Tutorial: High-Level Programming Languages

MapReduce Simplified

Pietro Michiardi

Eurecom

EURECOM

Sophia Antipolis

Introduction

Overview

- **Raising the level of abstraction for processing large datasets**
  - Scalable Algorithm Design is complex using MapReduce
  - Code gets messy, redundant, difficult to re-use
- **Many alternatives exists, based on different principles**
  - Data-flow programming
  - SQL-like declarative programming
  - Additional operators (besides `Map` and `Reduce`)
- **Optimization is a hot research topic**
  - Based on traditional RDBMS optimizations

Topics covered

- **Review foundations of relational algebra in light of MapReduce**

- **Hadoop PIG**
  - Data-flow language, originated from Yahoo!
  - Internals
  - Optimizations

- **Cascading + Scalding**

- **SPARK**[1]

[1] This is an abuse: SPARK is an execution enging that replaces Hadoop, based on Reliable Distributed Datasets, that reside in memory. The programming model is MapReduce, using Scala.

Relational Algebra and MapReduce

Introduction

- **Disclaimer**
  - This is not a full course on Relational Algebra
  - Neither this is a course on SQL

- **Introduction to Relational Algebra, RDBMS and SQL**
  - Follow the video lectures of the Stanford class on RDBMS `http://www.db-class.org/`

  → Note that you have to sign up for an account

- **Overview of this part**
  - Brief introduction to simplified relational algebra
  - Useful to understand Pig, Hive and HBase

Relational Algebra Operators

- **There are a number of operations on data that fit well the relational algebra model**
  - In traditional RDBMS, queries involve retrieval of small amounts of data
  - In this course, and in particular in this class, we should keep in mind the particular workload underlying MapReduce
  - → Full scans of large amounts of data
  - → Queries are not selective, they process all data

- **A review of some terminology**
  - A *relation* is a table
  - *Attributes* are the column headers of the table
  - The set of attributes of a relation is called a *schema*
    Example: $R(A_1, A_2, ..., A_n)$ indicates a relation called R whose attributes are $A_1, A_2, ..., A_n$

Operators

Operators

- **Let's start with an example**
  - Below, we have part of a relation called *Links* describing the structure of the Web
  - There are two *attributes*: *From* and *To*
  - A row, or *tuple*, of the relation is a pair of URLs, indicating the existence of a link between them
  - → The number of tuples in a real dataset is in the order of billions (10^9)

From	To
url1	url2
url1	url3
url2	url3
url2	url4
...	...

Operators

- **Relations (however big) can be stored in a distributed filesystem**
  - If they don't fit in a single machine, they're broken into pieces (think HDFS)

- **Next, we review and describe a set of relational algebra operators**
  - Intuitive explanation of what they do
  - "Pseudo-code" of their implementation in/by MapReduce

Operators

- **Selection:** $\sigma_C(R)$
  - Apply condition C to each tuple of relation R
  - Produce in output a relation containing only tuples that satisfy C
- **Projection:** $\pi_S(R)$
  - Given a *subset* S of relation R attributes
  - Produce in output a relation containing only tuples for the attributes in S
- **Union, Intersection and Difference**
  - Well known operators on sets
  - Apply to the set of tuples in two relations that have the same schema
  - Variations on the theme: work on *bags*

Operators

- **Natural join $R \bowtie S$**
  - Given two relations, *compare each pair of tuples*, one from each relation
  - If the tuples agree on all the attributes common to both schema $\rightarrow$ produce an output tuple that has components on each attribute
  - Otherwise produce nothing
  - *Join condition* can be on a subset of attributes
- **Let's work with an example**
  - Recall the *Links* relation from previous slides
  - `Query` (or data processing job): `find the paths of length two in the Web`

Join Example

- **Informally, to satisfy the query we must:**
  - find the triples of URLs in the form (u, v, w) such that there is a link from u to v and a link from v to w
- **Using the join operator**
  - Imagine we have two relations (with different schemas), and let's try to apply the natural join operator
  - There are two copies of *Links*: $L_1(U_1, U_2)$ and $L_2(U_2, U_3)$
  - Let's compute $L_1 \bowtie L_2$
    - ★ For each tuple t_1 of L_1 and each tuple t_2 of L_2, see if their U_2 component are the same
    - ★ If yes, then produce a tuple in output, with the schema (U_1, U_2, U_3)

Join Example

- **What we have seen is called (to be precise) a self-join**
  - Question: How would you implement a self join in your favorite programming language?
  - Question: What is the time complexity of your algorithm?
  - Question: What is the space complexity of your algorithm?

- **To continue the example**
  - Say you are not interested in the entire two-hop path but just the start and end nodes
  - Then you do a projection and the notation would be: $\pi_{U_1,U_3}(L_1 \bowtie L_2)$

Operators

- **Grouping and Aggregation: $\gamma_X(R)$**
  - Given a relation R, partition its tuples according to their values in one set of attributes G
    - ★ The set G is called the grouping attributes
  - Then, for each group, aggregate the values in certain other attributes
    - ★ Aggregation functions: `SUM`, `COUNT`, `AVG`, `MIN`, `MAX`, ...

- **In the notation, X is a list of elements that can be:**
  - A grouping attribute
  - An expression $\theta(A)$, where θ is one of the (five) aggregation functions and A is an attribute NOT among the grouping attributes

Operators

- **Grouping and Aggregation:** $\gamma_X(R)$
  - The result of this operation is a relation with one tuple for each group
  - That tuple has a component for each of the grouping attributes, with the value common to tuples of that group
  - That tuple has another component for each aggregation, with the aggregate value for that group

- **Let's work with an example**
  - Imagine that a social-networking site has a relation `Friends(User, Friend)`
  - The tuples are pairs (a, b) such that b is a friend of a
  - `Query: compute the number of friends each member has`

Grouping and Aggregation Example

- **How to satisfy the query**

  $\gamma_{User,\texttt{COUNT}(Friend))}(Friends)$

  - This operation groups all the tuples by the value in their frist component
  - → There is one group for each user
  - Then, for each group, it counts the number of friends

- **Some details**
  - The `COUNT` operation applied to an attribute does not consider the values of that attribute
  - In fact, it counts the number of tuples in the group
  - In SQL, there is a "count distinct" operator that counts the number of different values

MapReduce implementation of (some) Relational Operators

Computing Selection

- **In practice, selection does not need a full-blown MapReduce implementation**
  - They can be implemented in the map portion alone
  - Actually, they could also be implemented in the reduce portion

- **A MapReduce implementation of $\sigma_C(R)$**

Map:
  - ⋆ For each tuple t in R, check if t satisfies C
  - ⋆ If so, emit a key/value pair (t, t)

Reduce:
  - ⋆ Identity reducer
  - ⋆ Question: single or multiple reducers?

- **NOTE: the output is not exactly a relation**
  - WHY?

Computing Projections

- **Similar process to selection**
  - But, projection may cause same tuple to appear several times

- **A MapReduce implementation of $\pi_S(R)$**

Map:
  - ★ For each tuple t in R, construct a tuple t' by eliminating those components whose attributes are not in S
  - ★ Emit a key/value pair (t', t')

Reduce:
  - ★ For each key t' produced by any of the Map tasks, fetch $t', [t', \cdots, t']$
  - ★ Emit a key/value pair (t', t')

- **NOTE: the reduce operation is duplicate elimination**
  - This operation is associative and commutative, so it is possible to optimize MapReduce by using a `Combiner` in each mapper

Computing Unions

- **Suppose relations R and S have the same schema**
  - Map tasks will be assigned chunks from either R or S
  - Mappers don't do much, just pass by to reducers
  - Reducers do duplicate elimination

- **A MapReduce implementation of union**

Map:
  - ⋆ For each tuple t in R or S, emit a key/value pair (t, t)

Reduce:
  - ⋆ For each key t there will be either one or two values
  - ⋆ Emit (t, t) in either case

Computing Intersections

- **Very similar to computing unions**
  - Suppose relations R and S have the same schema
  - The map function is the same (an identity mapper) as for union
  - The reduce function must produce a tuple only if both relations have that tuple

- **A MapReduce implementation of intersection**

Map:
- ★ For each tuple t in R or S, emit a key/value pair (t, t)

Reduce:
- ★ If key t has value list $[t, t]$ then emit the key/value pair (t, t)
- ★ Otherwise, emit the key/value pair $(t, \texttt{NULL})$

EURECOM

Computing difference

- **Assume we have two relations *R* and *S* with the same schema**
  - The only way a tuple t can appear in the output is if it is in R but not in S
  - The map function can pass tuples from R and S to the reducer
  - NOTE: it must inform the reducer whether the tuple came from R or S

- **A MapReduce implementation of difference**

Map:
- ⋆ For a tuple t in R emit a key/value pair $(t, '\mathtt{R}')$ and for a tuple t in S, emit a key/value pair $(t, '\mathtt{S}')$

Reduce:
- ⋆ For each key t, do the following:
- ⋆ If it is associated to $'\mathtt{R}'$, then emit (t, t)
- ⋆ If it is associated to $['\mathtt{R}', '\mathtt{S}']$ or $['\mathtt{S}', '\mathtt{R}']$, or $['\mathtt{S}']$, emit the key/value pair $(t, \mathtt{NULL})$

Computing the natural Join

- **This topic is subject to continuous refinements**
  - There are many `JOIN` operators and many different implementations
  - We will see some of them in more detail in the Lab
- **Let's look at two relations** $R(A, B)$ **and** $S(B, C)$
  - We must find tuples that agree on their B components
  - We shall use the B-value of tuples from either relation as the key
  - The value will be the other component and the name of the relation
  - That way the reducer knows from which relation each tuple is coming from

Computing the natural Join

- **A MapReduce implementation of Natural Join**

Map:
- ★ For each tuple (a, b) of R emit the key/value pair $(b, ('\mathtt{R}', a))$
- ★ For each tuple (b, c) of S emit the key/value pair $(b, ('\mathtt{S}', c))$

Reduce:
- ★ Each key b will be associated to a list of pairs that are either $('\mathtt{R}', a)$ or $('\mathtt{S}', c)$
- ★ Emit key/value pairs of the form $(b, [(a_1, b, c_1), (a_2, b, c_2), \cdots, (a_n, b, c_n)])$

- **NOTES**
  - Question: what if the MapReduce framework wouldn't implement the distributed (and sorted) group by?
  - In general, for n tuples in relation R and m tuples in relation S all with a common B-value, then we end up with nm tuples in the result
  - If all tuples of both relations have the same B-value, then we're computing the **cartesian product**

Grouping and Aggregation in MapReduce

- **Let $R(A, B, C)$ be a relation to which we apply $\gamma_{A,\theta(B)}(R)$**
  - The map operation prepares the grouping
  - The grouping is done by the framework
  - The reducer computes the aggregation
  - Simplifying assumptions: one grouping attribute and one aggregation function

- **MapReduce implementation of $\gamma_{A,\theta(B)}(R)$**

Map:
  - ★ For each tuple (a, b, c) emit the key/value pair (a, b)

Reduce:
  - ★ Each key a represents a group
  - ★ Apply θ to the list $[b_1, b_2, \cdots, b_n]$
  - ★ Emit the key/value pair (a, x) where $x = \theta([b_1, b_2, \cdots, b_n])$

Hadoop PIG

Introduction

- **Collection and analysis of enormous datasets is at the heart of innovation in many organizations**
  - E.g.: web crawls, search logs, click streams
- **Manual inspection before batch processing**
  - Very often engineers look for exploitable trends in their data to drive the design of more sophisticated techniques
  - This is difficult to do in practice, given the sheer size of the datasets
- **The MapReduce model has its own limitations**
  - One input
  - Two-stage, two operators
  - Rigid data-flow

MapReduce limitations

- **Very often tricky workarounds are required**[2]
  - This is very often exemplified by the difficulty in performing `JOIN` operations
- **Custom code required even for basic operations**
  - Projection and Filtering need to be "rewritten" for each job

→ Code is difficult to reuse and maintain

→ Semantics of the analysis task are obscured

→ Optimizations are difficult due to opacity of `Map` and `Reduce`

[2] The term workaround should not only be intended as negative.

Use Cases

Rollup aggregates

- **Compute aggregates against user activity logs, web crawls, etc.**
  - Example: compute the frequency of search terms aggregated over days, weeks, month
  - Example: compute frequency of search terms aggregated over geographical location, based on IP addresses
- **Requirements**
  - Successive aggregations
  - Joins followed by aggregations
- **Pig vs. OLAP systems**
  - Datasets are too big
  - **Data curation** is too costly

Use Cases

Temporal Analysis

- **Study how search query distributions change over time**
  - Correlation of search queries from two distinct time periods (groups)
  - Custom processing of the queries in each correlation group
- **Pig supports operators that minimize memory footprint**
  - Instead, in a RDBMS such operations typically involve `JOINS` over very large datasets that do not fit in memory and thus become slow

Use Cases

Session Analysis

- **Study sequences of page views and clicks**
- **Example of typical aggregates**
  - Average length of user session
  - Number of links clicked by a user before leaving a website
  - Click pattern variations in time
- **Pig supports advanced data structures, and UDFs**

Pig Latin

- **Pig Latin, a high-level programming language developed at Yahoo!**
  - Combines the best of both declarative and imperative worlds
    - High-level declarative querying in the spirit of SQL
    - Low-level, procedural programming á la MapReduce

- **Pig Latin features**
  - Multi-valued, nested data structures instead of flat tables
  - Powerful data transformations primitives, including joins

- **Pig Latin program**
  - Made up of a series of operations (or transformations)
  - Each operation is applied to input data and produce output data

  → A Pig Latin program describes a data flow

Example 1

Pig Latin premiere

- **Assume we have the following table:**

```
urls:  (url, category, pagerank)
```

- Where:
  - `url`: is the url of a web page
  - `category`: corresponds to a pre-defined category for the web page
  - `pagerank`: is the numerical value of the pagerank associated to a web page

→ *Find, for each sufficiently large category, the average page rank of high-pagerank urls in that category*

Example 1

SQL

```
SELECT category, AVG(pagerank)
FROM urls WHERE pagerank > 0.2
GROUP BY category HAVING COUNT(*) > 10^6
```

Example 1

Pig Latin

```
good_urls = FILTER urls BY pagerank > 0.2;
groups = GROUP good_urls BY category;
big_groups = FILTER groups BY COUNT(good_urls) > 10^6;
output = FOREACH big_groups GENERATE
category, AVG(good_urls.pagerank);
```

Pig Execution environment

- **How do we go from Pig Latin to MapReduce?**
  - The Pig system is in charge of this
  - Complex execution environment that interacts with Hadoop MapReduce
  - → The programmer focuses on the data and analysis
- **Pig Compiler**
  - Pig Latin operators are translated into MapReduce code
  - NOTE: in some cases, hand-written MapReduce code performs better
- **Pig Optimizer**
  - Pig Latin data flows undergo an (automatic) optimization phase
  - These optimizations are borrowed from the RDBMS community

Pig and Pig Latin

- **Pig is not a RDBMS!**
  - This means it is not suitable for all data processing tasks
- **Designed for batch processing**
  - Of course, since it compiles to MapReduce
  - Of course, since data is materialized as files on HDFS
- **NOT designed for random access**
  - Query selectivity does not match that of a RDBMS
  - Full-scans oriented!

Comparison with RDBMS

- **It may seem that Pig Latin is similar to SQL**
  - We'll see several examples, operators, etc. that resemble SQL statements

- **Data-flow vs. declarative programming language**
  - Data-flow:
    - Step-by-step set of operations
    - Each operation is a single transformation
  - Declarative:
    - Set of constraints
    - Applied together to an input to generate output

→ **With Pig Latin it's like working at the query planner**

Comparison with RDBMS

- **RDBMS store data in tables**
  - Schemas are predefined and strict
  - Tables are flat
- **Pig and Pig Latin work on more complex data structures**
  - Schema can be defined at run-time for readability
  - *Pigs eat anything!*
  - UDF and streaming together with nested data structures make Pig and Pig Latin more flexible

Features and Motivations

Features and Motivations

- **Design goals of Pig and Pig Latin**
  - Appealing to programmers for performing ad-hoc analysis of data
  - Number of features that go beyond those of traditional RDBMS
- **Next: overview of salient features**
  - There will be a dedicated set of slides to optimizations later on

Dataflow Language

- **A Pig Latin program specifies a series of steps**
  - Each step is a single, high level data transformation
  - Stylistically different from SQL
- **With reference to Example 1**
  - The programmer supply an order in which each operation will be done
- **Consider the following snippet**

```
spam_urls = FILTER urls BY isSpam(url);
culprit_urls = FILTER spam_urls BY pagerank > 0.8;
```

Dataflow Language

- **Data flow optimizations**
  - Explicit sequences of operations can be overridden
  - Use of high-level, relational-algebra-style primitives (`GROUP`, `FILTER`,...) allows using traditional RDBMS optimization techniques

→ **NOTE: it is necessary to check whether such optimizations are beneficial or not, by hand**

- **Pig Latin allows Pig to perform optimizations that would otherwise by a tedious manual exercise if done at the MapReduce level**

Quick Start and Interoperability

- **Data I/O is greatly simplified in Pig**
  - No need to curate, bulk import, parse, apply schema, create indexes that traditional RDBMS require
  - Standard and ad-hoc "readers" and "writers" facilitate the task of ingesting and producing data in arbitrary formats

- **Pig can work with a wide range of other tools**

- **Why RDBMS have stringent requirements?**
  - To enable transactional consistency guarantees
  - To enable efficient point lookup (using physical indexes)
  - To enable data curation on behalf of the user
  - To enable other users figuring out what the data is, by studying the schema

Quick Start and Interoperability

- **Why is Pig so flexible?**
  - Supports read-only workloads
  - Supports scan-only workloads (no lookups)

  → No need for transactions nor indexes

- **Why data curation is not required?**
  - Very often, Pig is used for ad-hoc data analysis
  - Work on temporary datasets, then throw them

  → Curation is an overkill

- **Schemas are optional**
  - Can apply one on the fly, at runtime
  - Can refer to fields using positional notation
  - E.g.: `good_urls = FILTER urls BY $2 > 0.2`

Nested Data Model

- **Easier for "programmers" to think of nested data structures**
  - E.g.: capture information about positional occurrences of terms in a collection of documents
  - Map<documnetId, Set<positions> >
- **Instead, RDBMS allows only falt tables**
  - Only atomic fields as columns
  - Require normalization
  - From the example above: need to create two tables
  - term_info: (termId, termString, ...)
  - position_info: (termId, documentId, position)
  - → Occurrence information obtained by joining on termId, and grouping on termId, documentId

Nested Data Model

- **Fully nested data model (see also later in the presentation)**
  - Allows complex, non-atomic data types
  - E.g.: set, map, tuple

- **Advantages of a nested data model**
  - More natural than normalization
  - Data is often already stored in a nested fashion on disk
    - E.g.: a web crawler outputs for each crawled url, the set of outlinks
    - Separating this in normalized form imply use of joins, which is an overkill for web-scale data
  - Nested data allows to have an algebraic language
    - E.g.: each tuple output by `GROUP` has one non-atomic field, a nested set of tuples from the same group
  - Nested data makes life easy when writing UDFs

User Defined Functions

- **Custom processing is often predominant**
  - E.g.: users may be interested in performing natural language stemming of a search term, or tagging urls as spam
- **All commands of Pig Latin can be customized**
  - Grouping, filtering, joining, per-tuple processing
- **UDFs support the nested data model**
  - Input and output can be non-atomic

Example 2

- **Continues from Example 1**
  - Assume we want to find for each category, the top 10 urls according to pagerank

```
groups = GROUP urls BY category;
output = FOREACH groups GENERATE category,
top10(urls);
```

- `top10()` is a UDF that accepts a set of urls (for each group at a time)
- it outputs a set containing the top 10 urls by pagerank for that group
- final output contains non-atomic fields

User Defined Functions

- **UDFs can be used in all Pig Latin constructs**
- **Instead, in SQL, there are restrictions**
  - Only scalar functions can be used in `SELECT` clauses
  - Only set-valued functions can appear in the `FROM` clause
  - Aggregation functions can only be applied to `GROUP BY` or `PARTITION BY`
- **UDFs can be written in Java, Python and Javascript**[3]
  - With streaming, we can use also C/C++, Python, ...

[3] As of Pig 0.8.1 and later. We will use version 0.10.0 or more.

Handling parallel execution

- **Pig and Pig Latin are geared towards parallel processing**
  - Of course, the underlying execution engine is MapReduce
- **Pig Latin primitives are chosen such that they can be easily parallelized**
  - Non-equi joins, correlated sub-queries,... are not directly supported
- **Users may specify parallelization parameters at run time**
  - Question: Can you specify the number of maps?
  - Question: Can you specify the number of reducers?

Pig Latin

Introduction

- **Not a complete reference to the Pig Latin language**: refer to [1]
  - Here we cover some interesting aspects
- **The focus here is on some language primitives**
  - Optimizations are treated separately
  - How they can be implemented is covered later
- **Examples are taken from [2, 3]**

Data Model

- **Supports four types**
  - *Atom:* contains a simple atomic value as a string or a number, e.g. `‘alice’`
  - *Tuple:* sequence of *fields*, each can be of any data type, e.g., `(‘alice’, ‘lakers’)`
  - *Bag:* collection of tuples with possible duplicates. Flexible schema, no need to have the same number and type of fields

    ```
    {      (‘alice’,‘lakers’)       }
    { (‘alice’,(‘iPod’,‘apple’))    }
    ```

    The example shows that tuples can be nested

Data Model

- **Supports four types**
  - *Map:* collection of data items, where each item has an associated key for lookup. The schema, as with bags, is flexible.
    - ★ NOTE: keys are required to be data atoms, for efficient lookup.

$$\left[\begin{array}{c} \texttt{`fan of'} \rightarrow \left\{\begin{array}{c}\texttt{(`lakers')} \\ \texttt{(`iPod')}\end{array}\right\} \\ \texttt{(`age'} \rightarrow \texttt{20)} \end{array}\right]$$

    - ★ The key `‘fan of’` is mapped to a bag containing two tuples
    - ★ The key `‘age’` is mapped to an atom
  - Maps are useful to model datasets in which schema may be dynamic (over time)

Structure

- **Pig latin programs are a sequence of steps**
  - Can use an interactive shell (called `grunt`)
  - Can feed them as a "script"
- **Comments**
  - In line: with double hyphens (`- -`)
  - C-style for longer comments (`/* ... */`)
- **Reserved keywords**
  - List of keywords that can't be used as identifiers
  - Same old story as for any language

Statements

- **As a Pig Latin program is executed, each statement is *parsed***
  - The interpreter builds a logical plan for every relational operation
  - The logical plan of each statement is added to that of the program so far
  - Then the interpreter moves on to the next statement

- **IMPORTANT: No data processing takes place during construction of logical plan**
  - When the interpreter sees the first line of a program, it confirms that it is syntactically and semantically correct
  - Then it adds it to the logical plan
  - It does not even check the existence of files, for data load operations

Statements

→ **It makes no sense to start any processing until the whole flow is defined**
  - Indeed, there are several optimizations that could make a program more efficient (e.g., by avoiding to operate on some data that later on is going to be filtered)

- **The trigger for Pig to start execution are the `DUMP` and `STORE` statements**
  - It is only at this point that the logical plan is compiled into a physical plan

- **How the physical plan is built**
  - Pig prepares a series of MapReduce jobs
    - In *Local mode*, these are run locally on the JVM
    - In *MapReduce mode*, the jobs are sent to the Hadoop Cluster
  - IMPORTANT: The command `EXPLAIN` can be used to show the MapReduce plan

Statements

Multi-query execution

- **There is a difference between `DUMP` and `STORE`**
  - Apart from diagnosis, and interactive mode, in batch mode `STORE` allows for program/job optimizations

- **Main optimization objective: minimize I/O**
  - Consider the following example:

```
A = LOAD 'input/pig/multiquery/A';
B = FILTER A BY $1 == 'banana';
C = FILTER A BY $1 != 'banana';
STORE B INTO 'output/b';
STORE C INTO 'output/c';
```

Statements

Multi-query execution

- **In the example, relations `B` and `C` are both derived from `A`**
  - Naively, this means that at the first `STORE` operator the input should be read
  - Then, at the second `STORE` operator, the input should be read again
- **Pig will run this as a single MapReduce job**
  - Relation `A` is going to be read only once
  - Then, each relation `B` and `C` will be written to the output

Expressions

- **An expression is something that is evaluated to yield a value**
  - Lookup on [3] for documentation

$$t = \left(\text{`alice'}, \left\{ \begin{array}{c} (\text{`lakers'},\ 1) \\ (\text{`iPod'},\ 2) \end{array} \right\}, \left[ \text{`age'} \rightarrow 20 \right] \right)$$

Let fields of tuple `t` be called `f1, f2, f3`

Expression Type	Example	Value for t
Constant	'bob'	Independent of t
Field by position	\$0	'alice'
Field by name	f3	$\left[\text{`age'} \rightarrow 20 \right]$
Projection	f2.\$0	$\left\{ \begin{array}{c} (\text{`lakers'}) \\ (\text{`iPod'}) \end{array} \right\}$
Map Lookup	f3#'age'	20
Function Evaluation	SUM(f2.\$1)	1 + 2 = 3
Conditional Expression	f3#'age'>18? 'adult':'minor'	'adult'
Flattening	FLATTEN(f2)	'lakers', 1 'iPod', 2

Schemas

- **A relation in Pig may have an associated schema**
  - This is optional
  - A schema gives the fields in the relations names and types
  - Use the command `DESCRIBE` to reveal the schema in use for a relation
- **Schema declaration is flexible but reuse is awkward**
  - A set of queries over the same input data will often have the same schema
  - This is sometimes hard to maintain (unlike HIVE) as there is no external components to maintain this association

HINT:: You can write a UDF function to perform a personalized load operation which encapsulates the schema

Validation and nulls

- **Pig does not have the same power to enforce constraints on schema at load time as a RDBMS**
  - If a value cannot be cast to a type declared in the schema, then it will be set to a `null` value
  - This also happens for corrupt files
- **A useful technique to partition input data to discern good and bad records**
  - Use the `SPLIT` operator

```
SPLIT records INTO good_records IF temperature is
not null, bad _records IF temperature is NULL;
```

Other relevant information

- **Schema merging**
  - How schema are propagated to new relations?
- **Functions**
  - Look up on the web for **Piggy Bank**
- **User-Defined Functions**
  - Use [3] for an introduction to designing UDFs

Data Processing Operators

Loading and storing data

- **The first step in a Pig Latin program is to load data**
  - What input files are
  - How the file contents are to be deserialized
  - An input file is assumed to contain a sequence of tuples

- Data loading is done with the `LOAD` command

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

Data Processing Operators

Loading and storing data

- **The example above specifies the following:**
  - The input file is `query_log.txt`
  - The input file should be converted into tuples using the custom `myLoad` deserializer
  - The loaded tuples have three fields, specified by the schema

- **Optional parts**
  - `USING` clause is optional: if not specified, the input file is assumed to be plain text, tab-delimited
  - `AS` clause is optional: if not specified, must refer to fileds by position instead of by name

Data Processing Operators

Loading and storing data

- Return value of the `LOAD` command
  - Handle to a bag
  - This can be used by subsequent commands
  - → bag handles are only logical
  - → no file is actually read!

- The command to write output to disk is `STORE`
  - It has similar semantics to the `LOAD` command

Data Processing Operators

Per-tuple processing: Filtering data

- **Once you have some data loaded into a relation, the next step is to filter it**
  - This is done, e.g., to remove unwanted data
  - HINT: By filtering early in the processing pipeline, you minimize the amount of data flowing trough the system

- **A basic operation is to apply some processing over every tuple of a data set**
  - This is achieved with the `FOREACH` command

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

Data Processing Operators

Per-tuple processing: Filtering data

- **Comments on the example above:**
  - Each tuple of the bag `queries` should be processed independently
  - The second field of the output is the result of a UDF
- **Semantics of the `FOREACH` command**
  - There can be no dependence between the processing of different input tuples
  - → This allows for an efficient parallel implementation
- **Semantics of the `GENERATE` clause**
  - Followed by a list of expressions
  - Also *flattering* is allowed
    - ★ This is done to eliminate nesting in data
    - → Allows to make output data independent for further parallel processing
    - → Useful to store data on disk

Data Processing Operators

Per-tuple processing: Discarding unwanted data

- **A common operation is to retain a portion of the input data**
  - This is done with the `FILTER` command
    ```
    real_queries = FILTER queries BY userId neq
    'bot';
    ```
- **Filtering conditions involve a combination of expressions**
  - Comparison operators
  - Logical connectors
  - UDF

Data Processing Operators

Per-tuple processing: Streaming data

- **The `STREAM` operator allows transforming data in a relation using an external program or script**
  - This is possible because Hadoop MapReduce supports "streaming"
  - Example:

    ```
    C = STREAM A THROUGH 'cut -f 2';
    ```

    which use the Unix `cut` command to extract the second filed of each tuple in `A`

- **The `STREAM` operator uses `PigStorage` to serialize and deserialize relations to and from `stdin/stdout`**
  - Can also provide a custom serializer/deserializer
  - Works well with python

Data Processing Operators

Getting related data together

- **It is often necessary to *group* together tuples from one or more data sets**
  - We will explore several nuances of “grouping”

- **The first grouping operation we study is given by the COGROUP command**

  Example: Assume we have loaded two relations

  ```
  results:  (queryString, url, position)
  revenue:  (queryString, adSlot, amount)
  ```

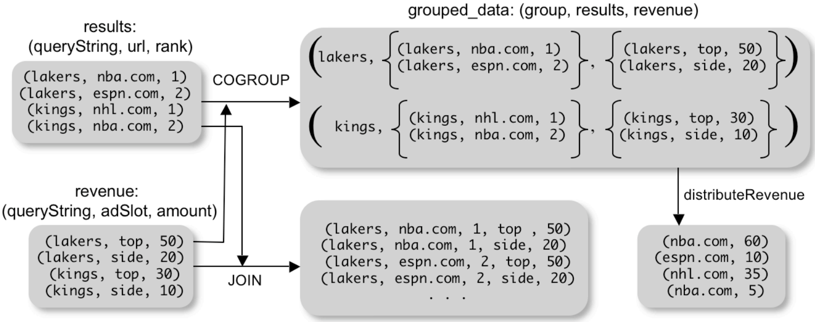
  - `results` contains, for different query strings, the urls shown as search results, and the positions at which they where shown
  - `revenue` contains, for different query strings, and different advertisement slots, the average amount of revenue

Data Processing Operators

Getting related data together

- **Suppose we want to group together all search results data and revenue data for the same query string**

```
grouped_data = COGROUP results BY queryString,
revenue BY queryString;
```



Data Processing Operators

The `COGROUP` command

- **Output of a `COGROUP` contains one tuple for each group**
  - First field (`group`) is the group identifier (the value of the `queryString`)
  - Each of the next fields is a bag, one for each group being co-grouped
- **Grouping can be performed according to UDFs**
- **Next: why `COGROUP` when you can use `JOINS`?**

Data Processing Operators

COGROUP vs JOIN

- JOIN vs. COGROUP
  - Their are equivalent: JOIN = COGROUP followed by a cross product of the tuples in the nested bags

- **Example 3: Suppose we try to attribute search revenue to search-results urls → compute monetary worth of each url**

```
grouped_data = COGROUP results BY queryString,
revenue BY queryString;
url_revenues = FOREACH grouped_data GENERATE
FLATTEN(distrubteRevenue(results, revenue));
```

  - Where distrubteRevenue is a UDF that accepts search results and revenue information for each query string, and outputs a bag of urls and revenue attributed to them

Data Processing Operators

`COGROUP` vs `JOIN`

- **More details on the UDF distribute Revenue**
  - Attributes revenue from the top slot entirely to the first search result
  - The revenue from the side slot may be equally split among all results
- **Let's see how to do the same with a `JOIN`**
  - `JOIN` the tables `results` and `revenues` by `queryString`
  - `GROUP BY` `queryString`
  - Apply a custom aggregation function
- **What happens behind the scenes**
  - During the join, the system computes the cross product of the search and revenue information
  - Then the custom aggregation needs to undo this cross product, because the UDF specifically requires so

Data Processing Operators

COGROUP in details

- **The COGROUP statement conforms to an algebraic language**
  - The operator carries out only the operation of grouping together tuples into nested bags
  - The user can the decide wether to apply a (custom) aggregation on those tuples or to cross-product them and obtain a join
- **It is thanks to the nested data model that COGROUP is an independent operation**
  - Implementation details are tricky
  - Groups can be very large (and are redundant)

Data Processing Operators

A special case of COGROUP: the GROUP operator

- **Sometimes, we want to operate on a single dataset**
  - This is when you use the GROUP operator
- **Let's continue from Example 3:**
  - Assume we want to find the total revenue for each query string. This writes as:

```
grouped_revenue = GROUP revenue BY queryString;
query_revenue = FOREACH grouped_revenue GENERATE
queryString, SUM(revenue.amount) AS totalRevenue;
```

  - Note that `revenue.amount` refers to a projection of the nested bag in the tuples of `grouped_revenue`

Data Processing Operators

`JOIN` in Pig Latin

- **In many cases, the typical operation on two or more datasets amounts to an equi-join**
  - IMPORTANT NOTE: large datasets that are suitable to be analyzed with Pig (and MapReduce) are generally not normalized
  - → `JOIN`s are used more infrequently in Pig Latin than they are in SQL

- **The syntax of a `JOIN`**

```
join_result = JOIN results BY queryString,
revenue BY queryString;
```

  - This is a classic inner join (actually an equi join), where each match between the two relations corresponds to a row in the `join_result`

Data Processing Operators

`JOIN` in Pig Latin

- **JOINs lend themselves to optimization opportunities**
  - We will work on this in the laboratory
- **Assume we join two datasets, one of which is considerably smaller than the other**
  - For instance, suppose a dataset fits in memory
- **Fragment replicate join**
  - Syntax: append the clause `USING "replicated"` to a `JOIN` statement
  - Uses a distributed cache available in Hadoop
  - All mappers will have a copy of the small input

$\rightarrow$ This is a Map-side join

Data Processing Operators

MapReduce in Pig Latin

- **It is trivial to express MapReduce programs in Pig Latin**
  - This is achieved using `GROUP` and `FOREACH` statements
  - A map function operates on one input tuple at a time and outputs a bag of key-value pairs
  - The reduce function operates on all values for a key at a time to produce the final result

- **Example**

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

  - where `map()` and `reduce()` are UDF

Implementation

Introduction

- **Pig Latin Programs are compiled into MapReduce jobs, and executed using Hadoop**
- **How to build a logical plan for a Pig Latin program**
- **How to compile the logical plan into a physical plan of MapReduce jobs**
- **How to avoid resource exhaustion**

Building a Logical Plan

- **As clients issue Pig Latin commands (interactive or batch mode)**
  - The Pig interpreter parses the commands
  - Then it verifies validity of input files and bags (variables)
    - ⋆ E.g.: if the command is `c = COGROUP a BY ..., b BY ...;`, it verifies if `a` and `b` have already been defined

- **Pig builds a logical plan for every bag**
  - When a new bag is defined by a command, the new logical plan is a combination of the plans for the input and that of the current command

Building a Logical Plan

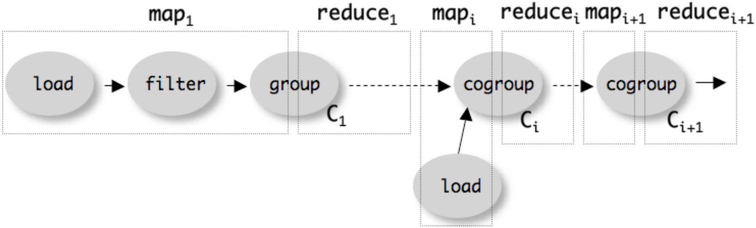
- **No processing is carried out when constructing the logical plans**
  - Processing is triggered only by `STORE` or `DUMP`
  - At that point, the logical plan is compiled to a physical plan
- **Lazy execution model**
  - Allows in-memory pipelining
  - File reordering
  - Various optimizations from the traditional RDBMS world
- **Pig is (potentially) platform independent**
  - Parsing and logical plan construction are platform oblivious
  - Only the compiler is specific to Hadoop

Building the Physical Plan

- **Compilation of a logical plan into a physical plan is "simple"**
  - MapReduce primitives allow a parallel `GROUP BY`
    - ★ Map assigns keys for grouping
    - ★ Reduce process a group at a time (actually in parallel)

- **How the compiler works**
  - Converts each `(CO)GROUP` command in the logical plan into distinct MapReduce jobs
  - *Map function* for `(CO)GROUP` command *C* initially assigns keys to tuples based on the `BY` clause(s) of *C*
  - *Reduce function* is initially a `no-op`

Building the Physical Plan



- **MapReduce boundary is the COGROUP command**
  - The sequence of `FILTER` and `FOREACH` from the `LOAD` to the first `COGROUP` C_1 are pushed in the Map function
  - The commands in later `COGROUP` commands C_i and C_{i+1} can be pushed into:
    - ★ the Reduce function of C_i
    - ★ the Map function of C_{i+1}

Building the Physical Plan

- **Pig optimization for the physical plan**
  - Among the two options outlined above, the first is preferred
  - Indeed, grouping is often followed by aggregation
  - $\rightarrow$ reduces the amount of data to be materialized between jobs

- **`COGROUP` command with more than one input dataset**
  - Map function appends an extra field to each tuple to identify the dataset
  - Reduce function decodes this information and inserts tuple in the appropriate nested bags for each group

Building the Physical Plan

- **How parallelism is achieved**
  - For `LOAD` this is inherited by operating over HDFS
  - For `FILTER` and `FOREACH`, this is automatic thanks to MapReduce framework
  - For `(CO)GROUP` uses the `SHUFFLE` phase

- **A note on the `ORDER` command**
  - Translated in two MapReduce jobs
  - First job: Samples the input to determine quantiles of the sort key
  - Second job: Range partitions the input according to quantiles, followed by sorting in the reduce phase

- **Known overheads due to MapReduce inflexibility**
  - Data materialization between jobs
  - Multiple inputs are not supported well

Efficiency measures

- **`(CO)GROUP` command place tuples of the same group in nested bags**
  - Bag materialization (I/O) can be avoided
  - This is important also due to memory constraints
  - Distributive or algebraic aggregation facilitate this task

- **What is an algebraic function?**
  - Function that can be structured as a tree of sub-functions
  - Each leaf sub-function operates over a subset of the input data

  → If nodes in the tree achieve data reduction, then the system can reduce materialization
  - Examples: `COUNT`, `SUM`, `MIN`, `MAX`, `AVERAGE`, ...

Efficiency measures

- **Pig compiler uses the combiner function of Hadoop**
  - A special API for algebraic UDF is available
- **There are cases in which `(CO)GROUP` is inefficient**
  - This happens with non-algebraic functions
  - Nested bags can be spilled to disk
  - Pig provides a disk-resident bag implementation
    - Features external sort algorithms
    - Features duplicates elimination

Debugging

Introduction

- **The process of creating Pig Latin programs is generally iterative**
  - The user makes an initial stab
  - The stab is executed
  - The user inspects the output check correctness
  - If not, revise the program and repeat the process

- **This iterative process can be inefficient**
  - The sheer size of data volumes hinders this kind of experimentation
  - → Need to create a side dataset that is a small sample of the original one

- **Sampling can be problematic**
  - Example: consider an equi-join on relations `A(x,y)` and `B(x,z)` on attribute `x`
  - If there are many distinct values of `x`, it is highly probable that a small sample of `A` and `B` will not contain matching `x` values
  - → Empty result

Welcome Pig Pen

- **Pig comes with a debugging environment, Pig Pen**
  - It creates a side dataset automatically
  - This is done in a manner that avoids sampling problems
  - $\rightarrow$ The side dataset must be tailored to the user program

- **Sandbox Dataset**
  - Takes as input a Pig Latin program *P*
    - This is a sequence of *n* commands
    - Each command consumes one or more input bags and produces one output bag
  - The output is a set of *example bags* $\{B_1, B_2, ..., B_n\}$
    - Each output example bag corresponds to the output of each command in *P*
  - The output set of example bags need to be consistent
    - The output of each operator needs to be that obtained with the input example bag

Properties of the Sandbox Dataset

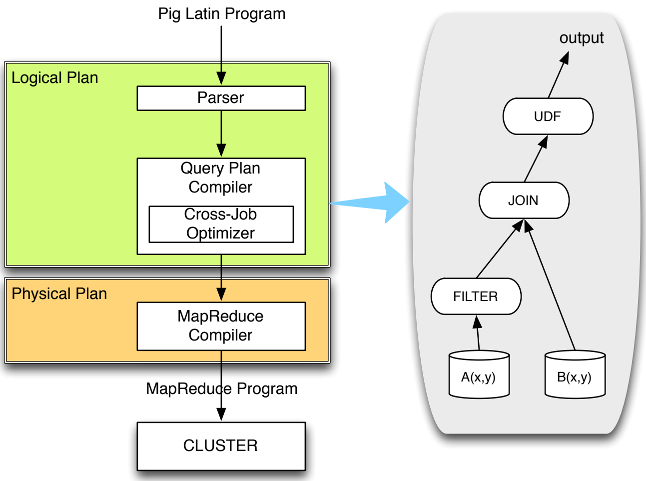
- **There are three primary objectives in selecting a sandbox dataset**
  - *Realism*: the sandbox should be a subset of the actual dataset. If this is not possible, individual values should be the ones in the actual dataset
  - *Conciseness*: the example bags should be as small as possible
  - *Completeness*: the example bags should collectively illustrate the key semantics of each command

- **Overview of the procedure to generate the sandbox**
  - Take small random samples of the original data
  - Synthesize additional data tuples to improve completeness
  - When possible use real data values on synthetic tuples
  - Apply a pruning pass to eliminate redundant example tuples and improve conciseness

Optimizations

Introduction

- **Pig implements several optimizations**
  - Most of them are derived from traditional works in RDBMS
  - Logical vs. Physical optimizations



Single-program Optimizations

- **Logical optimizations: query plan**
  - Early projection
  - Early filtering
  - Operator rewrites
- **Physical optimization: execution plan**
  - Mapping of logical operations to MapReduce
  - Splitting logical operations in multiple physical ones
  - Join execution strategies

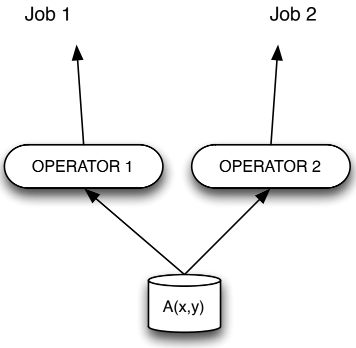
Cross-program Optimizations

- **Popular tables**
  - Web crawls
  - Search query log
- **Popular transformations**
  - Eliminate spam
  - Group pages by host
  - Join web crawl with search log
- **GOAL: minimize redundant work**

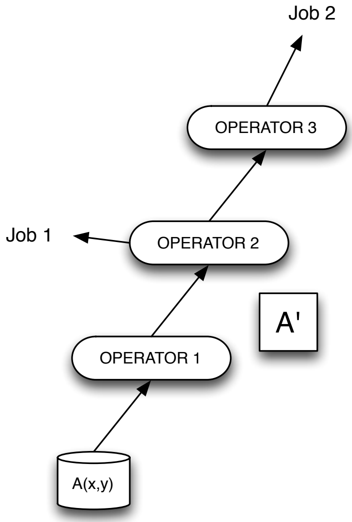
Cross-program Optimizations

- **Concurrent work sharing**
  - Execute related Pig Latin programs together to perform common work only once
  - This is difficult to achieve: scheduling, “sharability”
- **Non-concurrent work sharing**
  - Re-use I/O or CPU work done by one program, later in time
  - This is difficult to achieve: caching, replication

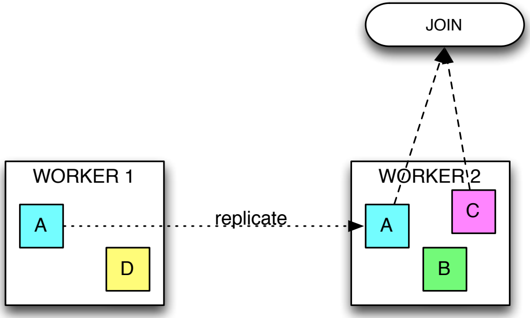
Work-Sharing Techniques



Work-Sharing Techniques



Work-Sharing Techniques



References I

[1] Pig wiki.
`http://wiki.apache.org/pig/`.

[2] C. Olston, B. Reed, U. Srivastava, R. Kumar, , and A. Tomkins.
Pig latin: A not-so-foreign language for data processing.
In *Proc. of ACM SIGMOD*, 2008.

[3] Tom White.
Hadoop, The Definitive Guide.
O'Reilly, Yahoo, 2010.

EURECOM