# Extension: Combiner Functions

- Recall earlier discussion about combiner function
  - Pre-reduces mapper output before transfer to reducers
  - Does not change program semantics
- Usually (almost) same as reduce function, but has to have same output type as Map
- Works only for some reduce functions that can be incrementally computed
  - MAX(5, 4, 1, 2) = MAX(MAX(5, 1), MAX(4, 2))
  - Same for SUM, MIN, COUNT, AVG (=SUM/COUNT)



```
import java.io.IOException;

import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapred.FileInputFormat;
import org.apache.hadoop.mapred.FileOutputFormat;
import org.apache.hadoop.mapred.JobClient;
import org.apache.hadoop.mapred.JobConf;

public class MaxTemperatureWithCombiner {

  public static void main(String[] args) throws IOException {
    if (args.length != 2) {
      System.err.println("Usage: MaxTemperatureWithCombiner <input path> " +
                         "<output path>");
      System.exit(-1);
    }

    JobConf conf = new JobConf(MaxTemperatureWithCombiner.class);
    conf.setJobName("Max temperature");

    FileInputFormat.addInputPath(conf, new Path(args[0]));
    FileOutputFormat.setOutputPath(conf, new Path(args[1]));

    conf.setMapperClass(MaxTemperatureMapper.class);
    conf.setCombinerClass(MaxTemperatureReducer.class);
    conf.setReducerClass(MaxTemperatureReducer.class);

    conf.setOutputKeyClass(Text.class);
    conf.setOutputValueClass(IntWritable.class);

    JobClient.runJob(conf);
  }
}
```

Note: combiner here is identical to reducer class.

## Extension: Custom Partitioner

- Partitioner determines which keys are assigned to which reduce task
- Default HashPartitioner essentially assigns keys randomly
- Create custom partitioner by implementing Partitioner interface in org.apache.hadoop.mapred
  - Write your own getPartition() method

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## Extension: MapFile

- Sorted file of (key, value) pairs with an index for lookups by key
- Must append new entries in order
  - Can create MapFile by sorting SequenceFile
- Can get value for specific key by calling MapFile's get() method
  - Found by performing binary search on index
- Method getClosest() finds closest match to search key

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# Extension: Counters

- Useful to get statistics about the MapReduce job, e.g., how many records were discarded in Map
- Difficult to implement from scratch
  - Mappers and reducers need to communicate to compute a global counter
- Hadoop has built-in support for counters
- See ch. 8 in Tom White's book for details

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# Hadoop Job Tuning

- Choose appropriate number of mappers and reducers
- Define combiners whenever possible
  - But see also later discussion about local aggregation
- Consider Map output compression
- Optimize the expensive shuffle phase (between mappers and reducers) by setting its tuning parameters
- Profiling distributed MapReduce jobs is challenging.

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## Hadoop and Other Programming Languages

- Hadoop Streaming API to write map and reduce functions in languages other than Java
  - Any language that can read from standard input and write to standard output
- Hadoop Pipes API for using C++
  - Uses sockets to communicate with Hadoop's task trackers

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## Multiple MapReduce Steps

- Example: find average max temp for every day of the year and every weather station
  - Find max temp for each combination of station and day/month/year
  - Compute average for each combination of station and day/month
- Can be done in two MapReduce jobs
  - Could also combine it into single job, which would be faster

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# Running a MapReduce Workflow

- Linear chain of jobs
  - To run job2 after job1, create JobConf's conf1 and conf2 in main function
  - Call JobClient.runJob(conf1); JobClient.runJob(conf2);
  - Catch exceptions to re-start failed jobs in pipeline
- More complex workflows
  - Use JobControl from org.apache.hadoop.mapred.jobcontrol
  - We will see soon how to use Pig for this

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# MapReduce Coding Summary

- Decompose problem into appropriate workflow of MapReduce jobs
- For each job, implement the following
  - Job configuration
  - Map function
  - Reduce function
  - Combiner function (optional)
  - Partition function (optional)
- Might have to create custom data types as well
  - WritableComparable for keys
  - Writable for values

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Let's see how we can create complex MapReduce workflows by programming in a high-level language.

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# The Pig System

- Christopher Olston, Benjamin Reed, Utkarsh Srivastava, Ravi Kumar, Andrew Tomkins: Pig Latin: a not-so-foreign language for data processing. SIGMOD Conference 2008: 1099-1110
- Several slides courtesy Chris Olston and Utkarsh Srivastava
- Open source project under the Apache Hadoop umbrella

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# Overview

- Design goal: find sweet spot between declarative style of SQL and low-level procedural style of MapReduce
- Programmer creates Pig Latin program, using high-level operators
- Pig Latin program is compiled to MapReduce program to run on Hadoop

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# Why Not SQL or Plain MapReduce?

- SQL difficult to use and debug for many programmers
- Programmer might not trust automatic optimizer and prefers to hard-code best query plan
- Plain MapReduce lacks convenience of readily available, reusable data manipulation operators like selection, projection, join, sort
- Program semantics hidden in “opaque” Java code
  - More difficult to optimize and maintain

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# Example Data Analysis Task

Find the top 10 most visited pages in each category

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 |

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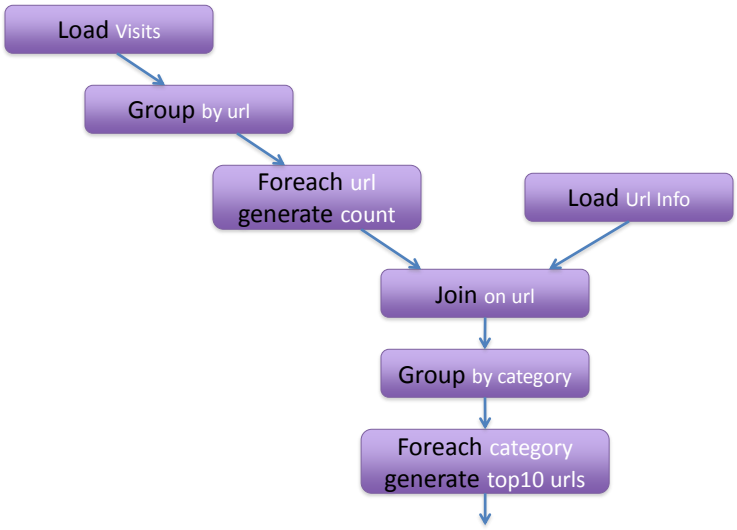
# Data Flow

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# In Pig Latin

```
visits       = load '/data/visits' as (user, url, time);
gVisits      = group visits by url;
visitCounts  = foreach gVisits generate url, count(visits);

urlInfo      = load '/data/urlInfo' as (url, category, pRank);
visitCounts  = join visitCounts by url, urlInfo by url;

gCategories = group visitCounts by category;
topUrls = foreach gCategories generate top(visitCounts,10);

store topUrls into '/data/topUrls';
```

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# Pig Latin Notes

- No need to import data into database
  - Pig Latin works directly with files
- Schemas are optional and can be assigned dynamically
  - Load '/data/visits' as (user, url, time);
- Can call user-defined functions in every construct like Load, Store, Group, Filter, Foreach
  - Foreach gCategories generate top(visitCounts,10);

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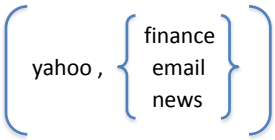
# Pig Latin Data Model

- Fully-nestable data model with:
  - Atomic values, tuples, bags (lists), and maps




- More natural to programmers than flat tuples
  - Can flatten nested structures using FLATTEN
- Avoids expensive joins, but more complex to process

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# Pig Latin Operators: LOAD

- Reads data from file and optionally assigns schema to each record
- Can use custom deserializer

queries = LOAD 'query_log.txt' USING myLoad()
AS (userID, queryString, timestamp);

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# Pig Latin Operators: FOREACH

- Applies processing to each record of a data set
- No dependence between the processing of different records
  - Allows efficient parallel implementation
- GENERATE creates output records for a given input record

```
expanded_queries = FOREACH queries
GENERATE userId, expandQuery(queryString);
```

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# Pig Latin Operators: FILTER

- Remove records that do not pass filter condition
- Can use user-defined function in filter condition

```
real_queries =
        FILTER queries BY userId neq `bot‘;
```

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# Pig Latin Operators: COGROUP

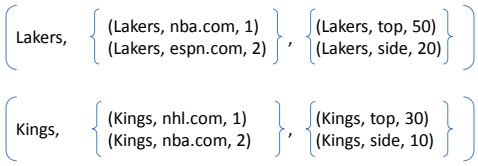
- Group together records from one or more data sets

results

| queryString | url | rank |
|---|---|---|
| Lakers | nba.com | 1 |
| Lakers | espn.com | 2 |
| Kings | nhl.com | 1 |
| Kings | nba.com | 2 |

revenue

| queryString | adSlot | amount |
|---|---|---|
| Lakers | top | 50 |
| Lakers | side | 20 |
| Kings | top | 30 |
| Kings | side | 10 |




COGROUP results BY queryString, revenue BY queryString



# Pig Latin Operators: GROUP

- Special case of COGROUP, to group single data set by selected fields
- Similar to GROUP BY in SQL, but does not need to apply aggregate function to records in each group

grouped_revenue = GROUP revenue BY queryString;

# Pig Latin Operators: JOIN

- Computes equi-join

join_result = JOIN results BY queryString, revenue BY queryString;

- Just a syntactic shorthand for COGROUP followed by flattening

temp_var = COGROUP results BY queryString, revenue BY queryString;

join_result = FOREACH temp_var GENERATE FLATTEN(results), FLATTEN(revenue);

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# Other Pig Latin Operators

- UNION: union of two or more bags
- CROSS: cross product of two or more bags
- ORDER: orders a bag by the specified field(s)
- DISTINCT: eliminates duplicate records in bag
- STORE: saves results to a file
- Nested bags within records can be processed by nesting operators within a FOREACH operator

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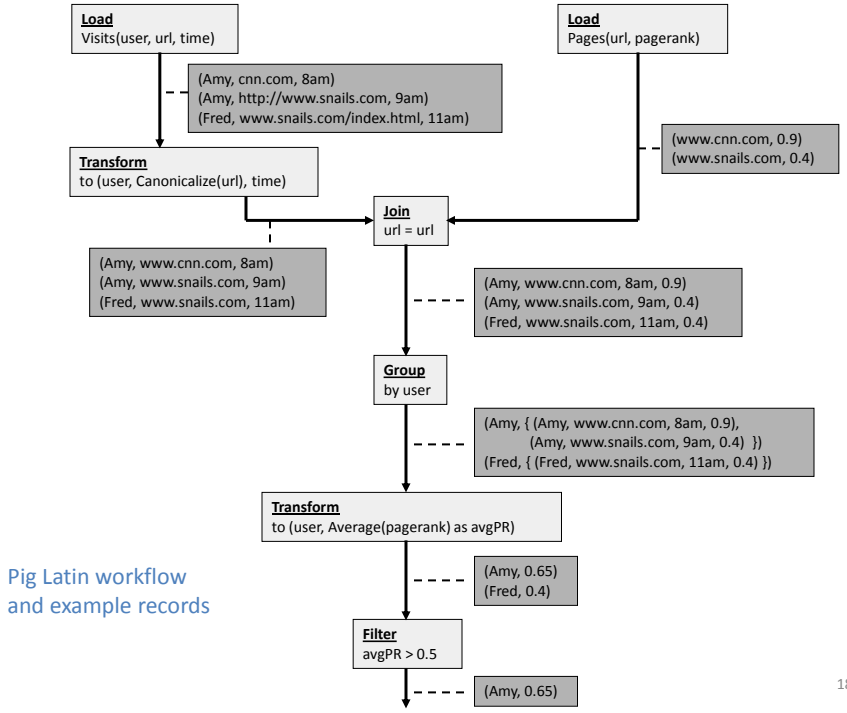


# MapReduce in Pig Latin

```
map_result = FOREACH input GENERATE
        FLATTEN(map(*));
key_groups = GROUP map_result BY $0;
output = FOREACH key_groups GENERATE reduce(*);
```

- Map() is a UDF, where * indicates that the entire input record is passed to map()
- $0 refers to first field, i.e., the intermediate key here
- Reduce() is another UDF

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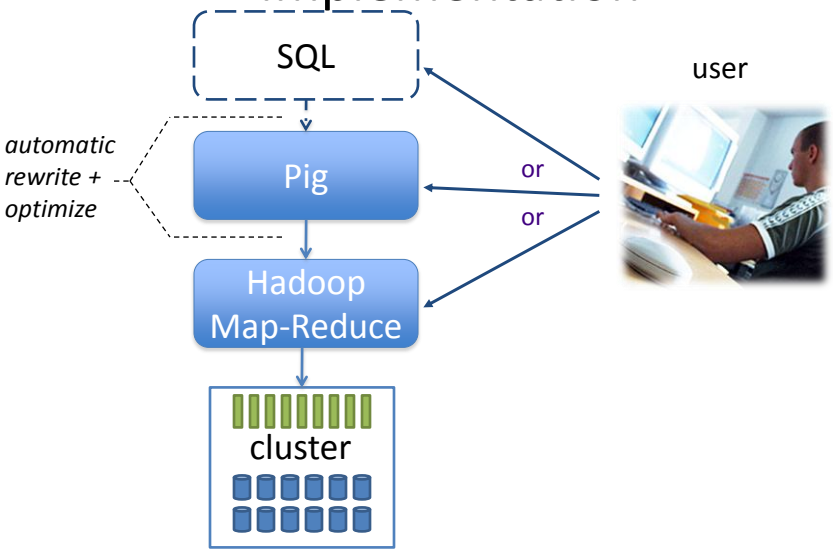
# Implementation

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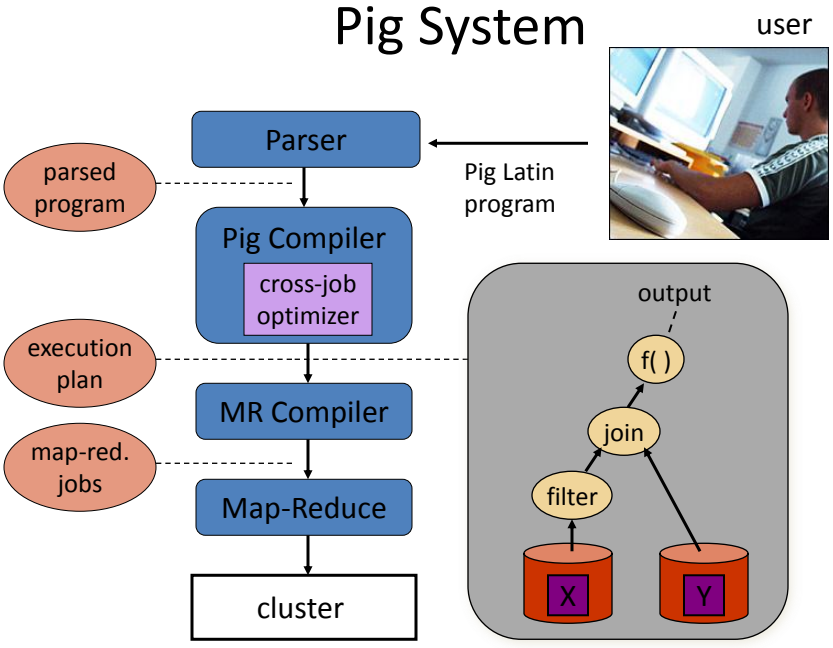
# Pig System

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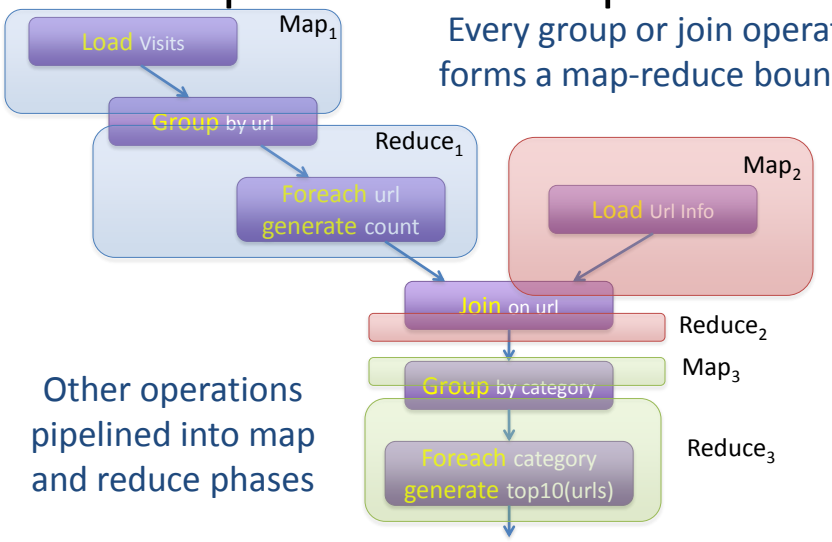
# Compilation into Map-Reduce




Every group or join operation forms a map-reduce boundary

Other operations pipelined into map and reduce phases

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# Is Pig a DBMS?

| | DBMS | Pig |
|---|---|---|
| workload | | |
| data representation | | |
| programming style | | |
| customizable processing | | |

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Now let's go back to plain Hadoop and look at important program "design patterns".

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# MapReduce Design Patterns

- This section is based on the book by Jimmy Lin and Chris Dyer
- Programmer can control program execution only through implementation of mapper, reducer, combiner, and partitioner
- No explicit synchronization primitives
- So how can a programmer control execution and data flow?

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# Taking Control of MapReduce

- Store and communicate partial results through complex data structures for keys and values
- Run appropriate initialization code at beginning of task and termination code at end of task
- Preserve state in mappers and reducers across multiple input splits and intermediate keys, respectively
- Control sort order of intermediate keys to control processing order at reducers
- Control set of keys assigned to a reducer
- Use “driver” program

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# (1) Local Aggregation

- Reduce size of intermediate results passed from mappers to reducers
  - Important for scalability: recall Amdahl’s Law
- Various options using combiner function and ability to preserve mapper state across multiple inputs
- Illustrated with word count example
  - Will use document-based version of Map

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# Word Count Baseline Algorithm

```
map(docID a, doc d)
 for all term t in doc d do
  Emit(term t, count 1)
```

```
reduce(term t, counts [c1, c2,…])
 sum = 0
 for all count c in counts do
  sum += c
 Emit(term t, count sum);
```

- Problem: frequent terms are emitted many times with count 1

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# Tally Counts Per Document

```
map(docID a, doc d)
 H = new hashMap
 for all term t in doc d do
  H{t} ++
 for all term t in H do
  Emit(term t, count H{t})
```

- Same Reduce function as before
- Limitation: only aggregates counts within document
- Map task usually receives split containing many documents
- Can we aggregate across all documents in the same task?

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# Tally Counts Across Documents

- Data structure is private member of mapper
- Initialize is called once before all map invocations
  - Configure() in old API
  - Setup() in new API
- Close is called after last document from split has been processed
  - Close() in old API
  - Cleanup() in new API

```
Class Mapper
 initialize()
  H = new hashMap

 map(docID a, doc d)
  for all term t in doc d do
   H{t} ++

 close()
  for all term t in H do
   Emit(term t, count H{t})
```

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# Design Pattern for Local Aggregation

- In-mapper combining
  - Done by preserving state across map calls in same task
- Advantages over using combiners
  - Combiner does not guarantee if, when or how often it is executed
  - Combiner combines data *after* it was generated, in-mapper combining avoids generating it!
- Drawbacks
  - Introduces complexity, e.g., result might depend on order of map executions (order-dependent bugs possible!)
  - Higher memory consumption for managing state
    - Might have to write memory-management code to page data to disk

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# (2) Counting of Combinations

- Needed for computing correlations, associations, confusion matrix (how many times does a classifier confuse $Y_i$ with $Y_j$)
- Co-occurrence matrix for a text corpus: how many times do two terms appear near each other
- Compute partial counts for some combinations, then aggregate them
  - At what granularity should Map work?

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