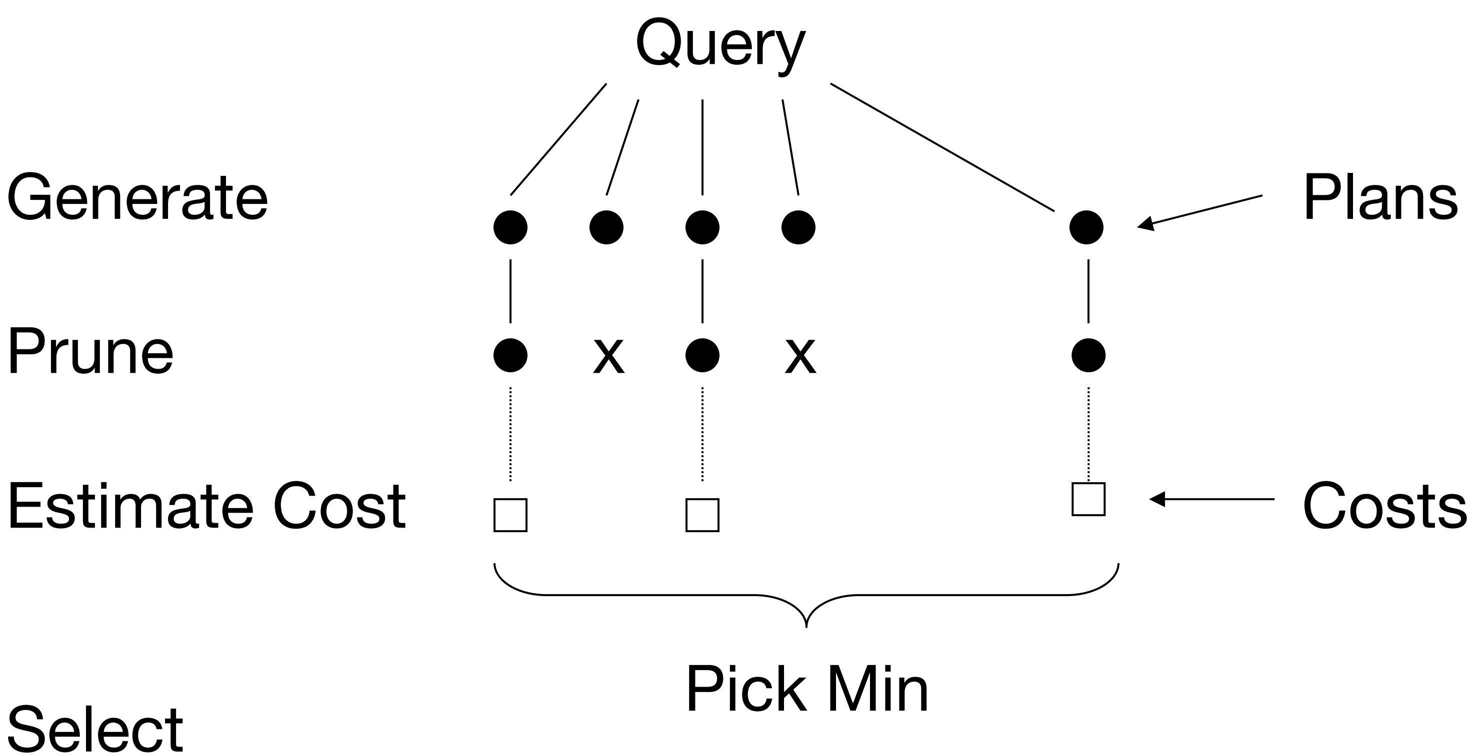
Complete CBO Process

Generate and compare possible query plans



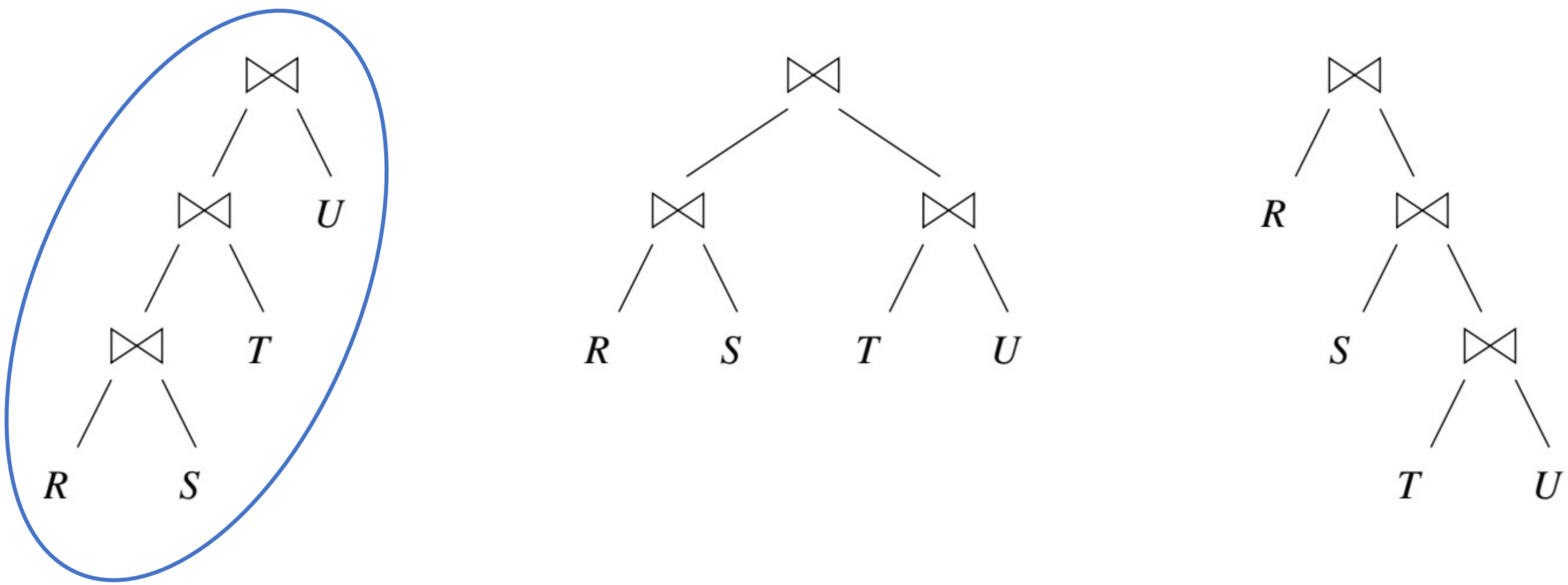
How to Generate Plans?

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



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!

Must 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 execution cost (e.g. join order)

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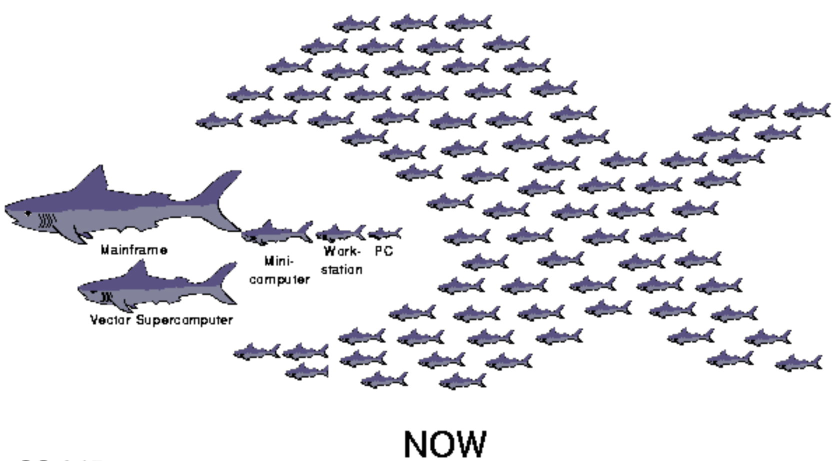
Background

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 models to bring MR's benefits to other apps

APACHE STORM™

GraphLab

APACHE GIRAPH

Google
Pregel

Google
Dremel

Impala

Microsoft
Dryad

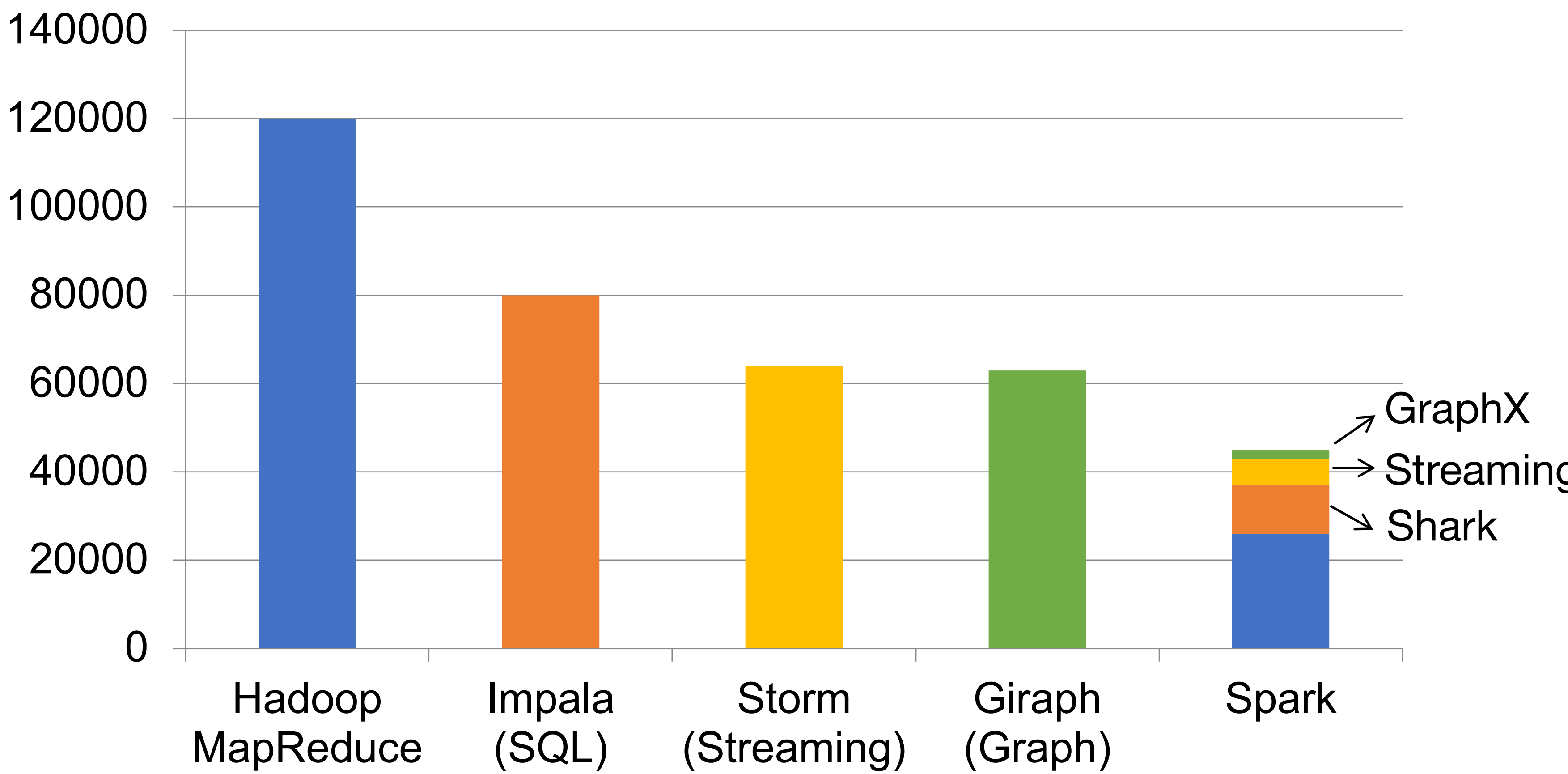
Background

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

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

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 DataFrames for integrating relational ops in Scala/Java/Python programs

Original Spark API

Resilient Distributed Datasets (RDDs)

» Immutable collections of objects that can be stored in memory or disk across a cluster

» Built via parallel transformations (map, filter, …)

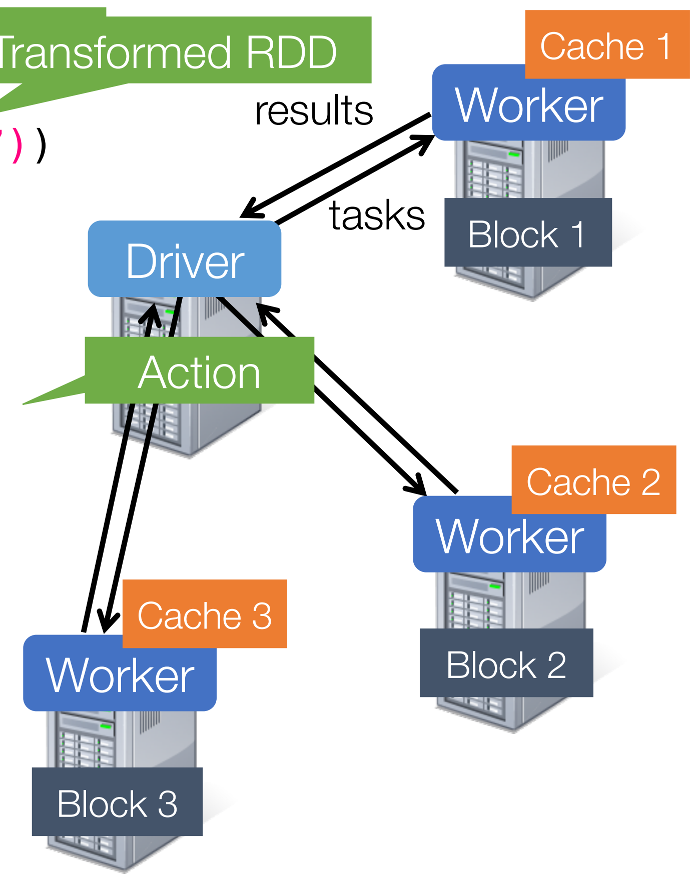
» Automatically rebuilt on failure

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()
. . .
```



Interactive ad-hoc queries in your favorite language

Challenges with Spark's Functional API

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

- Functions passed in are arbitrary 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

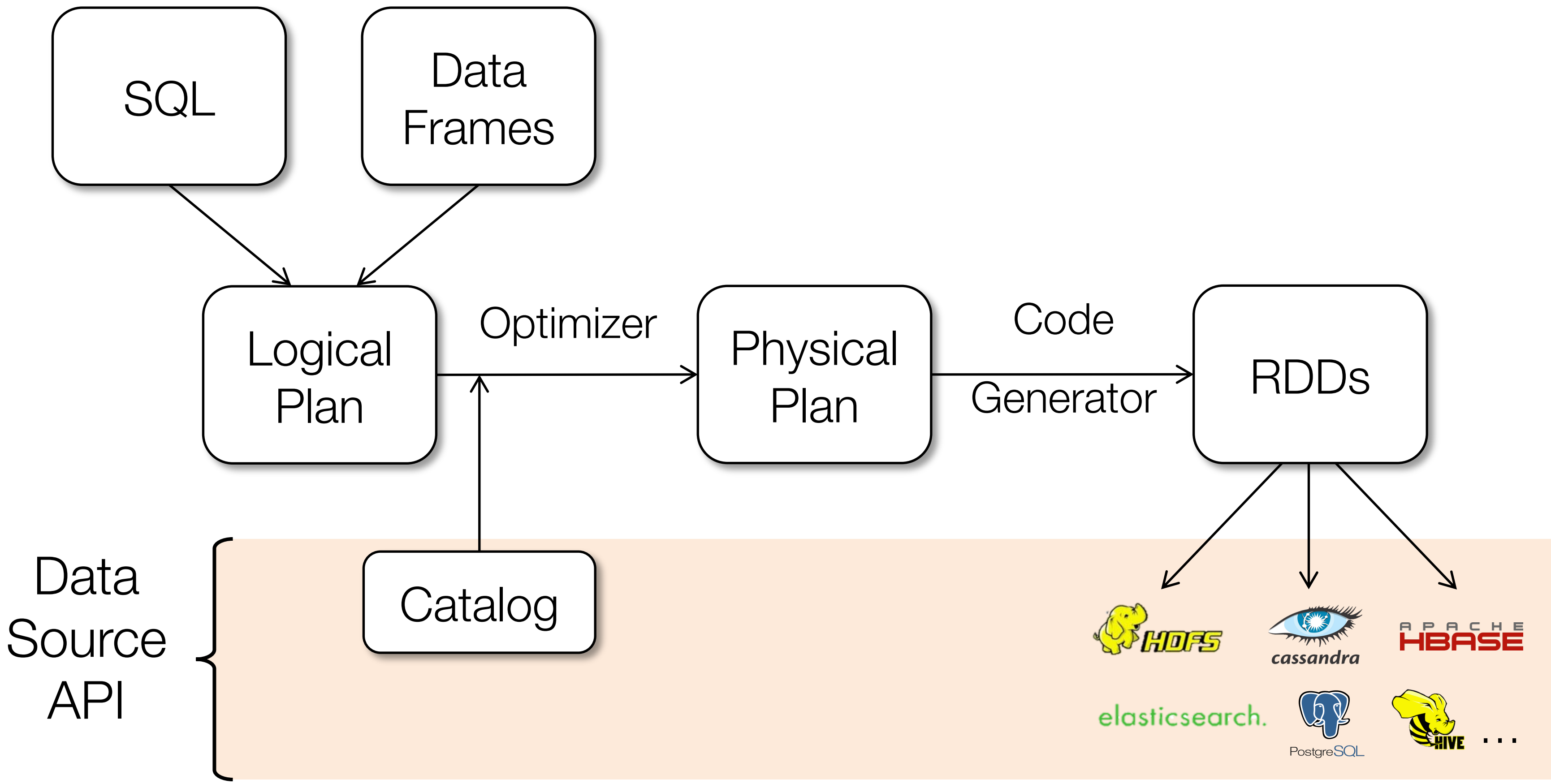
Then promptly aggregates them

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 & 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, Pandas

» 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

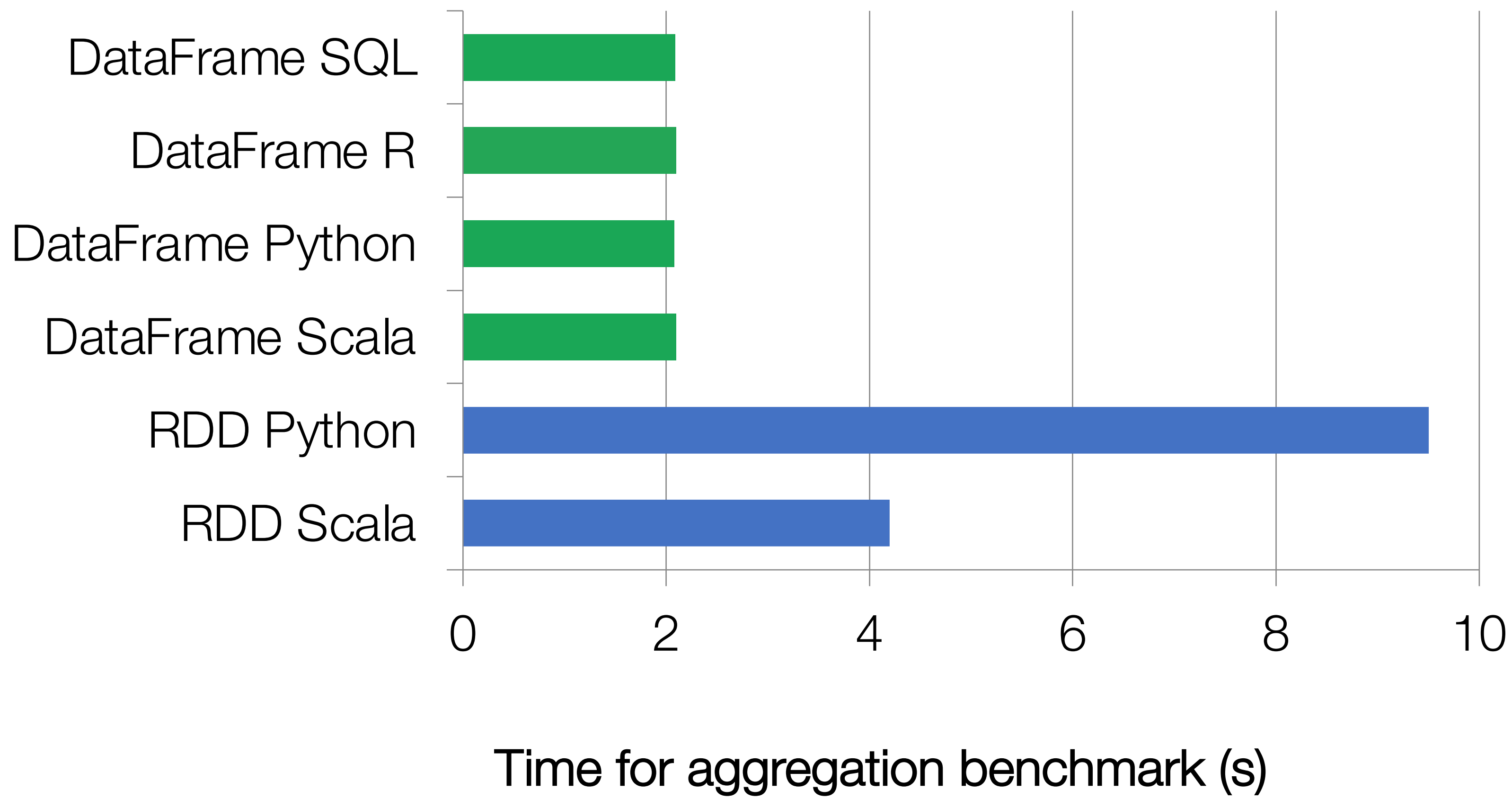
What DataFrames Enable

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

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

3. Runtime code generation

Performance



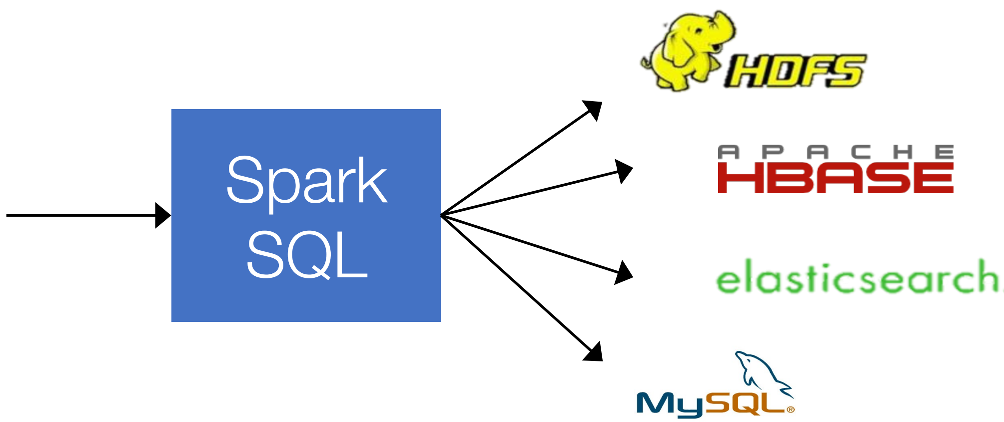
Data Sources

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

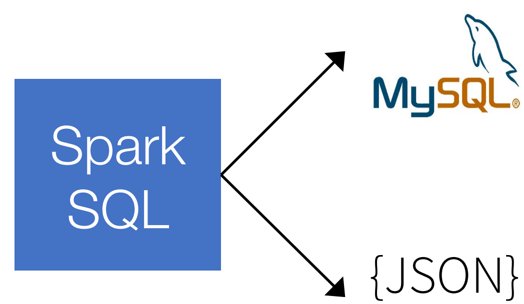
JDBC:

```
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”
```

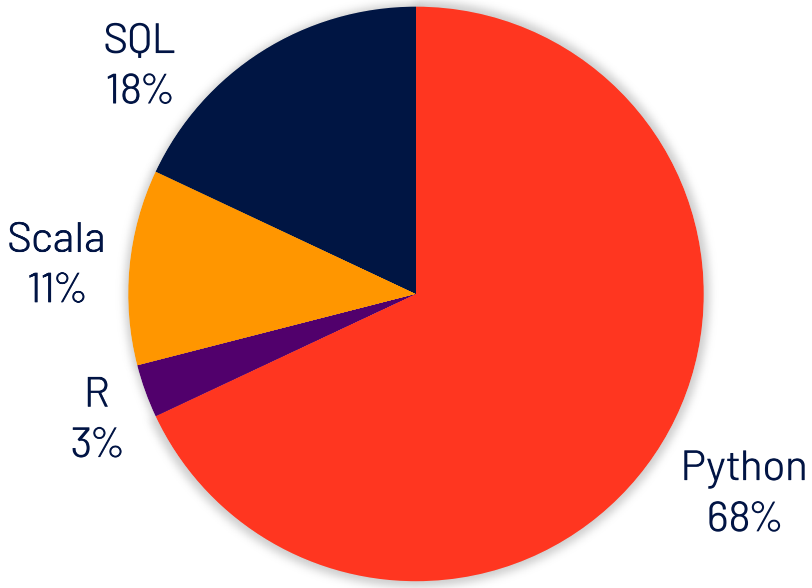


Extensible Optimizer

Uses Scala pattern matching (see demo!)

Spark Usage Today

Languages Used in Databricks Notebooks



>90%

of API calls run via Spark SQL engine

Extensions to Spark SQL

Structured Streaming (streaming SQL)

Many data sources using the pushdown API

Interval queries on genomic data

Geospatial package (Magellan)