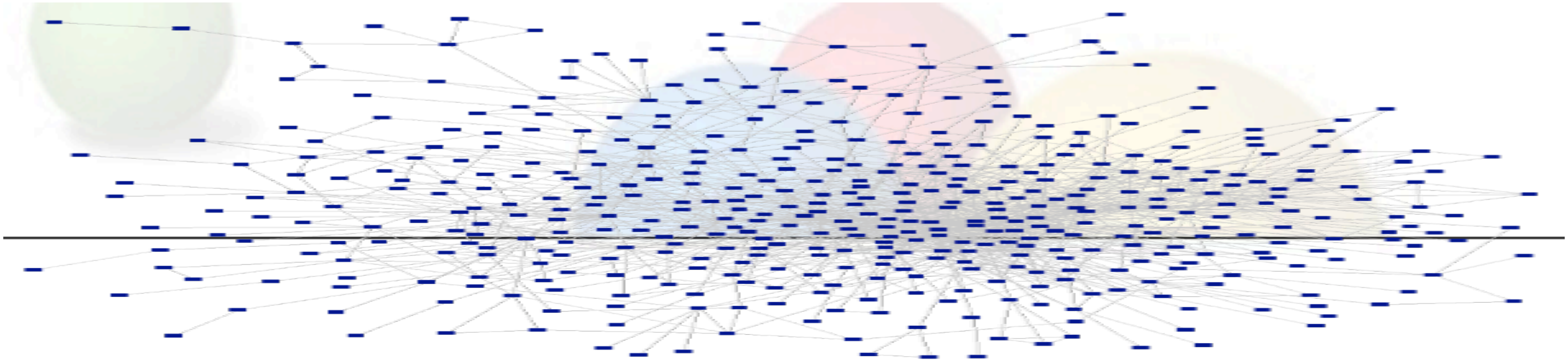

Think Like a {Vertex, Column, Parallel Collection}

David Konerding, Google Inc.

Pregel: a system for large-scale graph processing
Grzegorz Malewicz, Matthew H. Austern, Aart J.C. Bik, James C. Dehnert, Ilan Horn, Naty Leiser, Grzegorz Czajkowski
SIGMOD'10

Dremel: Interactive Analysis of Web-Scale Datasets
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VLDB'10

FlumeJava: Easy, Efficient data-parallel pipelines
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PLDI'10

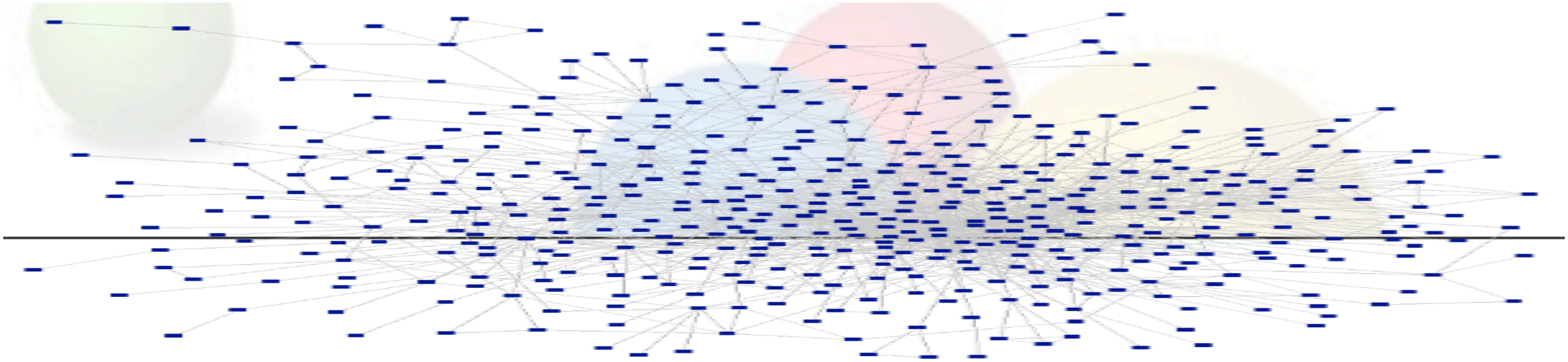
Google's data-intensive parallel processing toolbox

MapReduce is already well-known; external implementations are becoming popular in industry and academia.

MR is not designed to handle many kinds of problems, so in the past few years we have developed new toolkits/frameworks for doing data-intensive parallel processing.

Some common situations where we need alternatives:

- Large graph operations with multiple steps.
- Interactive tools for data analysts dealing with trillion-row datasets.
- Pipelines with complex data flow



Think Like a Vertex

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SIGMOD'10

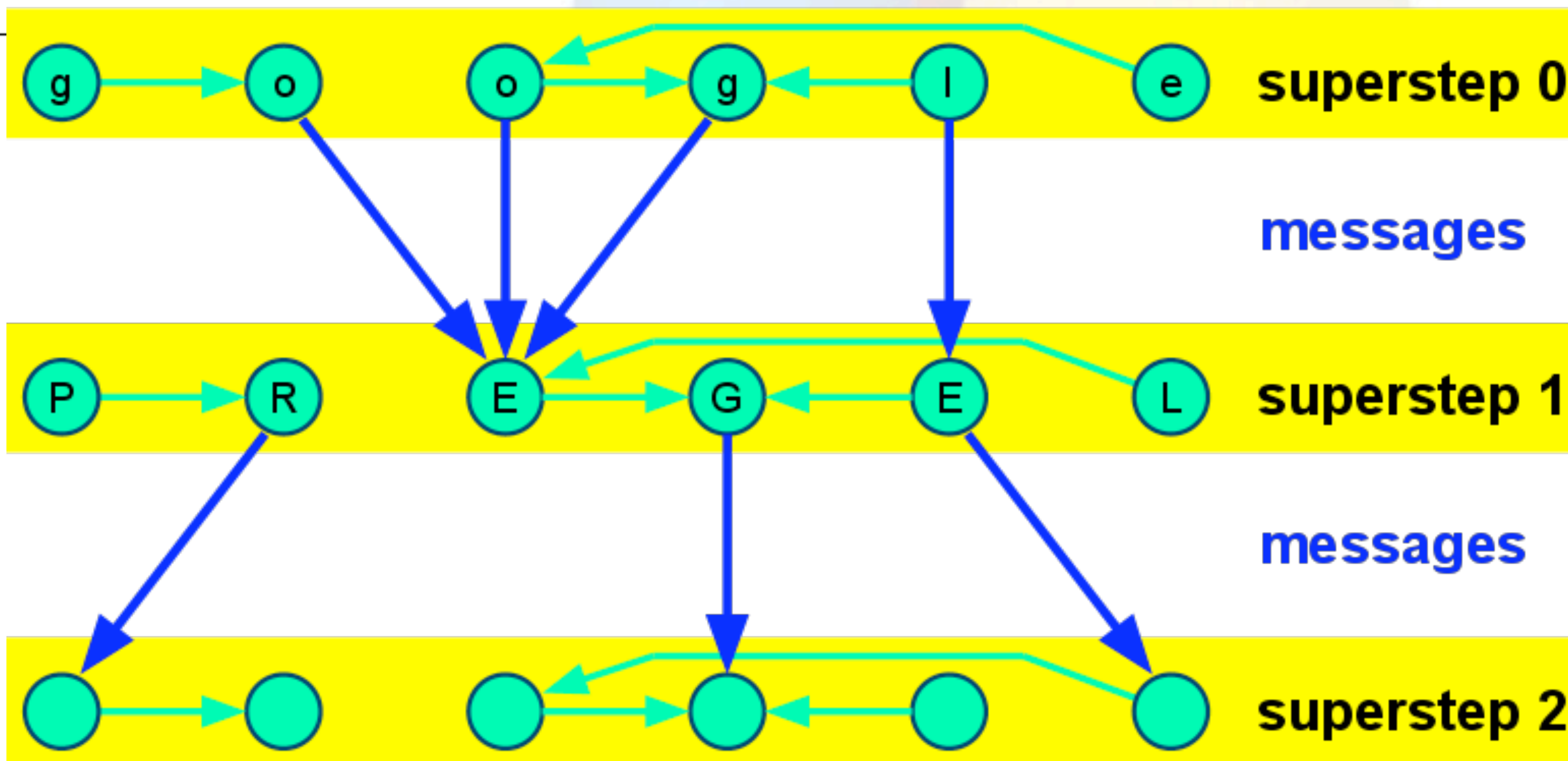
Most similar existing framework: Parallel Boost Graph

Google

Model of graph computation

graph

Motivated by:
Bulk Synchronous Parallel
Valiant, CACM'90



- computation on local data (parallelism, !deadlock, !race)
- "batch&push" communication, no "pull" (!latency)
- message sending overlaps with computing
- synchronization barriers (programmability)

halt

Single-source shortest paths in Pregel

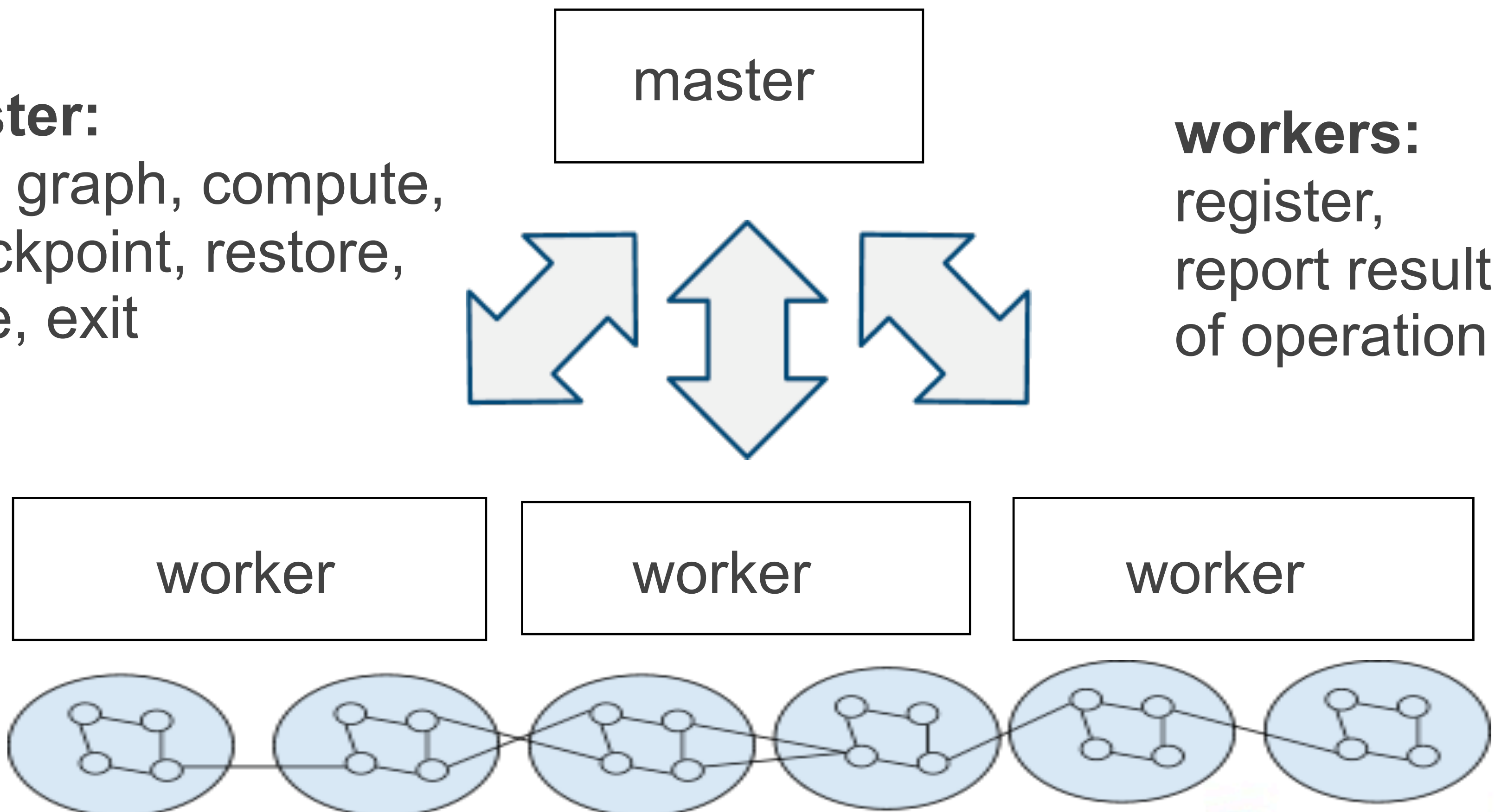
```
class ShortestPathVertex : public Vertex<int, int, int> {
 public:
  virtual void Compute(MessageIterator* messages) {
    int min_dist = IsSource(vertex_id()) ? 0 : INT_MAX;
    for (; !messages->Done(); messages->Next()) {
      min_dist = min(min_dist, messages->Value());
    }
    if (min_dist < GetValue()) {
      *MutableValue() = min_dist;
      OutEdgeIterator iter = GetOutEdgeIterator();
      for (; !iter.Done(); iter.Next()) {
        SendMessageTo(iter.Target(),
                      min_dist + iter.GetValue());
      }
    }
    VoteToHalt();
  }
};
```

vertex value is initialized to INT_MAX

Implementation

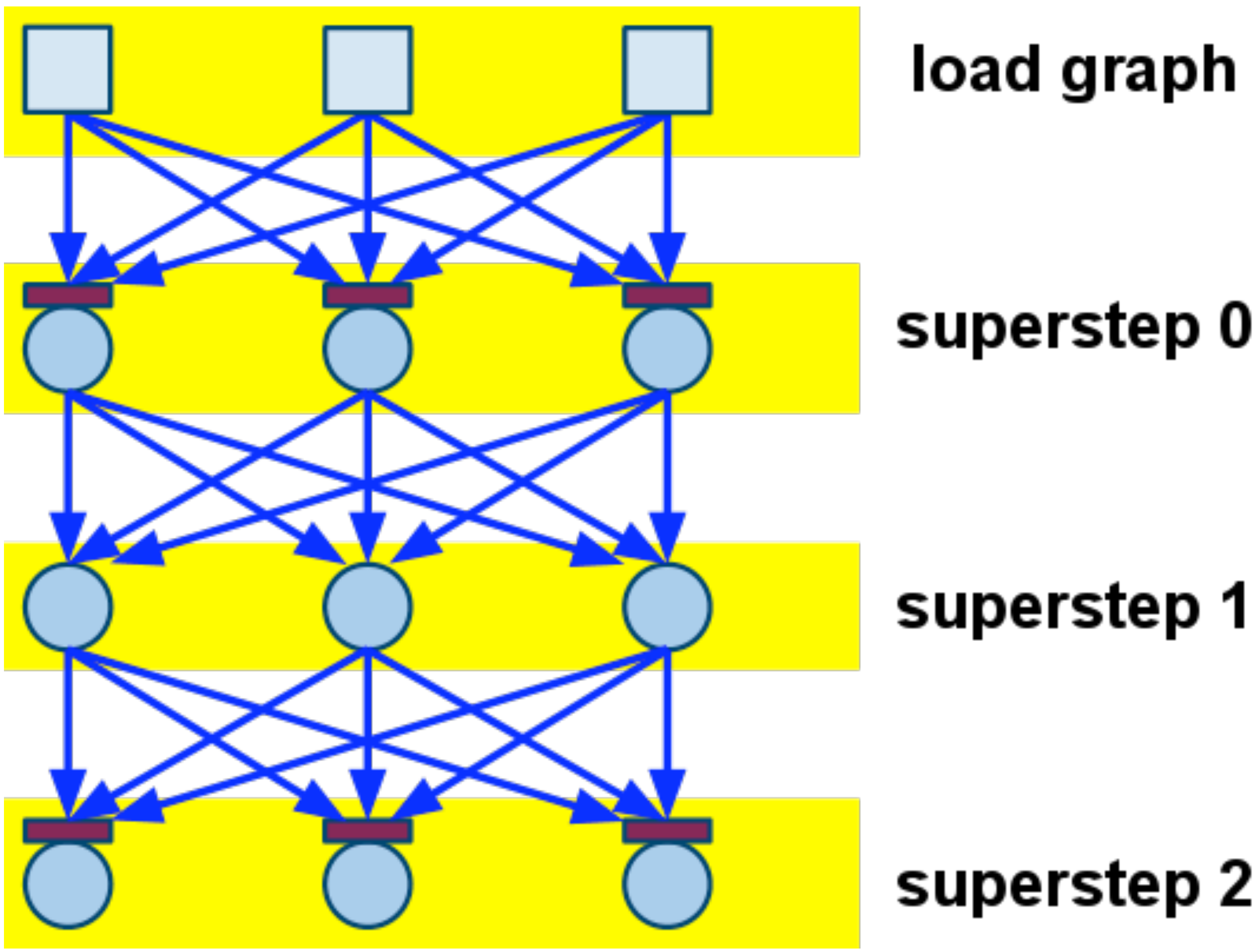
master:
load graph, compute, checkpoint, restore, save, exit

workers:
register, report result of operation



Graph partitioned across workers. Partitions reside in workers' memory

Fault-tolerance



Daly, FGCS '06 :

optimal time between checkpoints =

sqrt(2 * C * M) - C

C = [constant] checkpoint cost

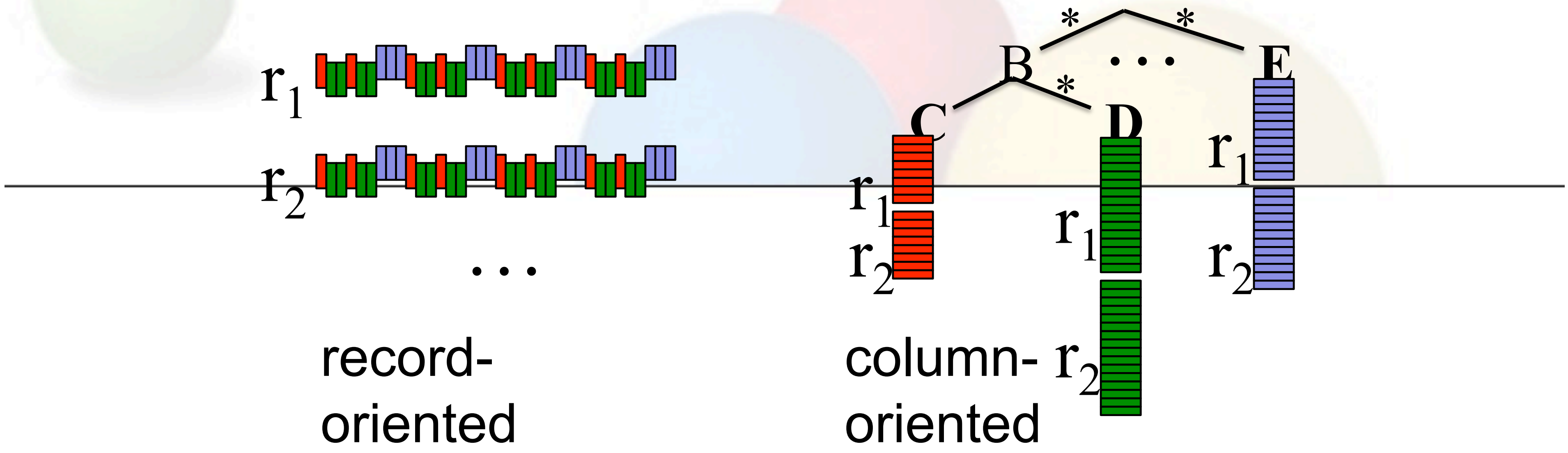
M = mean time to [Poisson] failure

Usage of Pregel at Google

Easy to program and expressive

- Breadth-first search
- Strongly connected components
- PageRank
- Label propagation algorithms
- Minimum spanning tree
- Δ-stepping parallelization of Dijkstra's SSSP algorithm
- Several kinds of vertex clustering
- Maximum and maximal weight bipartite matchings
- many more!

Used in dozens of projects at Google



Think Like a Column

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VLDB’10

Most similar external application: Hadoop Pig

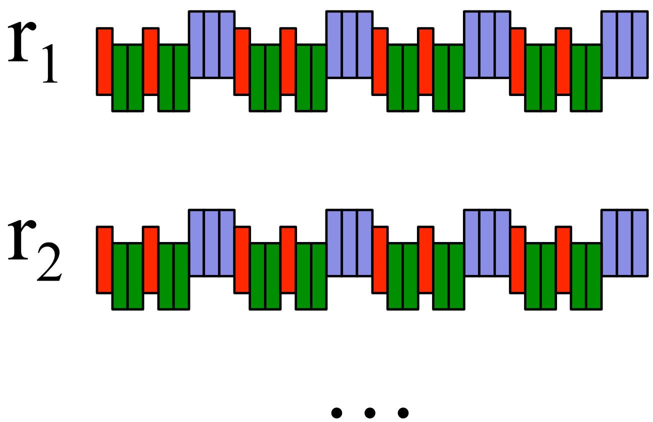
Dremel

- Trillion-record, multi-terabyte datasets
- Scales to thousands of nodes
- Interactive speed
- Nested data
- Columnar storage and processing
- *In situ* data access (e.g., GFS, Bigtable)
- Aggregation tree architecture
- Interoperability with Google's data management tools (e.g., MapReduce)

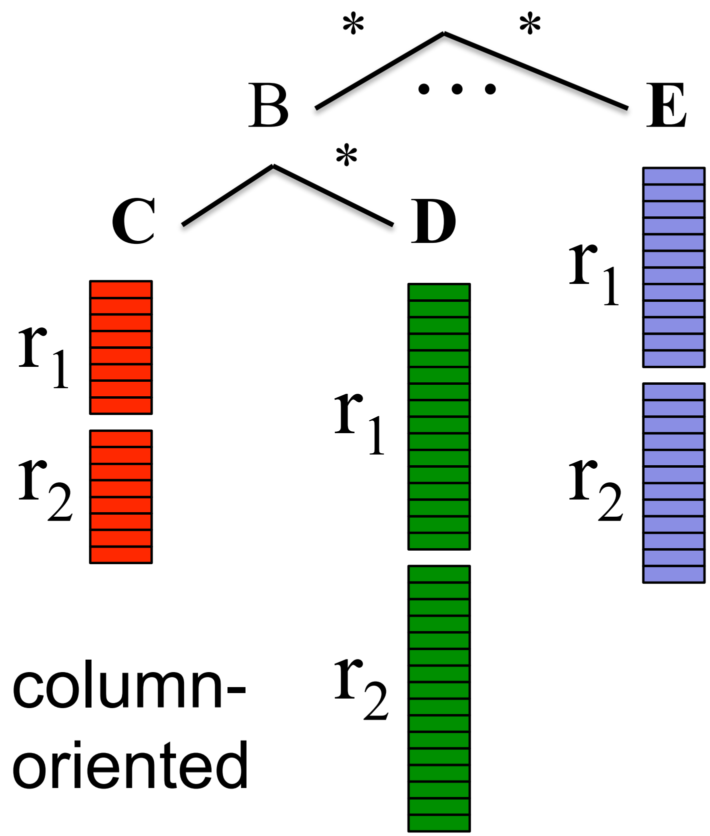
Query processing

- Data model: ProtoBufs (~nested relational)
- Select-project-aggregate (single scan)
  - Most common class of interactive queries
  - Aggregation within-record and cross-record
  - Filtering based on within-record aggregates
- Fault-tolerant execution
- Approximations: count(distinct), top-k
- Joins, temp tables, UDFs/TVFs, etc.
- Limited support for recursive types

Record versus column oriented data

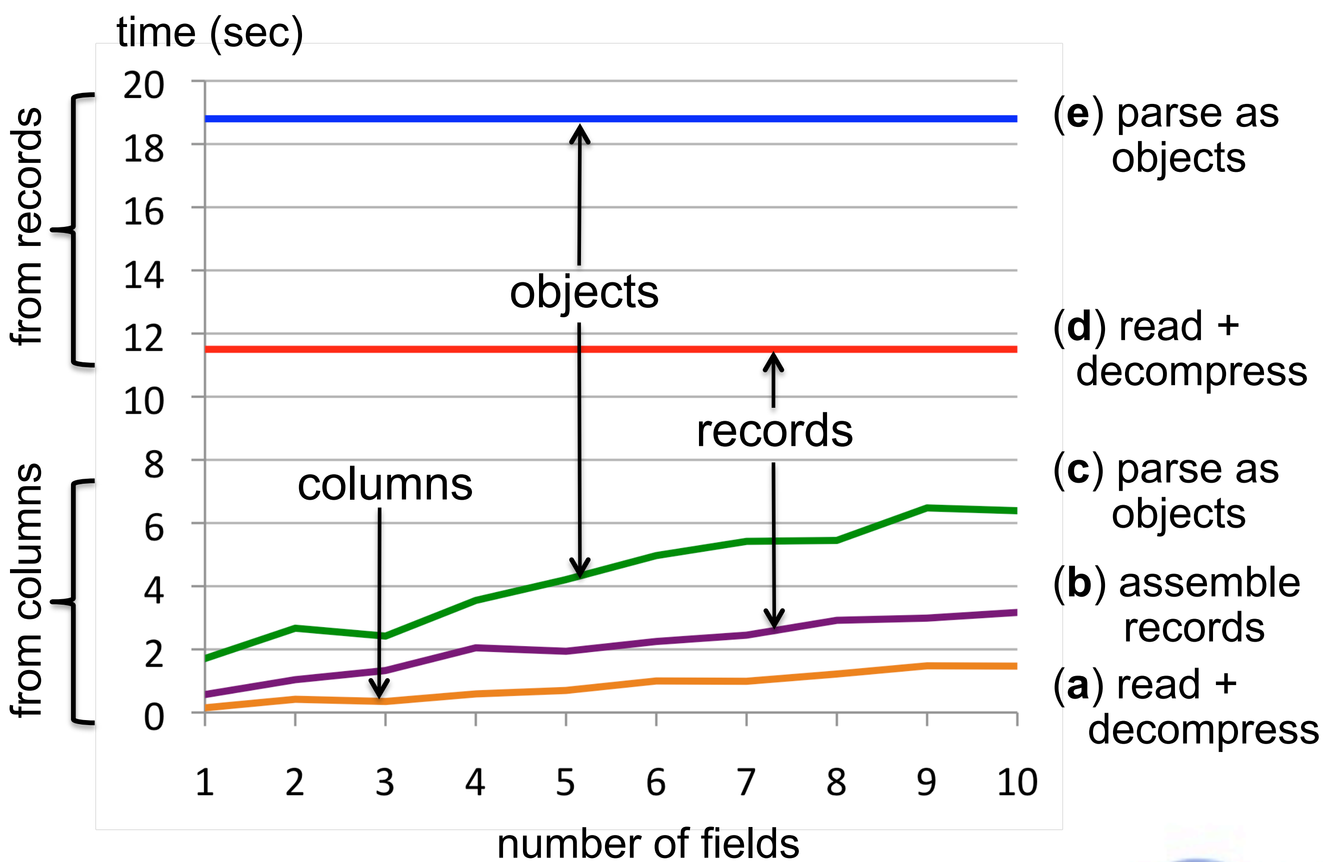


record-
oriented

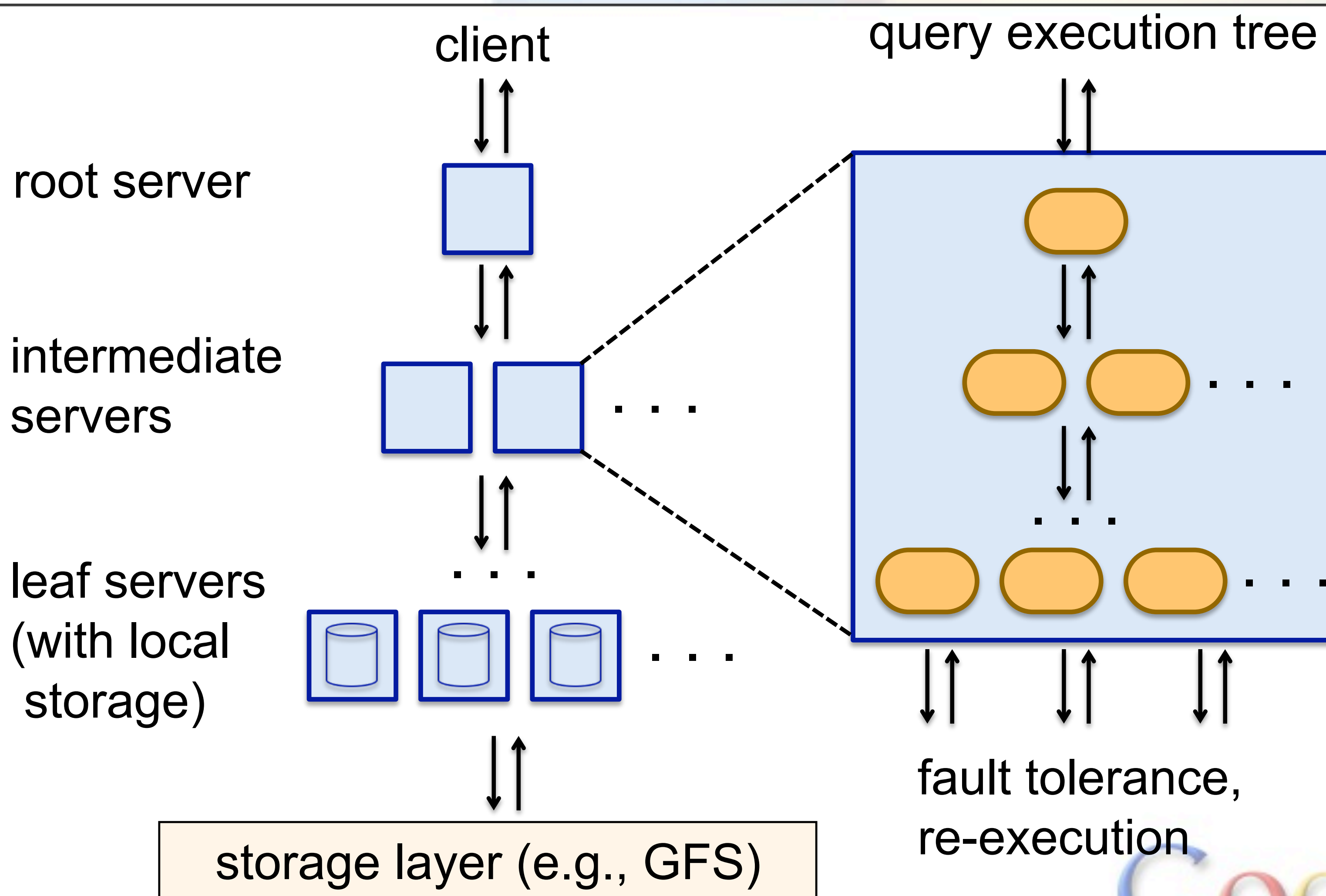


column-
oriented

Performance Breakdown comparing record reads to column reads



Mixer tree


client
query execution tree
root server
intermediate servers
leaf servers (with local storage)
storage layer (e.g., GFS)
fault tolerance, re-execution

Example: count(*)

0

SELECT A, COUNT(B) FROM T
GROUP BY A
T = {/gfs/1, /gfs/2, …, /gfs/100000}

→

SELECT A, SUM(c)
FROM ($R_1$1 UNION ALL $R_1$10)
GROUP BY A

1

$R_1$1

SELECT A, COUNT(B) AS c
FROM $T_1$1 GROUP BY A
$T_1$1 = {/gfs/1, …, /gfs/10000}

$R_1$2

SELECT A, COUNT(B) AS c
FROM $T_1$2 GROUP BY A
$T_1$2 = {/gfs/10001, …, /gfs/20000}

. . .

2

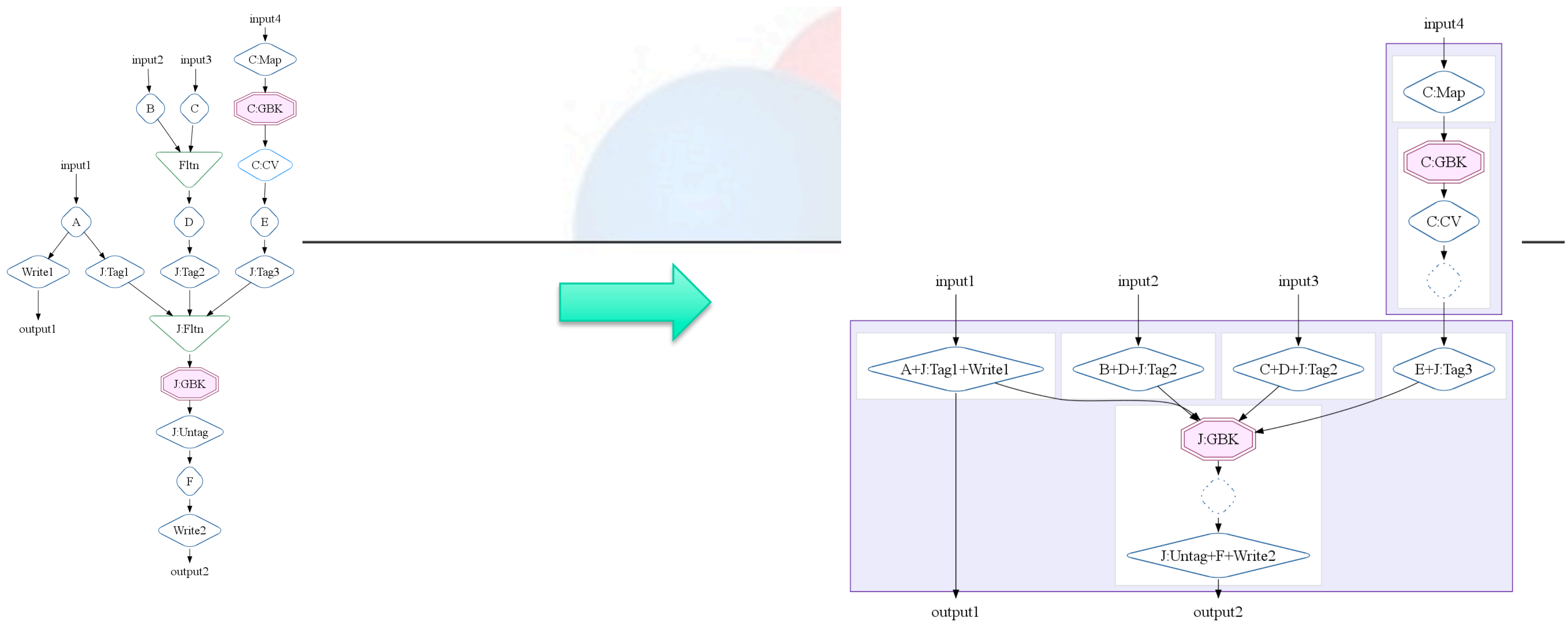
SELECT A, COUNT(B) AS c
FROM $T_2$1 GROUP BY A
$T_2$1 = {/gfs/1}

. . .

File::PRead()

Widely used inside Google

- Analysis of crawled web documents
- Tracking install data for applications on Android Market
- Crash reporting for Google products
- OCR results from Google Books
- Spam analysis
- Debugging of map tiles on Google Maps
- Tablet migrations in managed Bigtable instances
- Results of tests run on Google's distributed build system
- Disk I/O statistics for hundreds of thousands of disks
- Resource monitoring for jobs run in Google's data centers
- Symbols and dependencies in Google's codebase



Think Like a Parallel Collection

<u>FlumeJava: Easy, Efficient data-parallel pipelines</u>

Craig Chambers, Ashish Raniwala, Frances Perry, Stephen Adams, Robert R. Henry, Robert Bradshaw, Nathan Weizenbaum

PLDI'10

Most similar external application: Hadoop Cascading, Pipes, Dryad/LINQ

Parallel Collections

- PCollection<*T*>, PTable<*K*,*V*>:
  (possibly huge) parallel collections
  - parallelDo(*DoFn*) ← Map() equivalent
  - groupByKey() ← Shuffle() equivalent
  - combineValues(*CombineFn*) ← Combiner() / Reducer() equivalent
  - flatten(...)
  - read*File*(...), writeTo*File*(...)
- Work with Java data & control structures
  - join(...), count(), top(*CompareFn*,*N*), ...

```
PCollection<String> lines =
  readTextFileCollection("/gfs/data/shakes/hamlet.txt");
PCollection<DocInfo> docInfos =
  readRecordFileCollection("/gfs/webdocinfo/part-*",
  recordsOf(DocInfo.class));
```

Example: TopWords

```
readTextFile("/gfs/corpus/*.txt")
.parallelDo(new ExtractWordsFn())
.count()
.top(new OrderCountsFn(), 1000)
.parallelDo(new FormatCountFn())
.writeToTextFile("cnts.txt");

FlumeJava.run();
```

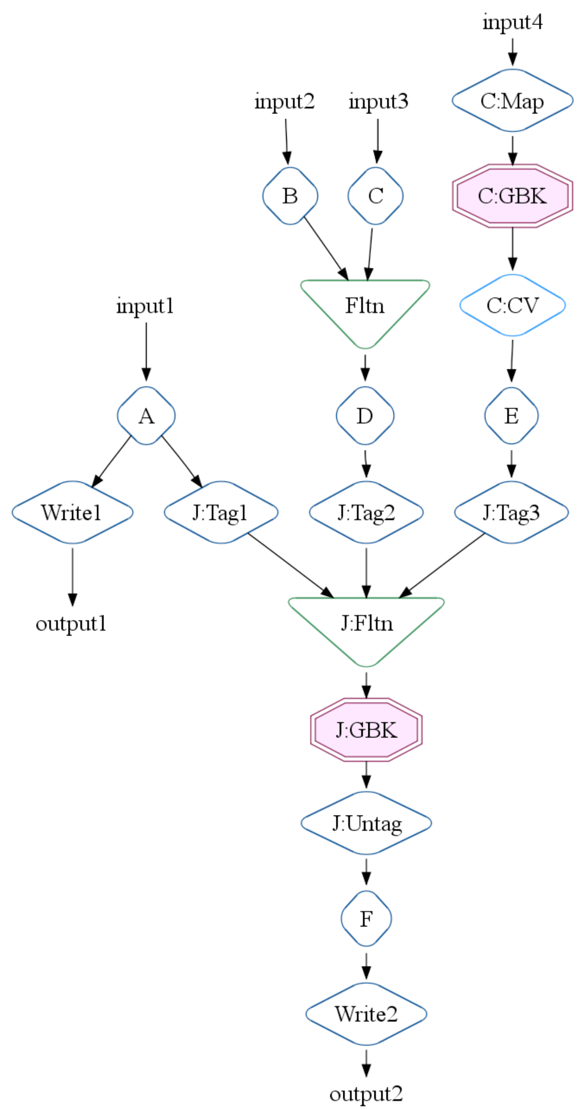
Deferred Evaluation & The Execution Graph

- Primitives, e.g., `parallelDo(...)`, are “lazy”
  - Just append to **execution graph**
  - Result PCollections are like “futures”
- Other code, e.g., `count()`, is “eager”
  - “Inlined” down to primitives
- `FlumeJava.run()` “demands” evaluation
  - Optimizes, then runs execution graph

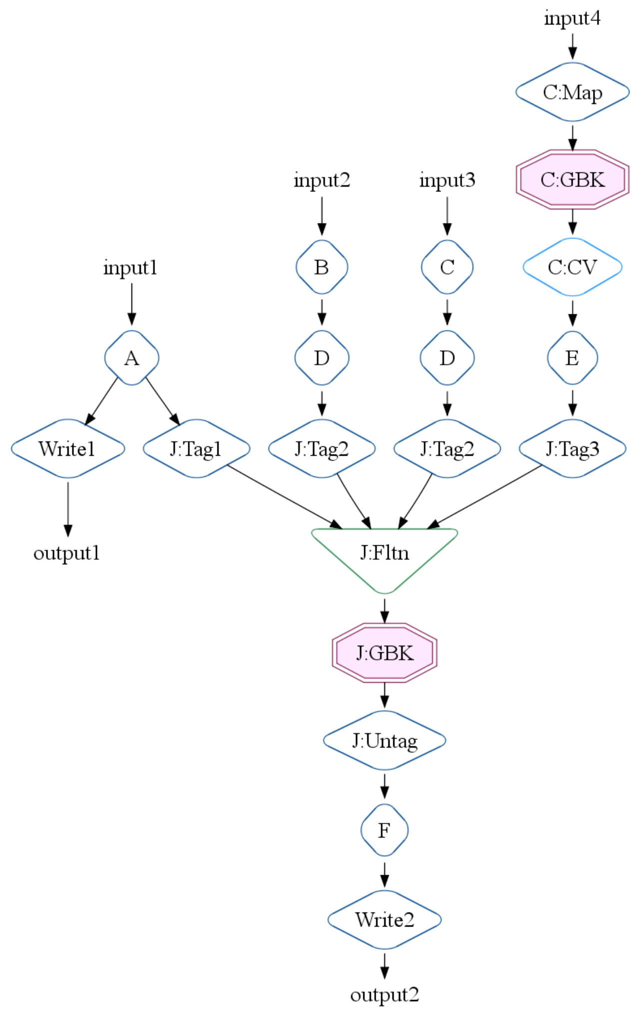
Optimizer

- Fuse trees of parallelDo operations into one
  - producer-consumer
  - co-consumers (“siblings”)
  - eliminate now-unused intermediate PCollections
- Form MapReduces
  - pDo + gbk + cv + pDo ➔ MapShuffleCombineReduce (MSCR)
  - multi-mapper, multi-reducer, multi-output

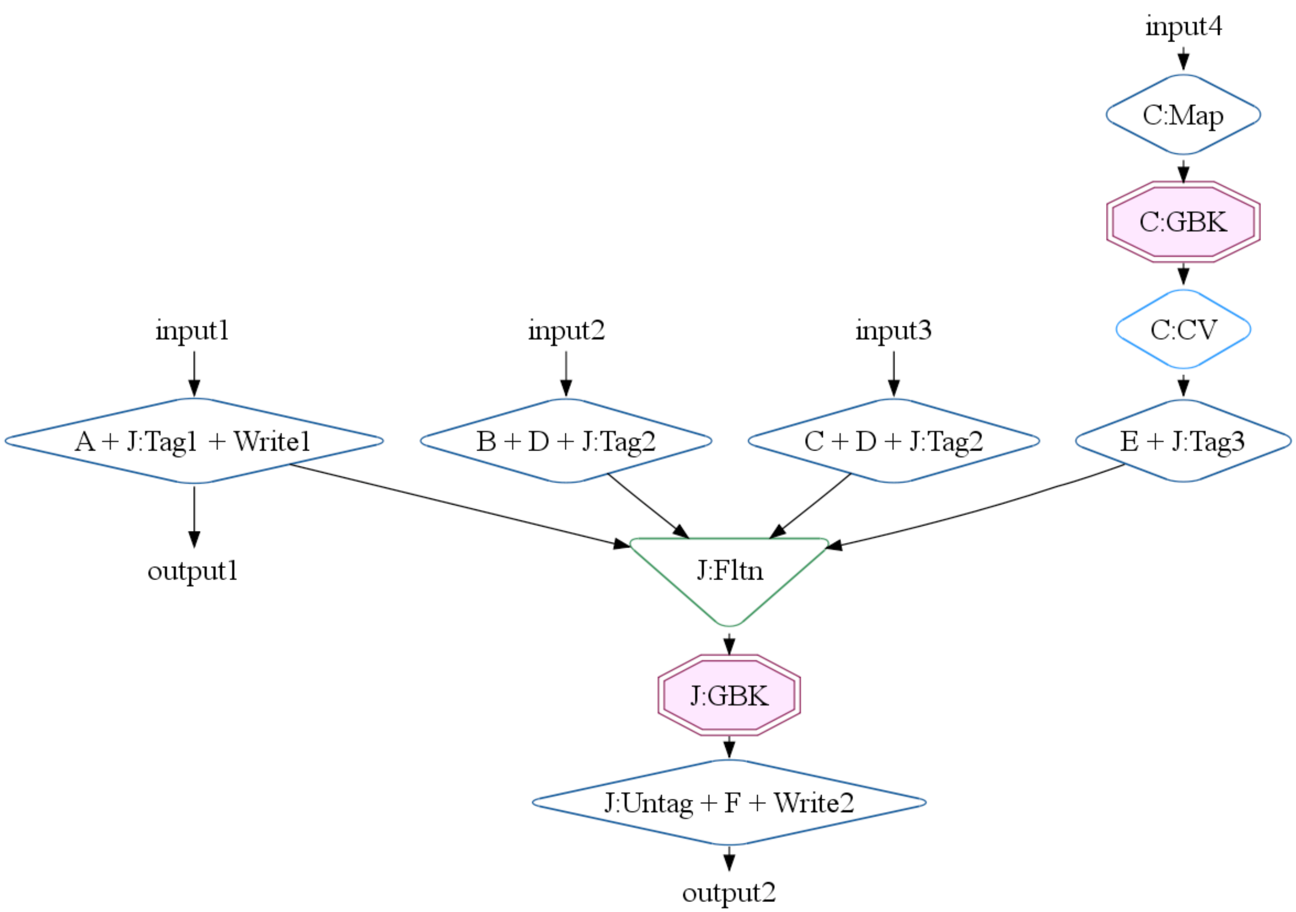
Initial pipeline



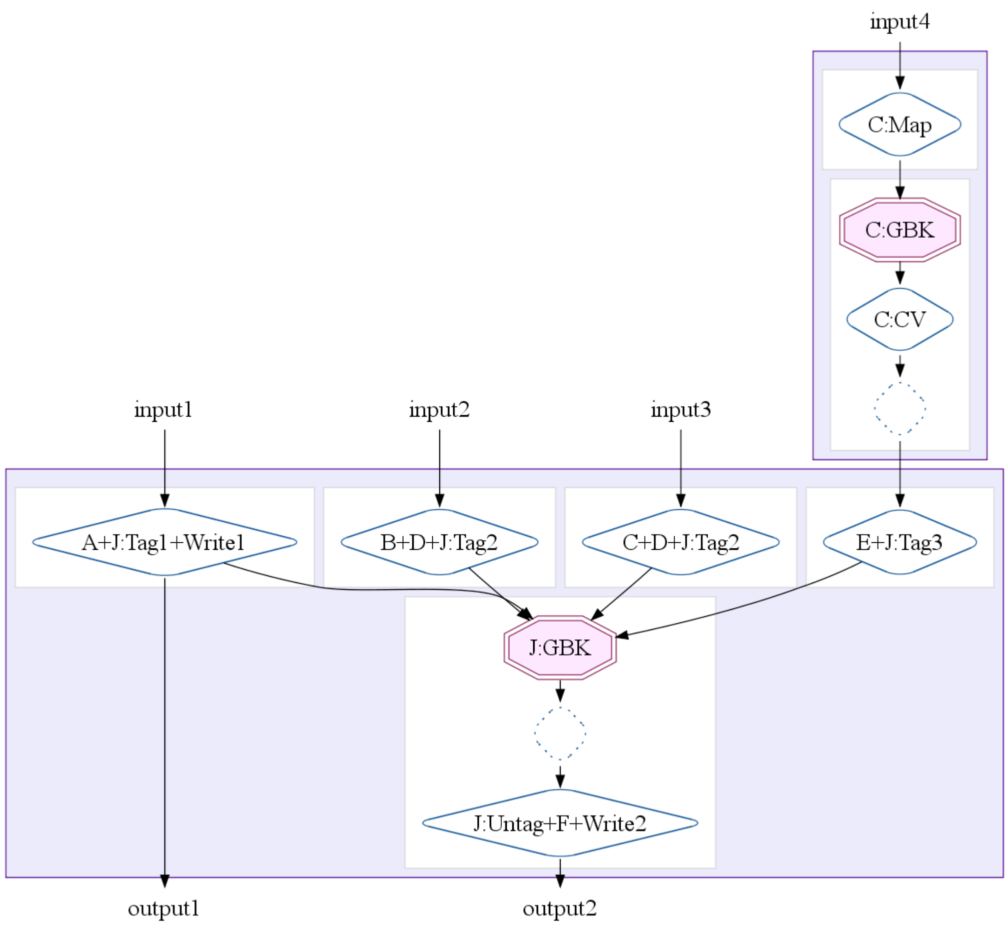
After sinking Flattens and lifting CombineValues



After ParallelDo fusion



After MSCR Fusion

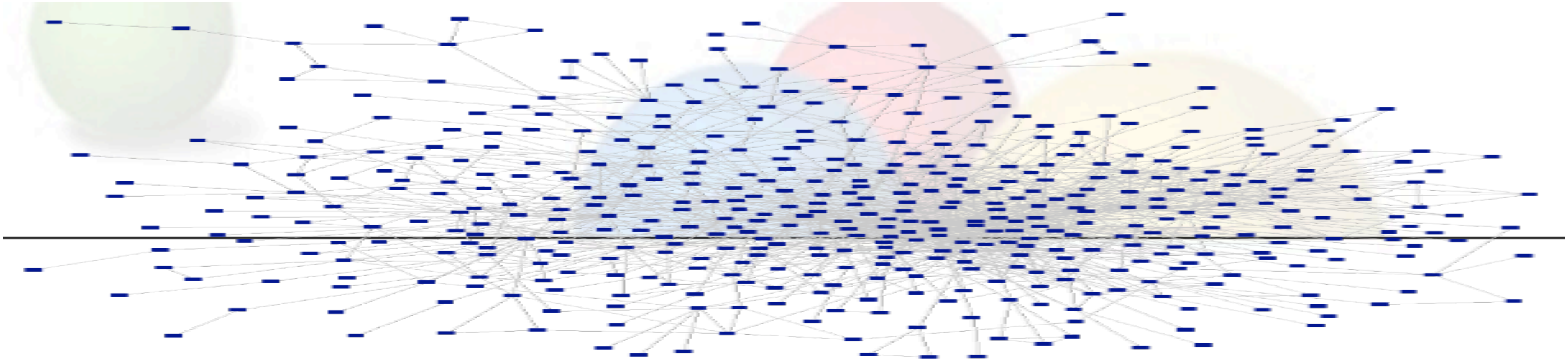


Executor

- Runs each optimized MSCR
  - If small data, runs locally, sequentially
    - develop and test in normal IDE
  - If large data, runs remotely, in parallel
- Handles creating, deleting temp files
- Supports fast re-execution
  - Caches, reuses partial pipeline results

Experience

- Released to Google users in May 2009
  - Now: hundreds of pipelines run by hundreds of users every month
  - Pipelines process gigabytes → petabytes
- Typically, find FlumeJava a lot easier to use than MapReduce
  - Can exert control over optimizer and executor if/when necessary
  - When things go wrong, lower abstraction levels intrude



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Conclusions

- All tools are fault-tolerant by design- failure of individual nodes just slows down completion.
- Work at large scale (trillions of rows, billions of vertices, petabytes of data).
- Used by multiple groups inside Google.
- We expect external developers will implement technologies similar to Pregel, Dremel and FlumeJava within Hadoop.