Cloud Programming

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January 16, 2010

Agenda

- Introduction
- Pig Latin
- DryadLINQ
- Comparison between Pig Latin and DryadLINQ
- Wave computing
- Related work
- Discussion

Background

- Huge Amount of data analysis
  Especially web service companies
  → Need of parallel/distributed system
- Parallel DB
  → Expensive at web scale, Limited SQL

Background

- Map/Reduce
  - More procedural programming model.
  - → Popular cloud computing environment
- Emergence of parallel computing tools
  - Ease of programming
    - User can just submit tasks in the specific form, then tools execute them in distributed manner.
    - Ex. Hadoop, Dryad, …

Limitations of Hadoop/Dryad

Power of programming

- Too low-level, Rigid
- Hard to maintain,
  Hard to reuse code
- Re-implement common queries
- Poor debugging environment

→ **Pig Latin, DryadLINQ**

Optimization across jobs

- Redundant computing
- Load imbalance
- Success rate
  vs. Window size

→ **Wave Computing**

Pig Latin:
A Not-So-Foreign Language for Data Processing
SIGMOD'08

Christopher Olston, Benjamin Reed, Utkarsh Srivastava,
Ravi Kumar, and Andrew Tomkins

Pig Latin

Example

- Find the users who tend to visit high-pagerank pages

SQL

```
SELECT user FROM visits, user WHERE avgpr > 0.6
IN ( SELECT user, AVG(pagerank)
```
… one nested SQL query

Pig Latin

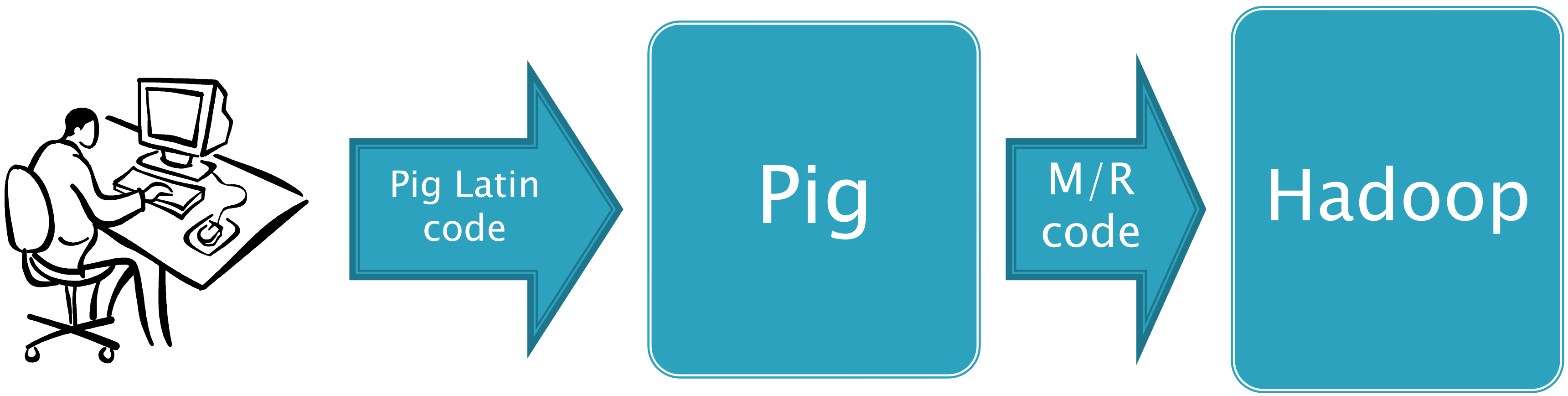
```
V_p = JOIN visits BY url, pages BY url;
Users = GROUP v_p BY user;
Useravg = FOREACH users GENERATE group,
AVG(v_p.pagerank) AS avgpr;
Answer = FILTER useravg BY avgpr > '0.5';
```
… sequence of commands

Java Map/Reduce

```
public static class Map extends MapReduceBase implements
Mapper<LongWritable, Text, Text, IntWritable> {
```
… more than 100 lines

Pig

- Execution engine on atop Hadoop
- Open source project
- Mainly developing/using in Yahoo



Example

- Find the users who tend to visit high-pagerank pages

Visits

User	URL	Time
Amy	cnn.com	8:00
Amy	bbc.com	10:00
Amy	flickr.com	10:05
Fred	cnn.com	12:00

⋮

URL Info

URL	Category	PageRank
cnn.com	News	0.9
bbc.com	News	0.8
flickr.com	Photos	0.7
espn.com	Sports	0.9

⋮

In Pig Latin

```
visits      = LOAD 'visits.txt' AS (user, url, time);
pages       = LOAD 'pages.txt' AS (url, pagerank);

v_p         = JOIN visits BY url, pages BY url;
users       = GROUP v_p BY user;
useravg = FOREACH users
            GENERATE group, AVG(v_p.pagerank) AS avgpr;
answer  = FILTER useravg BY avgpr > '0.5';
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In Pig Latin

```
visits    = LOAD 'visits.txt' AS (user, url, time);
pages     = LOAD 'pages.txt' AS (url, pagerank);
```

```
visits:  (Amy, cnn.com, 8am)
         (Amy, frogs.com, 9am)
         (Fred, snails.com, 11am)

pages:   (cnn.com, 0.8)
         (frogs.com, 0.8)
         (snails.com, 0.3)
```

In Pig Latin

```
visits  = LOAD 'visits.txt' AS (user, url, time);
pages   = LOAD 'pages.txt' AS (url, pagerank);

v_p     = JOIN visits BY url, pages BY url;
```

```
visits: (Amy, cnn.com, 8am)
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v_p: (Amy, cnn.com, 8am, cnn.com, 0.8)
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In Pig Latin

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visits = LOAD 'visits.txt' AS (user, url, time);
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v_p: (Amy, cnn.com, 8am, cnn.com, 0.8)
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users: (Amy, { (Amy, cnn.com, 8am, cnn.com, 0.8)
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       (Fred, { (Fred, snails.com, 11am, snails.com, 0.3) } )
```

In Pig Latin

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               (Amy, frogs.com, 9am, frogs.com, 0.8) } )
       (Fred, { (Fred, snails.com, 11am, snails.com, 0.3) } )
```

Nested data model

In Pig Latin

```
visits     = LOAD 'visits.txt' AS (user, url, time);
pages      = LOAD 'pages.txt' AS (url, pagerank);

v_p        = JOIN visits BY url, pages BY url;
users      = GROUP v_p BY user;
useravg = FOREACH users
        GENERATE group, AVG(v_p.pagerank) AS avgpr;
```

```
users:   (Amy, { (Amy, cnn.com, 8am, cnn.com, 0.8)
                 (Amy, frogs.com, 9am, frogs.com, 0.8) } )
         (Fred, { (Fred, snails.com, 11am, snails.com, 0.3) } )

useravg: (Amy, 0.8)
         (Fred, 0.3)
```

In Pig Latin

```
visits      = LOAD 'visits.txt' AS (user, url, time);
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users:    (Amy, { (Amy, cnn.com, 8am, cnn.com, 0.8)
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          (Fred, { (Fred, snails.com, 11am, snails.com, 0.3) } )

useravg: (Amy, 0.8)
         (Fred, 0.3)
```

Can use any UDFs

In Pig Latin

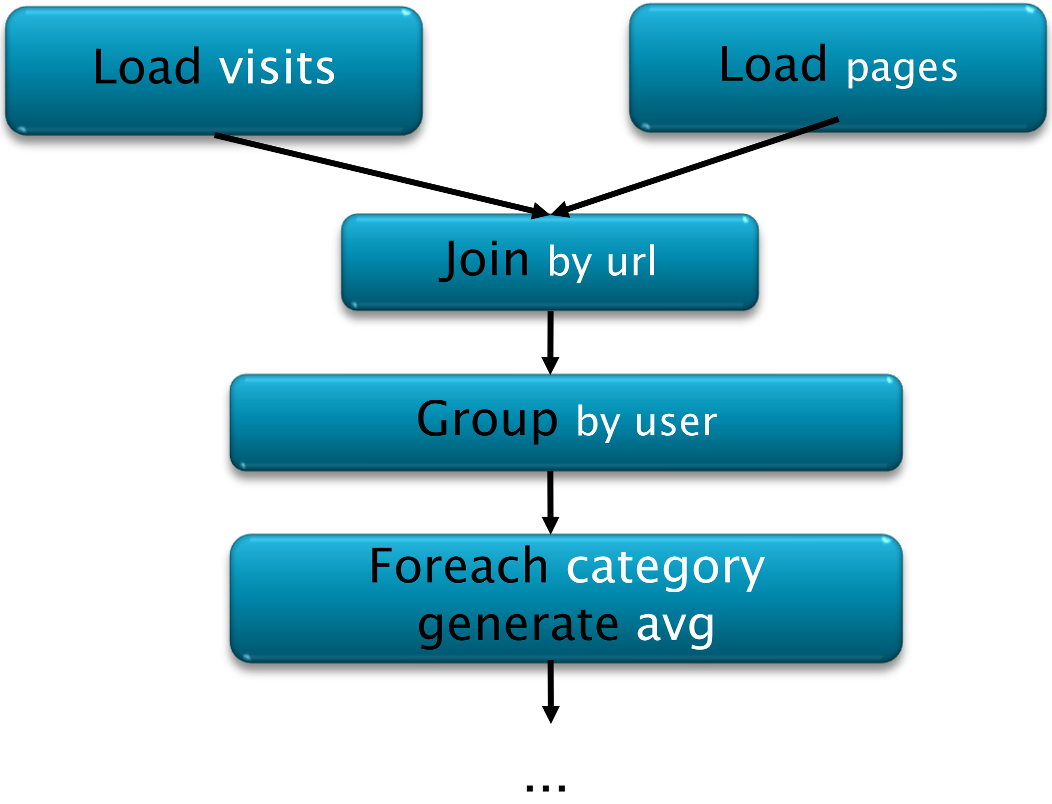
```
visits      = LOAD 'visits.txt' AS (user, url, time);
pages       = LOAD 'pages.txt' AS (url, pagerank);

v_p         = JOIN visits BY url, pages BY url;
users       = GROUP v_p BY user;
useravg = FOREACH users
        GENERATE group, AVG(v_p.pagerank) AS avgpr;
answer  = FILTER useravg BY avgpr > '0.5';
```

useravg: (Amy, 0.8)
(Fred, 0.3)

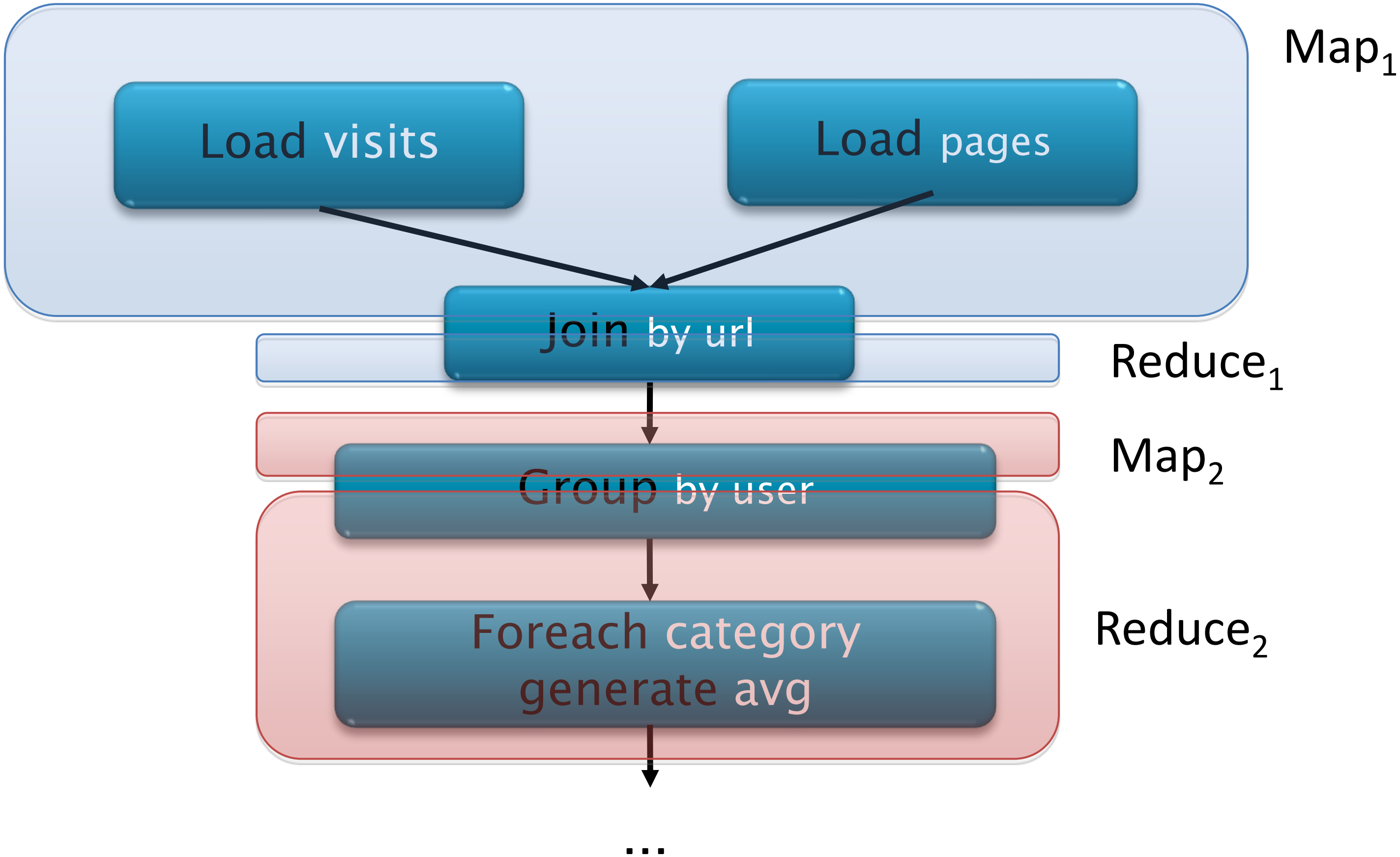
answer: (Amy, 0.8)

Data Flow



Load visits
Load pages
Join by url
Group by user
Foreach category
generate avg
...

Compilation into Map-Reduce



Every group or join operation forms a map-reduce boundary

Other operations pipelined into map and reduce phases

Data Model

- Atom

    ‘alice’
- Tuple

    (‘alice’ , ‘lakers’)
- Bag

    { (‘alice’, ‘lakers’)
    (‘alice’, (‘iPod’, ‘apple’)) }
- Map

    [‘age’ → 20]
- Nested Data Model

    (Amy, { (Amy, cnn.com, 8am, cnn.com, 0.8)
    (Amy, frogs.com, 9am, frogs.com, 0.8) })

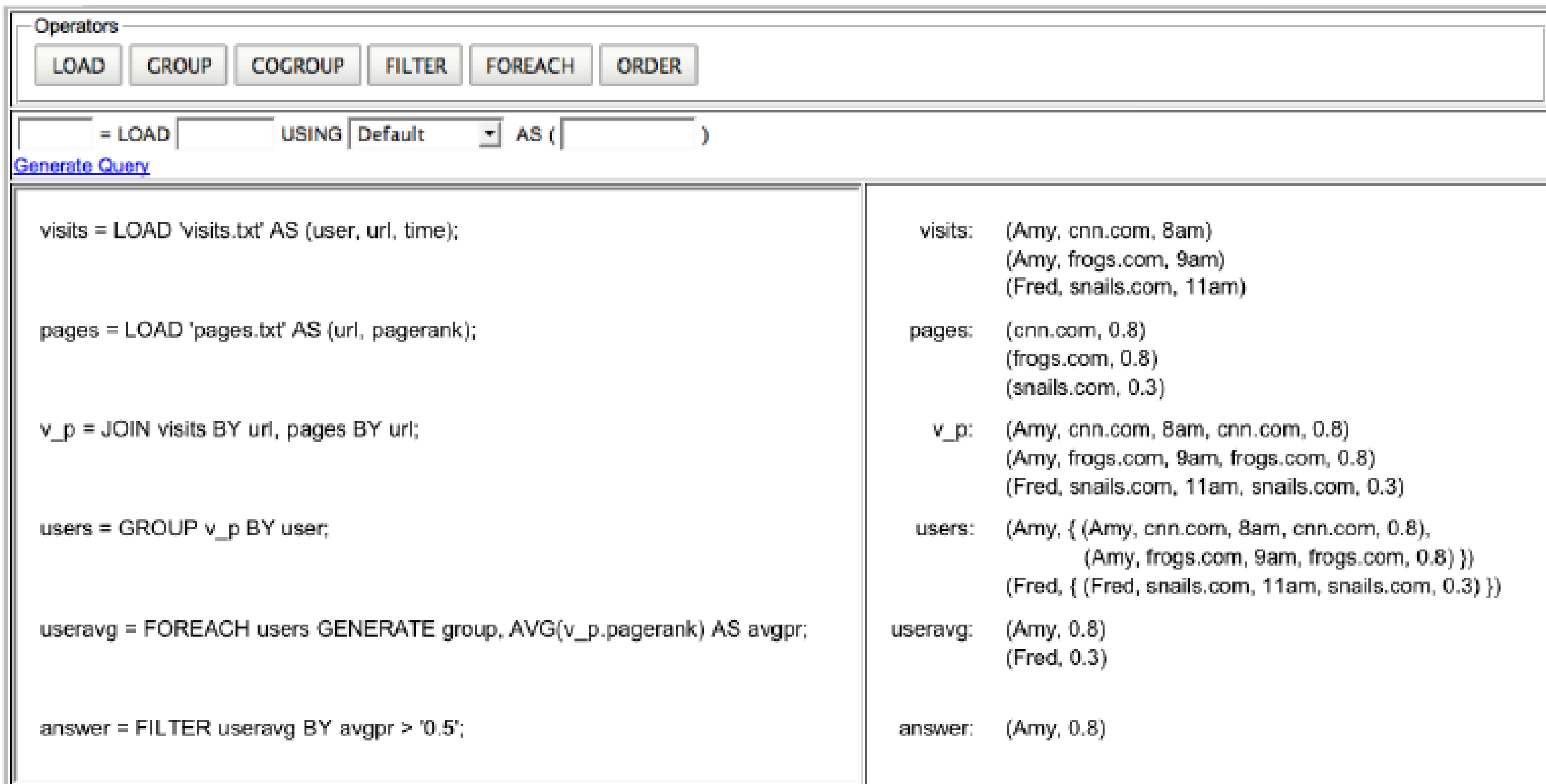
Pig Latin Command

- Specifying Input Data: LOAD
- Per-tuple Processing: FOREACH
- Discarding Unwanted Data: FILTER
- Getting Related Data Together: COGROUP
- Other Commends
  - UNION, CROSS, ORDER, DISTINCT
- Asking for Output: STORE

Very Similar to SQL commands

Debugging Environment

- Pig Pen



Future Work

- “Safe” optimizer
  - Performs only high-confidence rewrites
- User interface
  - Boxes and arrows UI
  - Promote collaboration, sharing code fragments and UDFs
- External functions
  - Provide UDF packages
- Unified environment
  - Use loops, conditionals of host language

Why Pig?

- Implementation productivity
  - 10 lines of Pig Latin = 200 lines of Java M/R
  - 15 minutes to write in Pig Latin = 4 hours Java M/R
- Provide common operations like join, group, filter, sort
- Open to non-Java programmers

Why not Pig?

- Slower speed
  - Code converting overload
  - Not task-specific optimization
- Not flexible for special operation
  - Implementing UDF takes time
- Not SQL
  - Weaker functions
  - Need additional effort to convert existing SQL query system to the distributed system with Pig

Discussion

- Should Pig Latin have all the SQL features?
- Is Pig really easier than Hadoop MapReduce Programming for whom does not know SQL?

DryadLINQ:
A System for General-Purpose Distributed Data-Parallel Computing Using a High-Level Language
OSDI'08 (Awarded Best Paper)

Yuan Yu, Michael Isard, Dennis Fetterly, Mihai Budiu,
Ulfar Erlingsson, Pradeep Kumar Gunda, and Jon Currey

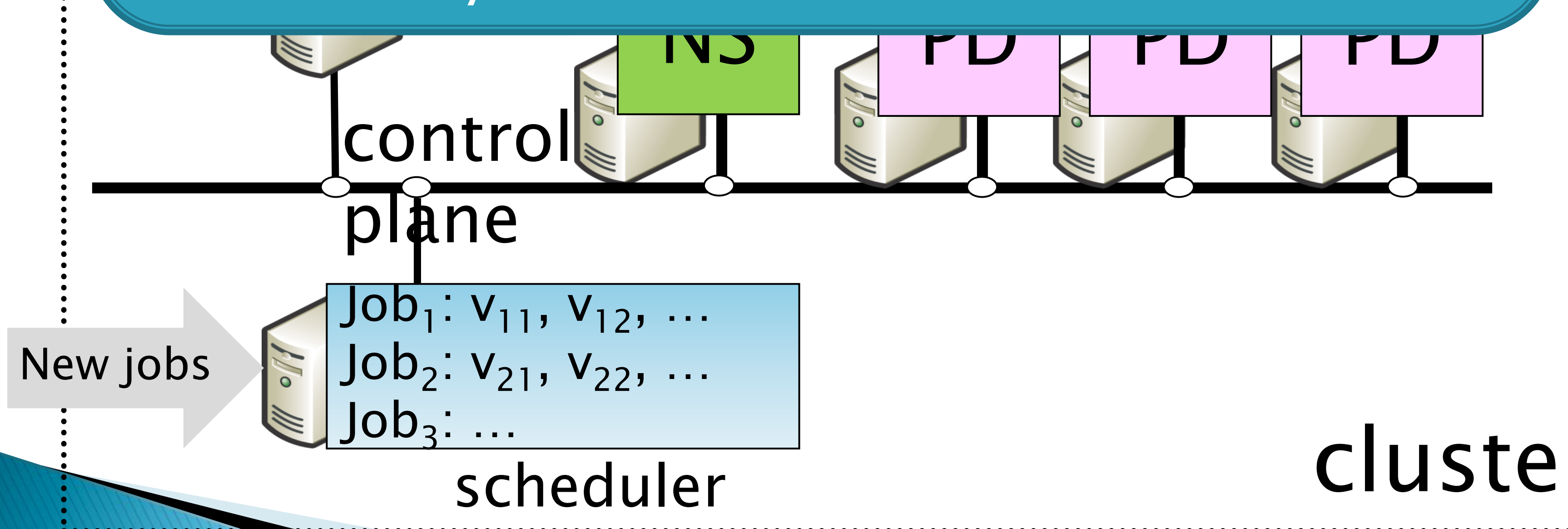
Is Pig + Hadoop enough?

- Obviously, Microsoft does not think so
- But, why?
  - Hadoop employs the MapReduce programming model
  - "…… aims for simplicity at the expense of generality and performance ……" [1]

- [1] Isard, M., Budiu, M., Yu, Y., Birrell, A., and Fetterly, D. 2007. Dryad: distributed data-parallel programs from sequential building blocks. In EuroSys '07.

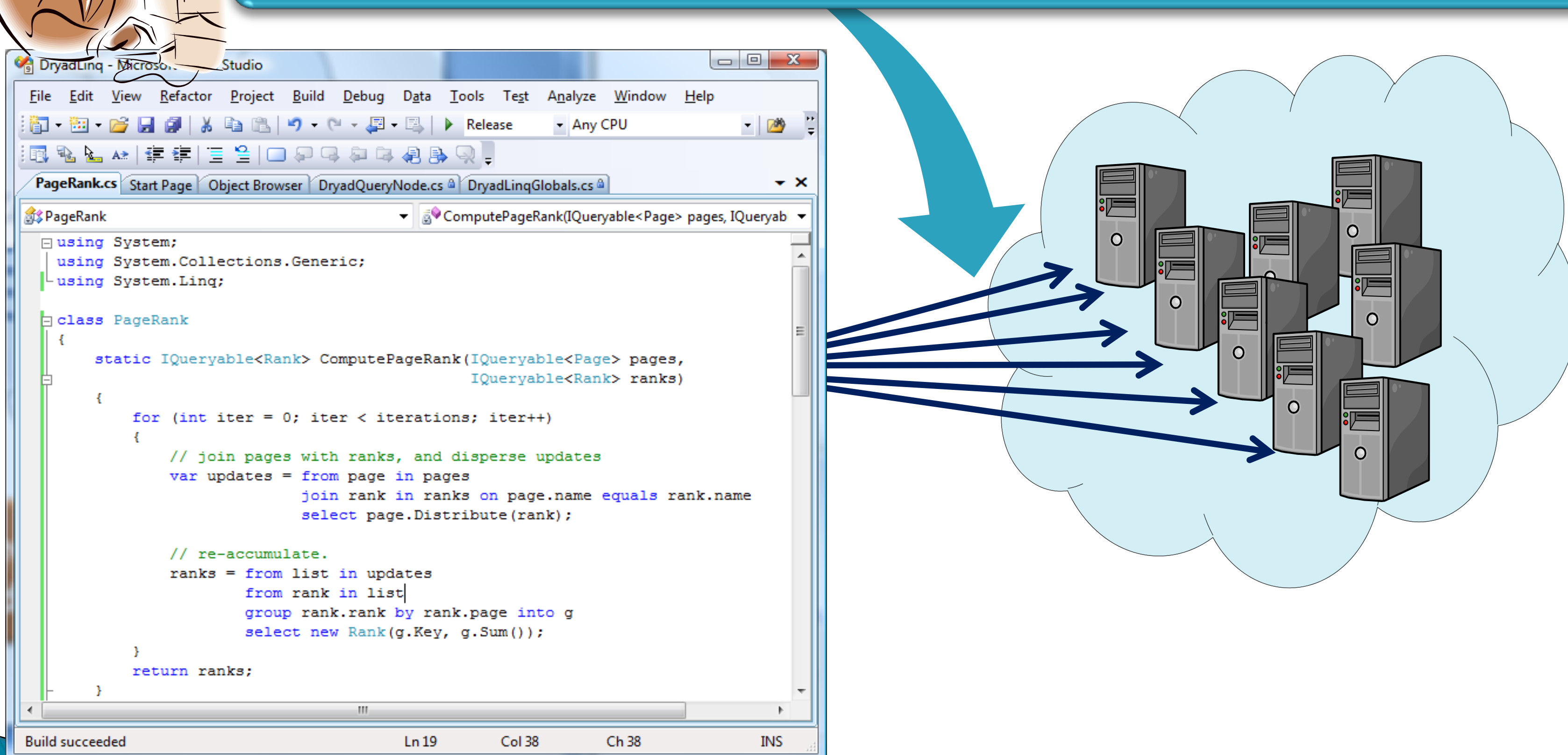
Dryad

- Directed-acyclic graph (DAG)
  - Flexible
  - Permits efficient execution plans for many algorithms
- However, it is oftentimes infeasible to specify the DAG by hand



What is missing?

DryadLINQ provides automatic query plan generation
Dryad provides automatic distributed execution

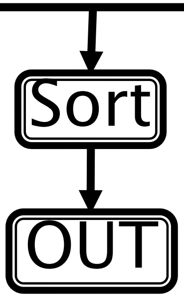


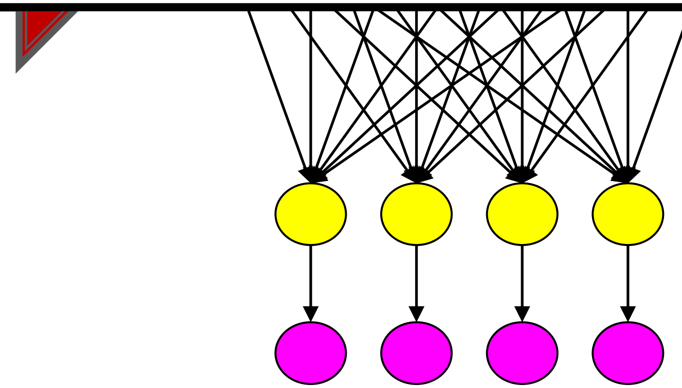
Dryad + LINQ = DryadLINQ

LINQ expression — **Dryad execution**

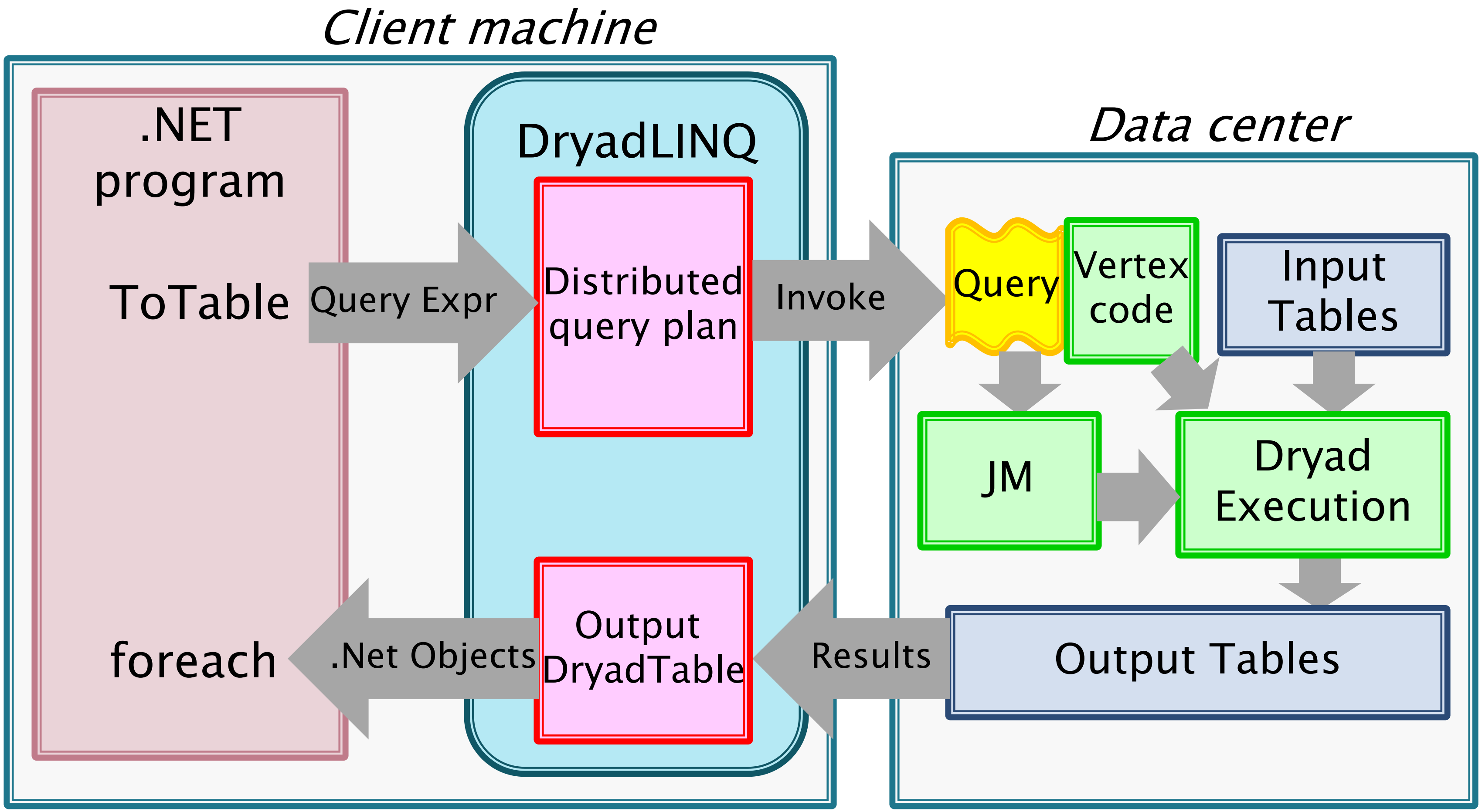
```
var docs = DryadLinq.GetTable<Doc>("file://docs.txt");
var words = docs.SelectMany(doc => doc.words);
var groups = words.GroupBy(word => word);
var counts = groups.Select(g => new WordCount(g.Key, g.Count()));

counts.ToDryadTable("counts.txt");
```





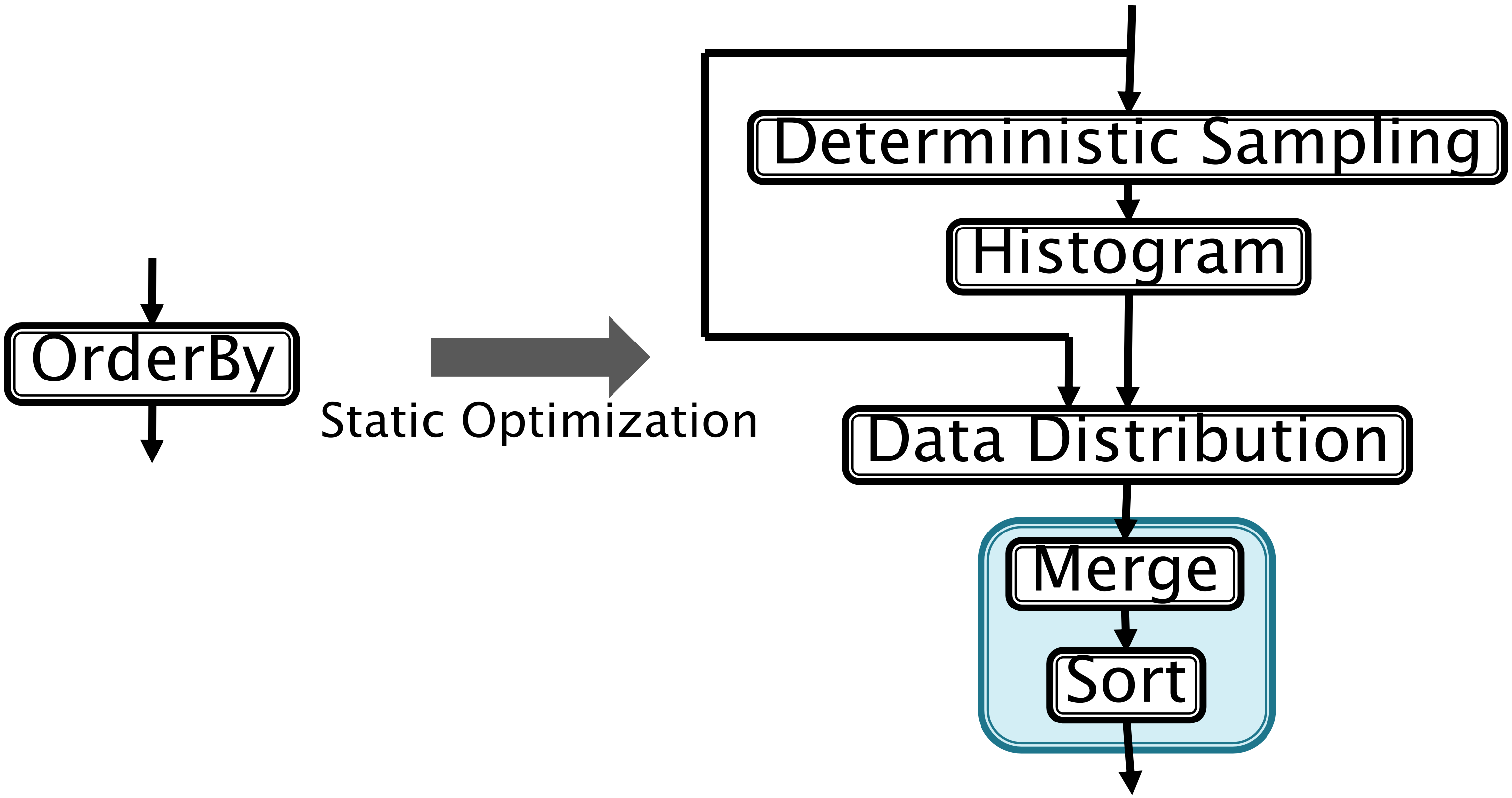
DryadLINQ System Architecture



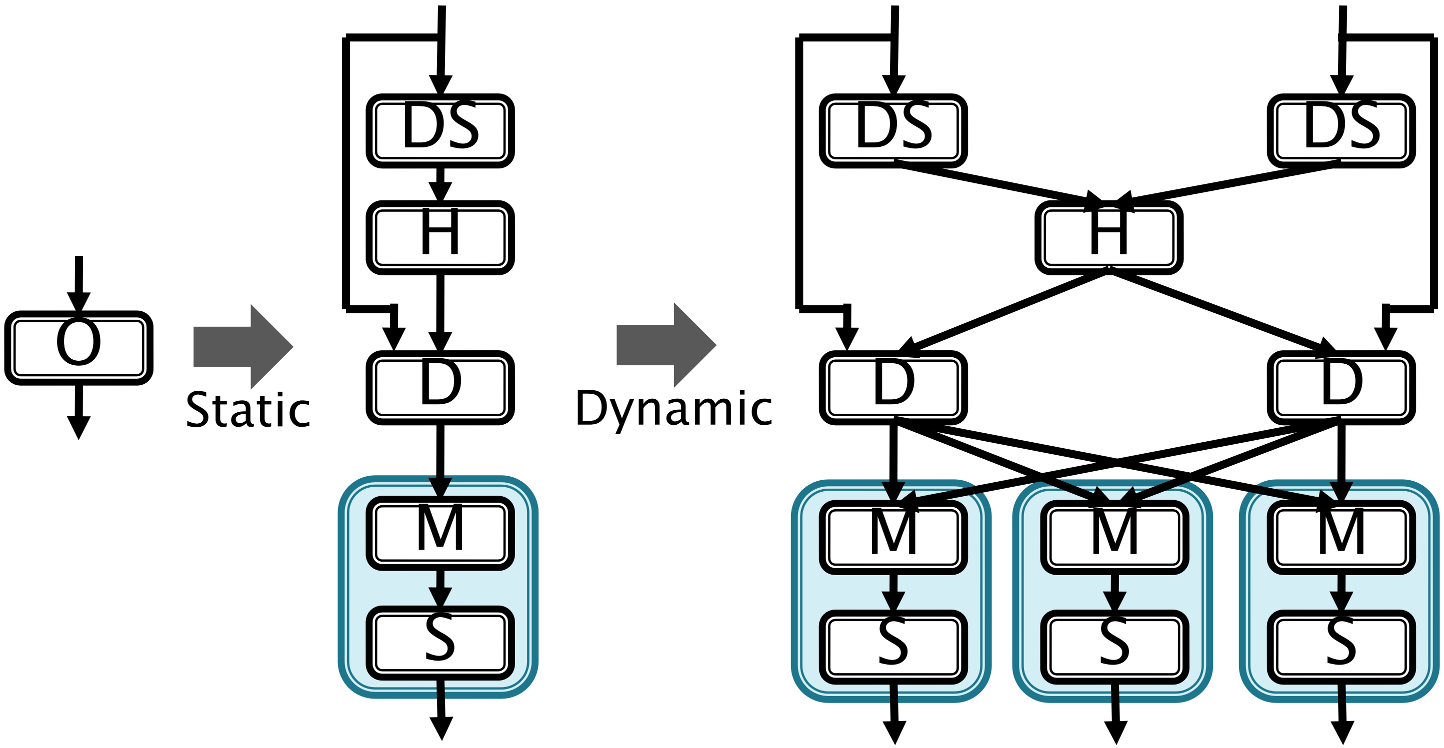
Static Optimizations

- Pipelining
  - Executing multiple operators in a single process
- Removing redundancy
  - Remove unnecessary partitioning steps
- Eager aggregation
  - Moving down-stream aggregations in front of partitioning operators
- I/O reduction
  - TCP-pipe and in-memory FIFO channels
  - Compresses data before performing a partitioning

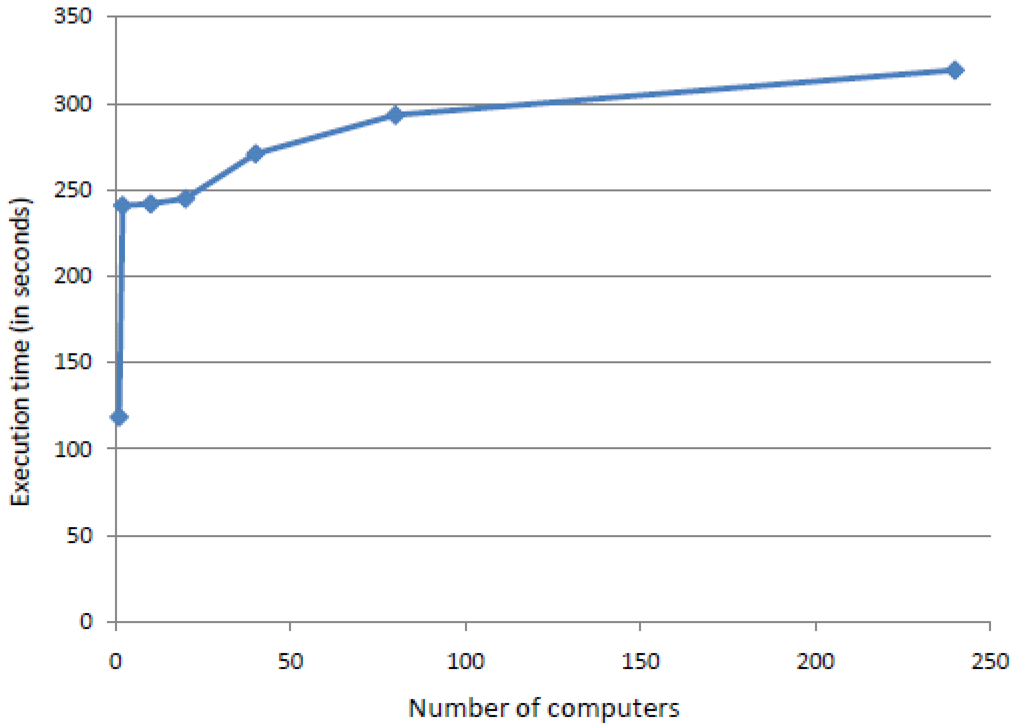
Optimization Example – OrderBy



Dynamic Optimizations

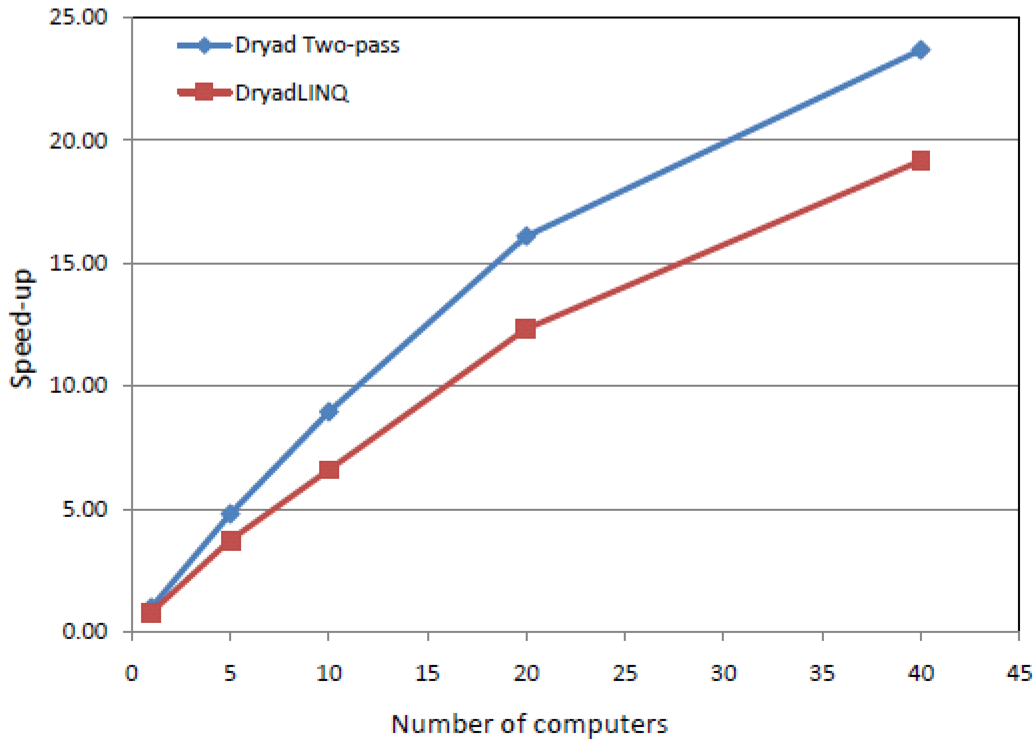


Evaluation – Terasort



- TeraByte Sort (Indy): 10 billion 100-Byte records with 10-Byte key

Evaluation – SkyServer



- Q18 from the Sloan Digital Sky Survey database: three-way Join over two input tables containing 11.8 GBytes and 41.8 GBytes of data, respectively

Conclusion and Discussion

- DryadLINQ is an elegant programming environment combining the benefits of LINQ with the power of Dryad
- Supports multiple languages including C#, VB, and F#
- Leverages other systems that use the same constructs such as PLINQ, LINQ-to-SQL, and LINQ-to-Object
- Clean separation of Dryad and DryadLINQ

Conclusion and Discussion

- Directed-acyclic graph provides generality but also brings complexity
- Dynamic optimizations on concurrent jobs
- Debugging, analyzing, and monitoring

Comparison between Pig Latin and DryadLINQ

Comparison

	Pig Latin	DryadLINQ
Base System	Hadoop (HDFS)	Dryad
Main Contributor	Yahoo, Open Source	Microsoft (Internal)
Programming	Imperative	Imperative & Declarative
Model Structure	Sequence of Map/Reduce	Directed Acyclic graph
Development environment	Mainly linux, Some eclipse plug-in	Windows, Visual Studio
Main Language	Java	C#
Compared to SQL	Similar	Very similar

- Both enable users to use parallel computing tool more conveniently
- But, slower speed than original system

→ Need for consideration in speed improvement

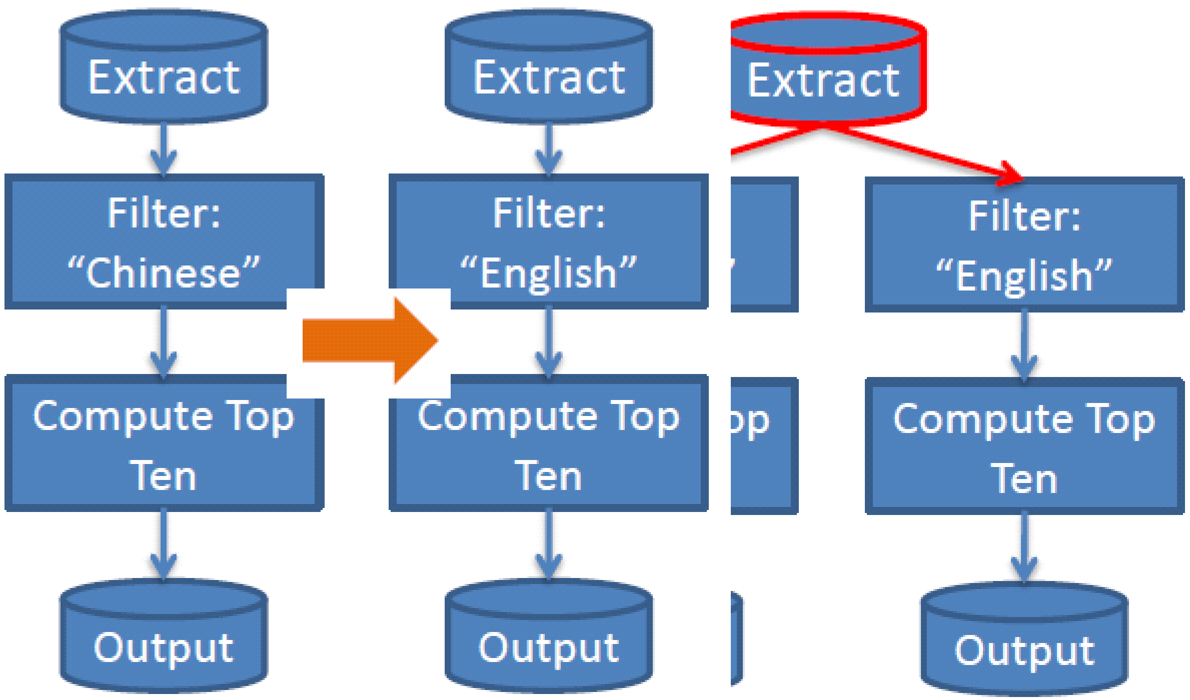
Wave Computing in the Cloud
HotOS'09

Bingsheng He, Mao Yang, Zhenyu Guo, Rishan Chen, Wei Lin,
Bing Su, Hongyi Wang, and Lidong Zhou

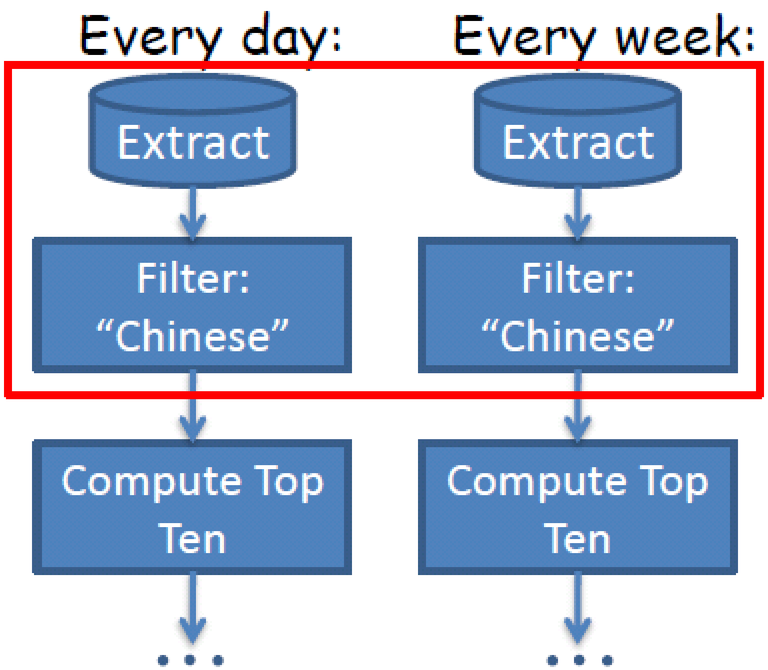
What do we have right now?

- Execution plans
  - Dryad and Hadoop
- High-level languages
  - DryadLINQ and Pig Latin
- Optimizations for performance and resource utilization in both dimensions for a single job
- However, regarding optimization, there are still something left ……

Can you identify the inefficiency?

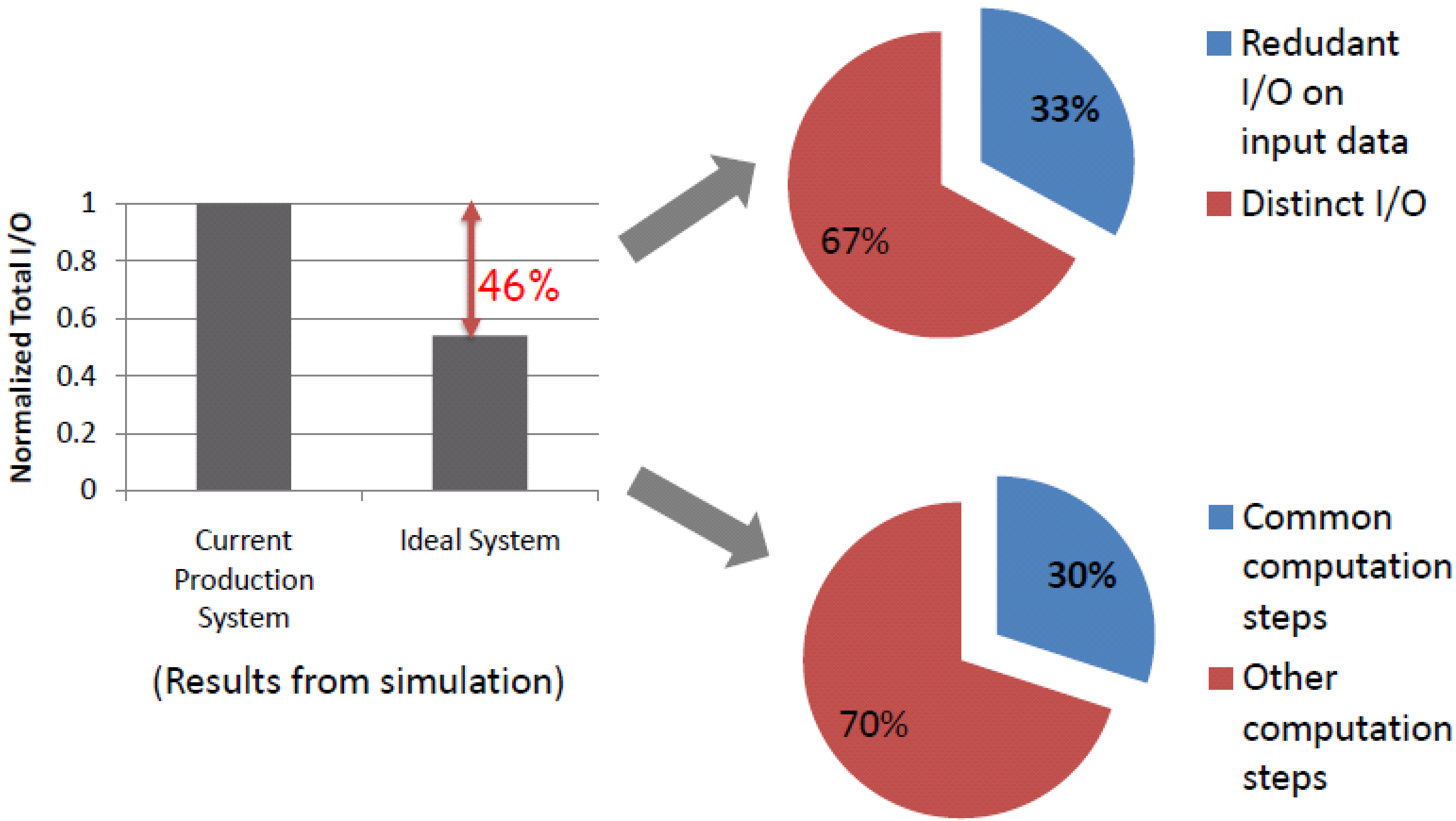


More Examples



Common computation on per-day log (Ideally)

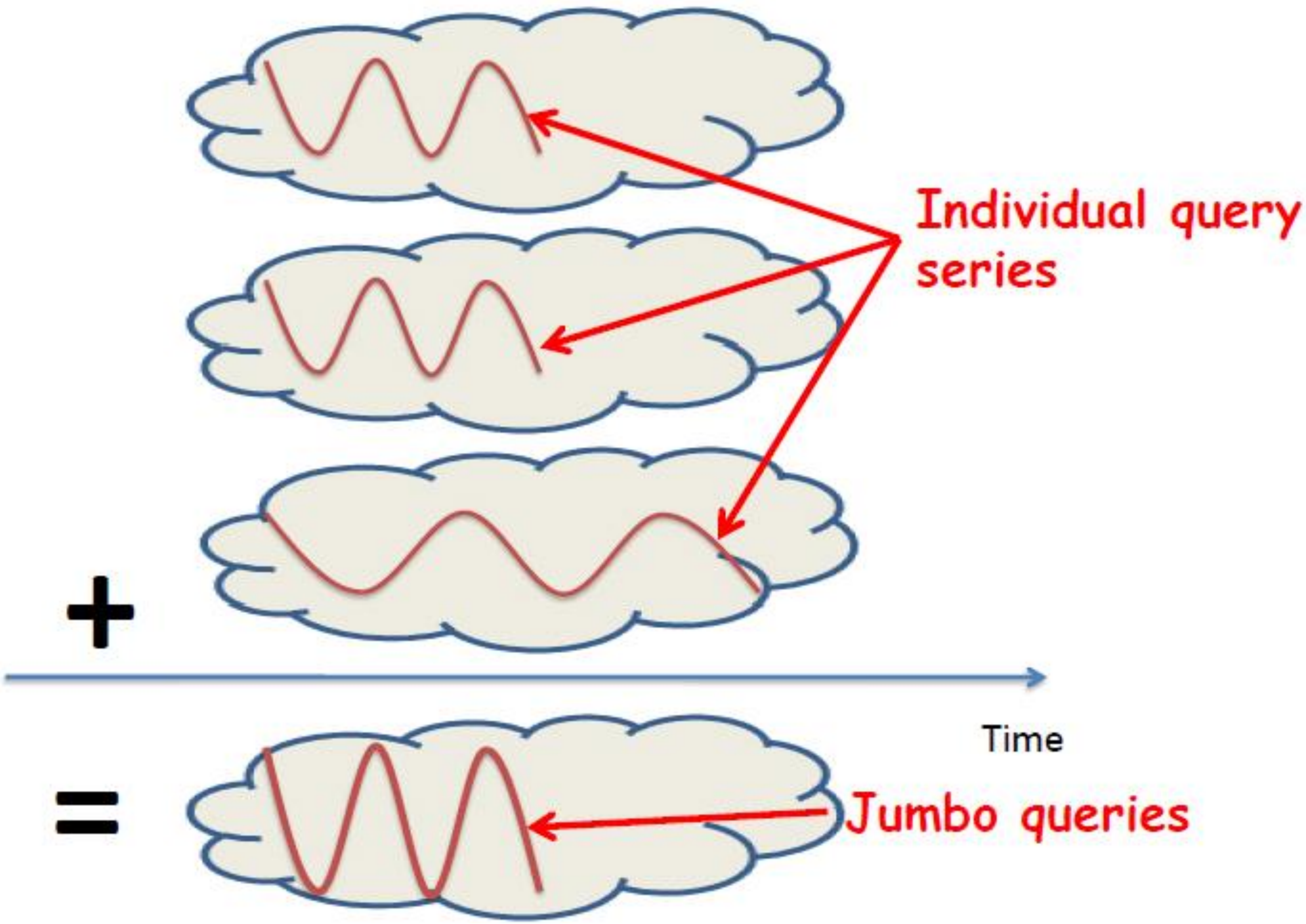
What do the statistics say?



The Wave Model

- Streams
  - Append-only files and partitioned on multiple machines
- Query series
  - Recurrent computations on a stream, with each performed on one or more stream segments

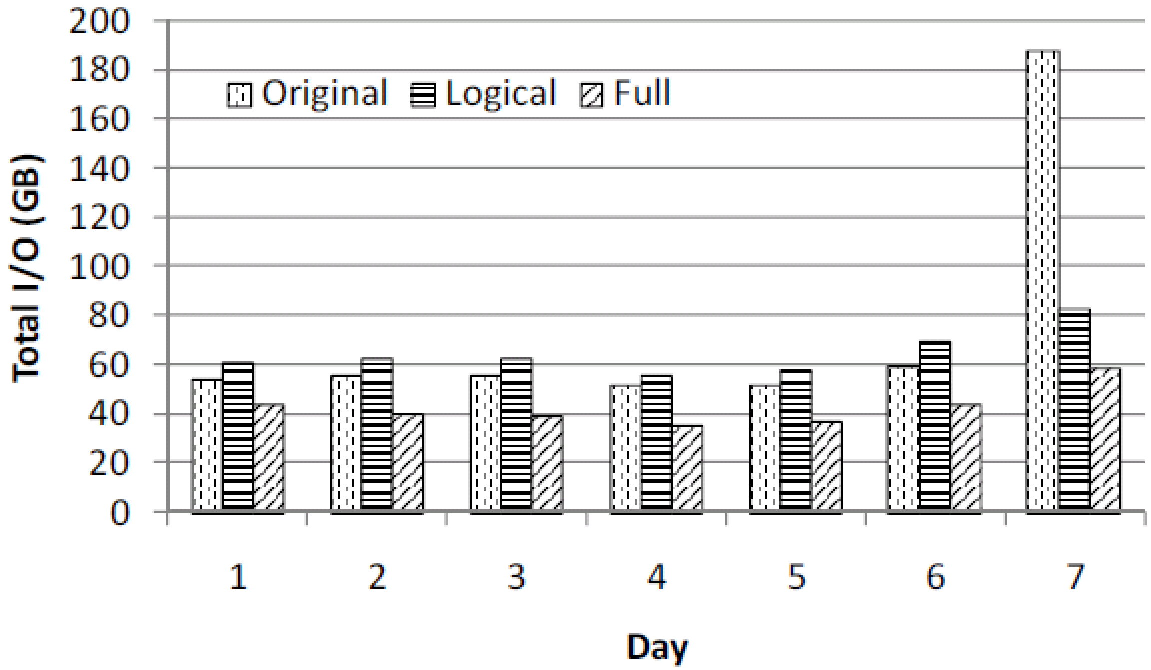
The Wave Model



Opportunities

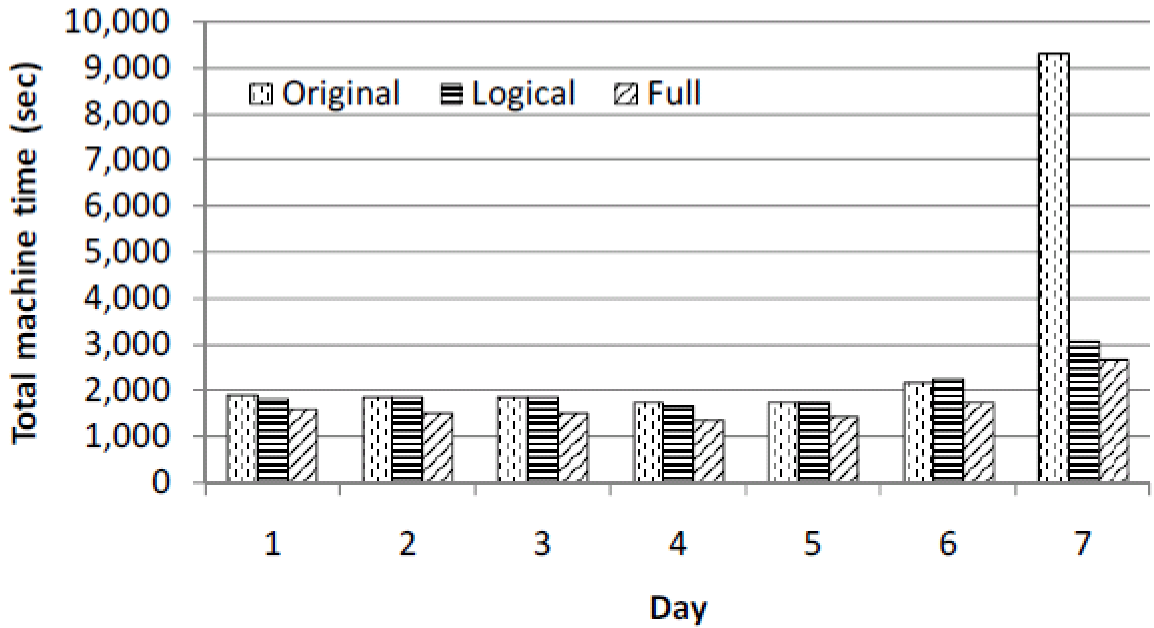
- Enabling prediction
  - Input and output data
  - Computation complexity of custom functions
  - Execution environment
- Wave optimizations
  - Shared scan and computation
  - Query decomposition, planning, and scheduling
- Waves into the cloud

Following Work: Comet – Total I/O



- Logical optimization (computation sharing) reduces the total I/O by 12.3%
- Full optimization (computation + data sharing) reduces the total I/O by 42.3%

Comet – Total Machine Time



- Logical optimization reduces the total machine time by 30.5%
- Full optimization reduces the total machine time by 42.0%

Conclusion and Discussion

- Wave computing introduces a new processing model that can potentially unlock the full power of data-intensive distributed computing
- Identifies computation and I/O redundancy
- Enables optimizations from other fields such as database

Conclusion and Discussion

- Feasibility of the model
  - Could we apply the model directly to community clouds?
- More opportunities
  - Caching/reusing intermediate results

Related Work

Related Work

- Map-reduce-merge
  - Map-reduce does not support processing multiple related heterogeneous datasets.(Joins)
    → Add Merge phase after reduce
- Hadoop Streaming
  - Want to use existing executables or other languages
    → Allows to create map/reduce using any executable or script
- Hbase
  - Slow in random, realtime read/write access to Big Data
    → Distributed column-oriented store model like Google's Bigtable for hadoop.

Related Work

- Hive
  - A data warehouse infrastructure that provides data summarization and ad hoc querying
- Zookeeper
  - A high-performance coordinate service for distributed applications

Thank You

References

References

- Pig Latin: A Not-So-Foreign Language for Data Processing, C. Olston et al., SIGMOD 2008 (Yahoo!)
- Cloudera Pig Tutorial
  http://www.cloudera.com/videos/introduction_to_pig
- Dryad: Distributed Data-Parallel Programs from Sequential Building Blocks, M. Isard et al., EuroSys 2007
- DryadLINQ: A System for General-Purpose Distributed Data-Parallel Computing Using a High-Level Language, Y. Yu et al., OSDI 2008

References

- Wave Computing in the Cloud, B. He et al., HotOS 2009
- Comet: Batched Stream Processing in Data Intensive Distributed Computing, B. He et al., Technical Report 2009

More Discussion

Backup Slides

Features

- Dataflow Language
- Nested Data Model
- Nested Operation
- Support UDF (User Defined Function)
- Parallelism Required
- Debugging Environment

Motivation

- Limitation of map/reduce
  - Difficulty in programming
    - Too low-level, Rigid
    - Hard to maintain, Hard to reuse code
    - Common queries that are difficult to program
    - Poor debugging environment
    - → Pig-Latin, DryadLINQ
  - Performance issues
    - Redundancy
    - Load Imbalance
    - Success Rate vs. Window size
    - → Wave computing

Example

- Find the average pagerank of high-pagerank urls for each sufficiently large category,

SQL

```
SELECT category, AVG(pagerank)
FROM urls WHERE pagerank > 0.2
GROUP BY category HAVING COUNT(*) > 106
```

Pig Latin

```
good_urls = FILTER urls BY pagerank > 0.2;
groups = GROUP good_urls BY category;
big_groups = FILTER groups BY COUNT(good_urls)>106;
output = FOREACH big_groups
            GENERATE category, AVG(good_urls.pagerank);
```

Java Map/Reduce

```
public static class Map extends MapReduceBase implements
Mapper<LongWritable, Text, Text, IntWritable> {
… more than 100 lines
```