PigReuse: A Reuse-based Optimizer for Pig Latin

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ABSTRACT

Pig Latin is a popular language which is widely used for parallel processing of massive data sets. Currently, subexpressions occurring repeatedly in Pig Latin scripts are executed as many times as they appear, and the current Pig Latin optimizer does not identify reuse opportunities.

We present a novel optimization approach aiming at identifying and reusing repeated subexpressions in Pig Latin scripts. Our optimization algorithm, named *PigReuse*, operates on a particular algebraic representation of Pig Latin scripts. PigReuse identifies subexpression merging opportunities, selects the best ones to execute based on a cost function, and reuses their results as needed in order to compute exactly the same output as the original scripts. Our experiments demonstrate the effectiveness of our approach.

Keywords

Reuse-based Optimization; Linear Programming; PigLatin

1. INTRODUCTION

The efficient processing of very large volumes of data has lately relied on massively parallel processing models, of which MapReduce is the most well known. However, the simplicity of these models leads to relatively complex programs to express even moderately complex tasks. Thus, to facilitate the specification of data processing tasks to be executed in a massively parallel fashion, several higher-level query languages have been introduced. Languages that have gained wide adoption include Pig Latin [21], HiveQL [31], or Jaql [4].

In this work, we consider Pig Latin which has raised significant interest from the application developers as well as the research community. Pig Latin provides dataflow-style primitives for expressing complex analytical data processing tasks. Pig Latin programs (also named *scripts*) are automatically optimized and compiled into parallel processing jobs by the Apache Pig system [22], which is included in all leading Hadoop distributions e.g., HDP [12], CDH [5].

In a typical batch of Pig Latin scripts, there may be many identical (or equivalent) sub-expressions, that is: script fragments applying the same processing on the same inputs, but appearing in distinct places within the same (or several) scripts. While the Pig Latin engine includes a query optimizer, it is currently not capable of recognizing such repeated subexpressions. As a consequence, they are executed as many times as they appear in the Pig Latin script batch, whereas there is obviously an opportunity for enhancing performance by identifying common subexpressions, executing them only once, and reusing the results of the computation in every script needing them.

Identifying and reusing common subexpressions occurring in Pig Latin scripts automatically is the target of the present work. The problem bears obvious similarities with the known multi-query optimization and workflow reuse problems; however, as we discuss in Section 6, the Pig Latin primitives lead to several novel aspects of the problem, which lead us to propose dedicated algorithms to solve them.

Motivating example. A Pig Latin script consists of a set of *binding expressions* and *store expressions*. Each binding expression follows the syntax var = op, meaning that the expression op will be evaluated, and the bag of tuples thus generated will be bound to the variable var. Then, var can be used by follow-up expressions in a script.

Consider the following Pig Latin script a_1:

```
1 A = LOAD 'page_views' AS (user, time, www);
2 B = LOAD 'users' AS (name, zip);
3 R = JOIN A BY user, B BY name;
4 S = FOREACH R GENERATE user, time, zip;
5 STORE S INTO 'a1out1';
6 T = JOIN A BY user LEFT, B BY name;
7 STORE T INTO 'a1out2';
```

Line 1 loads data from a file `page_views` and creates a bag of tuples that is bound to variable `A`. Each of these tuples consists of three attributes `(user,time,www)`. Line 2 loads data from a second file, and binds the resulting tuple bag to `B`. Line 3 joins the tuples of `A` and `B` based on the equality of the values bound to attributes `user` and `name`. The next line uses the Pig Latin operator `FOREACH`, that applies a function on every tuple of the input bag. In this case, line 4 projects the attributes `user`, `time` and `zip` of every tuple in `R`. Then the result is stored in the file `a1out1`. In turn, line 6 executes a left outer join over the tuples of `A` and `B` based on the equality of the values bound to the same attributes `user` and `name`, and the result is stored in `a1out2`.

The following script a_2 only executes a left outer join over the same inputs:

```
1 A = LOAD 'page_views' AS (user, time, www);
2 B = LOAD 'users' AS (name, zip);
3 R = JOIN A BY user LEFT, B BY name;
4 STORE R INTO 'a2out';
```

Part of this work was performed while the authors were with Université Paris-Sud and INRIA.

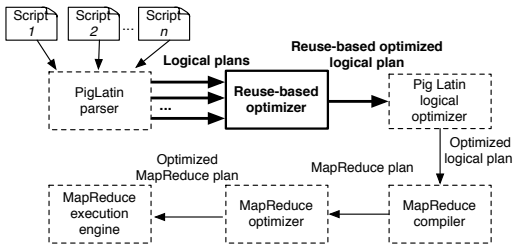


Figure 1: Integration of PigReuse optimizer within Pig Latin execution engine.

The script b that we introduce next produces the same outputs as a_1 and a_2:

```
1  A = LOAD 'page_views' AS (user, time, www);
2  B = LOAD 'users' AS (name, zip);
3  R = COGROUP A BY user, B BY name;
4  S = FOREACH R GENERATE flatten(A), flatten(B);
5  T = FOREACH S GENERATE user, time, zip;
6  STORE T INTO 'a1out1';
7  U = FOREACH R GENERATE flatten(A),
8                 flatten (isEmpty(B) ? {(null,null,null)} : B);
9  STORE U INTO 'a1out2';
10 STORE U INTO 'a2out';
```

However, *b's execution time is 45% of the combined running time of a_1 and a_2*. The reason is twofold. First, observe that the joins are rewritten into a `COGROUP`[1] operation (line 3) and `FOREACH` operations (lines 4 and 7-8). The interest of cogroup is that through some simple restructuring, one can carve out of the cogroup output various flavors of joins (natural, outer, nested, semijoin etc.) This restructuring operation differs depending on whether we want to generate the join between `A` and `B` needed for script a_1 (line 4), or the left outer join between `A` and `B` for scripts a_1 and a_2 (lines 7-8). The detailed semantics of these restructuring operations will become clear in Section 4. Thus, the first reason for the speedup of b w.r.t. a_1 and a_2 is that the `COGROUP` output is reused to generate the result for both joins. The second reason is that in b, the left outer join is computed only once, and its result is used to produced the desired output of scripts a_1 (line 9) and a_2 (line 10).

Figure 1 depicts the integration of our reuse-based optimization into the Pig Latin architecture; modules, indicated by dashed lines, belong to the original Pig Latin query processor. As illustrated, our reuse-based optimizer works on the algebraic representation of Pig Latin scripts. Thus, our proposal is orthogonal to the Pig Latin query evaluation and execution process. This allows our approach (i) to benefit from the Pig Latin optimizer, and (ii) to apply our optimization independently of the underlying Pig Latin query compilation and execution engines.

Contributions. The technical contributions of this work are the following.

- We propose PigReuse, a multi-query optimization algorithm that merges equivalent subexpressions it identifies in Directed Acyclic Graph (DAGs) of algebraic representation of a batch of Pig Latin scripts. After identifying such reutilization opportunities, PigReuse produces an optimal merged plan where redundant computations have been eliminated. PigReuse relies on Binary Integer Linear Programming to select the best plan based on the provided cost function.
- We present techniques to improve *effectiveness* of our baseline PigReuse optimization approach.
- We have implemented PigReuse as an extension module within the Apache Pig system. We present an experimental evaluation of our techniques using two different cost functions to select the best plan.

Outline. Section 2 is dedicated to preliminaries. Section 3 presents the main techniques over which PigReuse relies on, while Section 4 presents strategies to enhance it. Section 5 describes our experimental evaluation. Finally, Section 6 discusses related work, and then we conclude.

2. PRELIMINARIES

Pig Latin operations translation. Since our approach strictly depends on rewriting Pig Latin expressions into equivalent ones, we rely on algebraic representation of Pig Latin scripts. Actually, the Pig Latin data model features complex data types (e.g., tuple, map etc.) and nested relations with duplicates (bags). Thus, we rely on the Nested Relational Algebra for Bags [10] (NRAB, for short) to represent Pig Latin scripts.

We consider a subset of the NRAB algebra and extend it with other operators. Table 1 lists and describes all basic operators of NRAB (top part) and the additional operators we introduce (bottom part). All additional operators but *scan* and *store* are redundant, i.e., they can be expressed using the basic operators. We decided to introduce additional operators for two main reasons: (i) allowing a one-to-one representation of Pig Latin scripts into the algebra, as complex operators are efficiently executed by underlying execution engines (e.g., cogroup), and (ii) giving our algorithm additional opportunities to detect common subexpressions by exploring different rewritings. For instance, any type of join can (also) be expressed by a combination of *cogroup*, *restructure*, and *bag destroy*. Using this alternative join representation simplifies matching it with any other operators.

Pig Latin scripts translation. We have formalized (and implemented) the entire Pig Latin-to-NRAB translation process; formal details of the translation are presented in Appendix B.

To illustrate, Figure 2.a introduces four different Pig Latin scripts s_1-s_4; we will reuse them throughout the paper. The scripts read data from the three input relations `page_views`, `users`, and `power_users`; from now on, we denote these relations as `A`, `B`, and `C`. Consider s_1 in Figure 2. Its translation yields the following set of of NRAB binding expressions:

$$\begin{aligned}\Gamma = \{\ A &= scan\langle\text{`}page\_views\text{'}\rangle,\\ B &= scan\langle\text{`}users\text{'}\rangle,\\ R &= \bowtie\langle user, name\rangle(A, B),\\ S &= \pi\langle user, time, zip\rangle(R),\\ &store\langle\text{`}s1out\text{'}\rangle(S)\ \}\end{aligned}$$

In turn, we represent a set Γ of NRAB binding expressions obtained from a Pig Latin program as follows:

[1] `COGROUP` can be seen as a generalization of the *group-by* operation on two or more relations: for every distinct value of the grouping key occurring in any of the inputs, it outputs a tuple that includes an attribute *group* bound to the grouping key, and a bag of tuples for each input R_i such that the bag R_i includes all tuples in R_i that contain the value of the grouping key.

Notation	Name	Input arity	Output description
ϵ	Duplicate elimination	Unary	Distinct tuples from the input relation.
$map\langle\varphi\rangle$	Restructure	Unary	All the tuples in the input after applying a function φ.
$\sigma\langle p\rangle$	Selection	Unary	All the tuples in the input that satisfy the boolean predicate p.
$\uplus$	Additive union	n-ary, $n \geq 2$	Union of input relations, including duplicates.
$-$	Substraction	Binary	Difference between relations, including duplicates.
$\times$	Cartesian product	n-ary, $n \geq 2$	Cartesian product of input relations, including duplicates.
δ	Bag-destroy function	Unary	Unnests one level for the tuples in the input relation.

Notation	Name	Input arity	Output description
$scan\langle fileID\rangle$	Load	-	Reads a file and loads it as a relation.
$store\langle dir\rangle$	Store	Unary	Writes the contents of the tuples for an input relation to a file.
$\pi\langle a_1,\ldots,a_n\rangle$	Projection	Unary	Projects attributes $a_1,\ldots,a_n$ from the input tuples.
$cogroup\langle a_1,\ldots,a_n\rangle$	Cogroup	n-ary, $n \geq 1$	Groups tuples together from input relations based on the equality of their values for attributes $(a_1,\ldots,a_n)$.
$\bowtie\langle a_1,\ldots,a_n\rangle$	Join	n-ary, $n \geq 2$	Returns the combination of tuples from input relations based on the equality of their values for attributes $(a_1,\ldots,a_n)$.
$⟕\langle a_1,a_2\rangle$	Left outer join	Binary	Returns the combination of tuples from input relations for which $a_1{=}a_2$, and the tuples in the left relation without a matching right tuple.
$⟖\langle a_1,a_2\rangle$	Right outer join	Binary	Returns the combination of tuples from input relations for which $a_1{=}a_2$, and the tuples in the right relation without a matching left tuple.
$⟗\langle a_1,a_2\rangle$	Full outer join	Binary	Returns the combination of tuples from input relations for which $a_1{=}a_2$, the tuples in the left relation without a matching right tuple, and the tuples in the right relation without a matching left tuple.
$mapconcat\langle\varphi\rangle$	Restructure and concatenate	Unary	Applies $map\langle\varphi\rangle$ and concatenates its result to the original tuple.
$empty$	Empty function	Unary	Returns true if and only if the input relation is empty.
sum, max, min, $count$	Aggregate functions	Unary	Returns the sum of integer values for an attribute field in an input relation, maximum integer value, minimum integer value of an attribute field in an input relation, and total number of tuples in an input relation.

Table 1: Basic NRAB operators (top) and proposed extension (bottom) to express Pig Latin semantics.

s_1

```
A = LOAD 'page_views' AS (user, time, www);
B = LOAD 'users' AS (name, zip);
R = JOIN A BY user, B BY name;
S = FOREACH R GENERATE user, time, zip;
STORE S INTO 's1out';
```

s_2

```
A = LOAD 'page_views' AS (user, time, www);
B = LOAD 'users' AS (name, zip);
C = LOAD 'power_users' AS (id, phone);
R = JOIN A by user, B BY name;
S = FOREACH R GENERATE user, time, zip;
T = JOIN S BY user, C by id;
STORE T INTO 's2out';
```

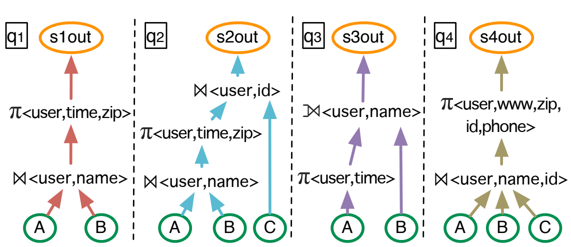
s_3

```
A = LOAD 'page_views' AS (user, time, www);
B = LOAD 'users' AS (name, zip);
R = FOREACH A GENERATE user, time;
S = JOIN R by user LEFT, B by name;
STORE S INTO 's3out';
```

s_4

```
A = LOAD 'page_views' AS (user, time, www);
B = LOAD 'users' AS (name, zip);
C = LOAD 'power_users' AS (id, phone);
R = JOIN A BY user, B by name, C by id;
S = FOREACH R GENERATE user, www, zip, id, phone;
STORE S INTO 's4out';
```

(a)



(b)

Figure 2: Sample Pig Latin scripts (a) and their corresponding algebraic DAG representation (b).

Definition 1. The DAG representation of a set of bindings $\Gamma = \{var_1{=}A_1,\ldots,var_n{=}A_n\}$ is a pair $(V,\vec{E})$ where V is a set of $\langle var_i, op_i^A\rangle$ tuples such that for each $v_i \in V$:

- var_i is the variable associated to the node (thus, it is the unique identifier of a node);
- op_i^A is the top-most algebraic operator in the expression bound to var_i;

Further, $\vec{E}$ is a set of edges representing the data flow among the nodes of V. Specifically, there is an edge $e_{i,j} \in \vec{E}$ from v_i to v_j, iff the operation op_j^A is applied on the bag of tuples produced by op_i^A. $\diamond$

In our DAG representation, a *source* i.e., a node with no incoming edges, always contains a *scan* operator. In turn, a *sink* i.e., a node with no outgoing edges, always corresponds to a *store* operator. For instance, after connecting the different algebraic expressions generated from s_1, we obtain the DAG query q_1 shown in Figure 2.b, also including the DAG-based representations of s_2-s_4.

3. REUSE-BASED QUERY OPTIMIZATION

We have previously shown how to translate Pig Latin scripts into NRAB DAGs. Based on this, we now introduce our PigReuse algorithm that optimizes the query plans corresponding to a batch of scripts by reusing results of repeated subexpressions. More specifically, given a collection of NRAB DAG queries Q, PigReuse proceeds in two steps:
Step (1). *Identify and merge all the equivalent subexpressions in Q.* To this end, we use an AND-OR DAG, in which an AND-node (or operator node) corresponds to an algebraic operation in Q, while an OR-node (or equivalence node) represents a set of subexpressions that generate the same result.

Step (2). *Find the optimal plan from the AND-OR DAG.* Based on a cost model, we make a globally optimal choice of the set of operator nodes to be actually evaluated. Our approach is independent of the particular cost function chosen; we discuss in Section 5.2 the functions that we have implemented for PigReuse.

The final output of PigReuse is an optimized plan that contains (i) the operator nodes leading to *minimizing the cummulated cost* of all the queries in Q, while *producing, together, the same set of outputs* as the original Q, and (ii) equivalence nodes that represent *result sharing* of an operator node with other operators in Q. In the following sections, we describe each step of our reuse-based optimization algorithm in detail.

3.1 Equivalence-based merging

To join all detected equivalent expressions in Q, we build an AND-OR DAG, which we term *equivalence graph* (EG, in short); the construction is carried out in the spirit of previous optimization works [8, 27]. In the EG, an AND-node corresponds to an algebraic operation (e.g., selection, projection etc.). An OR-node o is introduced whenever a set of expressions $e_1, e_2, \ldots, e_k$ have been identified as equivalent; in the EG, o has as children the algebraic nodes at the roots of the expressions $e_1, e_2, \ldots, e_k$. In the following, we refer to AND-nodes as *operator nodes*, and OR-nodes as *equivalence nodes*. Formally, we define an EG as follows.

Definition 2. An equivalence graph (EG) is a DAG, defined by the pair $(O \cup A \cup T_o, E)$, with O, A, and T_o disjoint sets of nodes, and:

- O is the set of equivalence nodes, A is the set of operator nodes, T_o is the set of sink nodes.
- $E \subseteq (O \times A) \cup (A \times O) \cup (A \times T_o)$ is a set of directed edges such that: each node $a \in A$ has an in-degree of at least one, and an out-degree equal to one; each node $o \in O$ has an in-degree of at least one, and an out-degree of at least one; each node $t_o \in T_o$ has an in-degree of at least one. ◇

Observe that in an EG, O nodes can only point to A nodes, while A nodes can point to O or T_o nodes.

An important point to stress here is that *equivalence nodes with more than one child amount to optimization opportunities* as they indicate that several operator nodes have a common (equivalent) child subexpression. In this case, we can choose the "best" way to compute the result of the subexpression among the choices given by the OR-node. The choice is based on a cost model, where the best plan corresponds to the plan with overall minimal cost. Optimal plan selection is discussed in detail in the next section.

Building the equivalence graph. To build the equivalence graph, we need to identify equivalent expressions within the input NRAB query set Q. We reuse the classical notion of query equivalence here, i.e., two expressions are *equivalent* iff their result is provably the same regardless of the data on which they are computed.

We build the EG in the following fashion. First, we create the EG eg with a single equivalence node o_s, i.e., the EG *source*. We take every NRAB query $q \in Q$ and perform a *breadth-first* traversal of its nodes. Each source node $s \in q$ is added to eg, and an edge (o_s, s) is created.

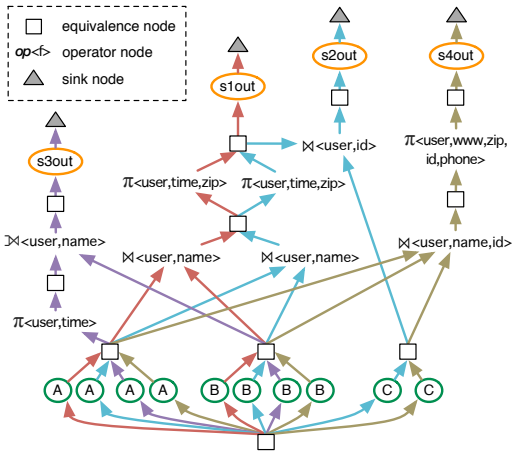


Figure 3: EG corresponding to NRAB DAGs q_1-q_4.

Subsequently, for each node n having the source node s as an input, we verify whether there exists a node n_{eg} in eg, such that the expression rooted in n is equivalent to the one rooted in n_{eg}.

If such an equivalence is detected, we connect n to the equivalence node o that n_{eg} feeds. If no such equivalent node is found, n is added to eg, a new equivalence node o is added to eg, and an edge (n, o) is created. In either case, for each node n' that is a parent of n in the original query, n' is added to eg and an edge (o, n') is created. Within a set of equivalent nodes, each node is the root of a sub-DAG that represents a NRAB expression; the expressions corresponding to all these nodes are equivalent.

In the spirit of [18], we rely on data structures representing *logical properties* to check whether two expressions A, A' rooted at nodes n and n' are equivalent. The logical properties are set properly by the known commutativity, associativity etc. laws that have been extensively studied for the bag relational algebra [3, 9, 24, 25]. If A and A' are equivalent, they become children of the same equivalence node. Our equivalence search algorithm is sound but not complete; details about the equivalences we are capable of detecting can be found in Appendix D. Recall that the problem of checking equivalence of two arbitrary Relational Algebra expressions is undecidable [30], and so the problem is for NRAB. Thus, no terminating equivalence checking algorithm exists for NRAB. However, as our experimental evaluation shows, the equivalences detected by PigReuse allow it to bring significant performance savings.

As mentioned above, the equivalence detection rules we apply are those previously identified for NRAB, i.e., they only cover operators that have been previously defined as (extensions of) NRAB operators (i.e., $\uplus$, $-$, $\times$, ϵ, δ, *map*, σ, π, and $\bowtie$, see Table 1). As we will discuss in Section 4, we provide a set of new equivalence rules involving operators we introduced in this work (e.g., *cogroup* and outer join variants). These rules allow identifying more equivalences in an efficient way, and thus improve over the baseline PigReuse algorithm presented in this section.

Figure 3 depicts the EG corresponding to the NRAB DAGs q_1 to q_4 in Figure 2.b. In Figure 3, we use boxes to represent equivalence nodes, while sink nodes are represented by shadowed triangles. All the leaf nodes in the NRAB DAGs that correspond to the same *scan* operation (namely, nodes A, B, and C) feed the same equivalence

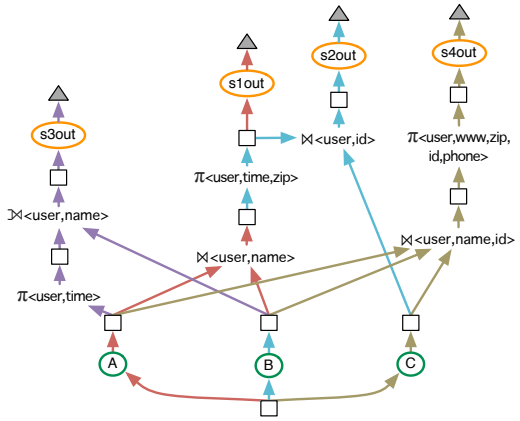


Figure 4: Possible REG for the EG in Figure 3.

node. The equi-joins coming from DAGs q_1 and q_2 on relations A and B over attributes *user* and *name* are also inputs to the same equivalence node.

3.2 Cost-based plan selection

Once an EG has been generated from a set of NRAB queries, our goal is to find the best alternative plan (having the smallest possible cost) computing the same outputs as the original scripts, on any input instance.

We call the output plan a *result equivalence graph* (or REG, in short).

Definition 3. A result equivalence graph (REG) with respect to an EG defined by $(O \cup A \cup T_O, E)$ is itself a DAG, defined by the pair $(O^* \cup A^* \cup T_O, E^*)$ such that:

- $O^* \subseteq O$, $A^* \subseteq A$, $E^* \subseteq E$.
- The set of sink nodes T_o is identical in EG and REG. Each sink node has an in-degree of exactly one.
- Each operator node in-degree in the REG is equal to its in-degree in the EG. Each equivalence node has an in-degree of exactly one, and an out-degree of at least one. ◇

In the REG, we choose exactly one among the alternatives provided by each EG equivalence nodes; the REG produces the same outputs as the original EG, as all sink nodes are preserved. Further, each REG can be straightforwardly translated into a NRAB DAG which is basically an executable Pig Latin expression. The latter expression is the one we turn to Pig for execution.

The choice of which alternative to pick for each equivalence node is guided by a *cost function*, the overall goal being to minimize the global cost of the plan. We assign a cost (weight) to each edge $n_1 \rightarrow n_2$ in the EG, representing all the processing cost (or effort) required to fully build the result of n_2 out of the result of n_1.

Figure 4 shows a possible REG produced for the EG depicted in Figure 3. This REG could have been for instance obtained by using a cost function based on counting the operator nodes in the optimized script. In the REG, each equivalence node has exactly one input edge, i.e., the *scans* and other operator nodes are shared across queries, whenever possible. In Section 5, we consider different cost functions and compare them experimentally.

$$\text{Minimize } \mathcal{C} = \sum_{e \in E} \mathcal{C}_e x_e \quad \text{subject to:}$$

$$x_e \in \{0,1\} \qquad \forall e \in E \qquad (1)$$

$$\sum_{e \in E_{t_o}^{in}} x_e = 1 \qquad \forall t_o \in T_o \qquad (2)$$

$$\sum_{e \in E_a^{in}} x_e = x_{E_a^{out}} \times |E_a^{in}| \qquad \forall a \in A \qquad (3)$$

$$\sum_{e \in E_o^{in}} x_e = \max_{e \in E_o^{out}} x_e \qquad \forall o \in O \qquad (4)$$

Figure 5: BIP reduction of the optimization problem.

$$d_{e \in E_o^{out}} \in \{0,1\} \qquad \forall o \in O \qquad (4.1)$$

$$\sum_{e \in E_o^{in}} x_e \geq x_{e \in E_o^{out}} \qquad \forall o \in O \qquad (4.2)$$

$$\sum_{e \in E_o^{in}} x_e \leq (x_e - d_e + 1)_{e \in E_o^{out}} \qquad \forall o \in O \qquad (4.3)$$

$$\sum_{e \in E_o^{out}} d_e = 1 \qquad \forall o \in O \qquad (4.4)$$

Figure 6: BIP representation of the *max* constraint.

3.3 Cost minimization based on binary integer programming

We model the problem of finding the minimum-cost REG relying on *Binary Integer Programming* (BIP), a well-explored branch of mathematical optimizations that has been used previously to solve many optimization problems in the database literature [15, 33]. Broadly speaking, a typical linear programming problem can be expressed as: **given** a set of linear inequality constraints over a set of variables **find** value assignments for the variables **such that** the value of an objective function depending on these variables is minimized.

Such problems can be tackled by dedicated binary integer program *solvers*, some of which are extremely efficient, benefiting from many years of research and development.

Generating the result equivalence graph. Given an input EG, for each of its nodes $n \in O \cup A \cup T_o$, we denote by E_n^{in} and E_n^{out} the sets of incoming and outgoing edges for n, respectively. For each edge $e \in E$, we introduce a variable x_e, denoting whether or not e is part of the REG. Since in our specific problem formulation a variable x_e can only take values within $\{0,1\}$, our problem is formulated as a BIP problem. Further, for each edge $e \in E$, we denote by $\mathcal{C}_e$ the cost assigned to e by some cost function $\mathcal{C}$. Importantly, the model we present in the following is independent of the chosen cost function.

Our optimization problem is stated in BIP terms in Figure 5. Equation (1) states that each x_e variable takes values in $\{0,1\}$. (2) ensures that every output is generated exactly once. (3) states that if the (only) outgoing edge of an operator node is selected, all of its inputs are selected as well. This is required in order for the algebraic operator to be capable of correctly computing its results. Finally, (4) states that if an equivalence node is generated, it should be used at least once, which is modeled by means of a *max* expression.

Since *max* is not directly supported in the BIP model, the actual BIP constraints which we use to express (4) are shown in Figure 6. These constraints encode the *max* constraint as follows. Equation (4.1) introduces a binary variable $d_{e \in E_o^{out}}$ used to model the *max* function. Equation (4.2) states that if an outgoing edge of an equivalence node is selected, then

ϵ	*map*	σ	π	*mapconcat*
■	□	□	□	□

$\uplus$	$\times$	*cogroup*	$\bowtie$	$\rtimes$	$\ltimes$	$\rtimes\!\!\ltimes$
■	□◇	□◇	□◇	□◇	□◇	□◇

□ *Child π operator can be swapped with the parent operator, iff none of the fields used by the parent operator is projected by π.*

◇ *Child π operator can be swapped with the parent operator only after rewriting the original π operator.*

■ *Child π operator cannot be swapped with the parent operator.*

Figure 7: Reordering and rewriting rules for π.

one of its incoming edges is selected too. (4.3) states that if no outgoing edge of an equivalence node is selected, then none of its incoming edges is selected. Further, (4.3) and (4.4) together ensure that if an outgoing edge of an equivalence node is selected, only one of its incoming edges will be selected. Observe that we can model the *max* function in this fashion since in equation (4), *max* is computed over a set of inputs whose values are in $[0, 1]$.

4. EFFECTIVE REUSE-BASED OPTIMIZATION

We present a set of techniques for identifying and exploiting additional subexpression factorization opportunities that go beyond those possible with the standard NRAB operators. The three extensions we bring to the basic PigReuse algorithm are: normalization, join decomposition, and aggressive merge.

Normalization of the input NRAB DAGs is carried out by *reordering* π operator nodes as follows: we push them away from *scan* operators or closer to *store* operators. We do this by visiting all operator nodes in a NRAB DAG, starting from a *scan*, and by moving each π operator up one level at a time. Although pushing projections up through a plan is counterintuitive from the classical optimization point of view, *it increases the chances to find equivalent subexpressions*, as we will shortly illustrate. Further, after our reuse-based algorithm produces the optimized REG, we push the π operators back down to avoid the performance loss incurred by manipulating many attributes at all levels.

Figure 7 spells out the conditions under which a π can be swapped with its parent operator. Each column in the topmost row represents a parent operator with which the child π may be swapped, and the value of each cell represents different conditions under which the swap is possible. For example, a child π can be swapped with a parent σ, iff the selection predicate does not carry over the attributes projected in π.

A special case is the *cogroup* operator. Since *cogroup* nests the input relations, reordering π with this operator requires complex rewriting. In particular, we will rewrite it into a *map* that applies the projection π on the bag of tuples corresponding to the input relation. *map* operators containing only combinations of *map* and π can still be pushed up following the conditions in Figure 7. This means that, in general, during normalization, one may need to introduce *map* operators nested more than two levels deep. Although the Pig Latin query language does not allow more than two levels of nested `FOREACH` expressions, our NRAB representation *map* allows it; furthermore, as we have found examining the code for executable plans within the Pig Latin engine, more

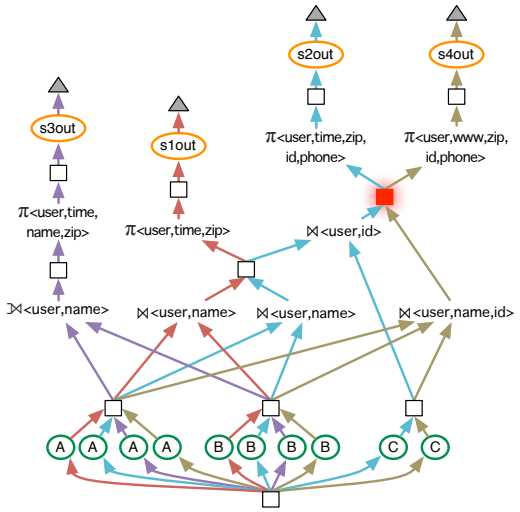


Figure 8: EG generated by PigReuse on the *normalized* NRAB DAGs q_1-q_4.

than two levels of nesting *are* supported at the level of the execution engine[2].

Observe that operators such as ϵ or $\uplus$ restrict the possibilities of moving π operators across the DAG. It turns out also that they do not commute with the other algebraic operators; we term these "unmovable" operators, *bordering* operators in the sense that they raise borders to the moving of π across the DAG.

After our reuse-based algorithm produces the optimized REG, to avoid the performance loss incurred by manipulating many attributes at all levels (due to the pulling up of the projections), we push the π operators back, as close to the *scan* as possible. As our normalization algorithm may rewrite π operators using *map*, we extended the Pig Latin optimizer to support the (unnesting) rewriting of such cases, so that the π can be pushed back down through the plan. Recall that even if they cannot be pushed back down, the resulting plan (no matter how many levels the π operators are nested) will be executable by the Pig engine.

To illustrate the advantages of our normalization phase, Figure 8 shows the EG generated by PigReuse over the *normalized* NRAB DAGs q_1 to q_4. Comparing this EG with the one shown in Figure 3, we see that due to the swapping of the π operator corresponding to q_2, our algorithm can identify an additional common subexpression between q_2 and q_4, by determining the equivalence between the joins over A, B, and C; the corresponding equivalence node is highlighted in Figure 8.

Join decomposition. The semantics of Pig Latin 's join operators e.g., $\bowtie$, $\rtimes$, $\ltimes$, or $\rtimes\!\!\ltimes$ allow rewriting (or *decomposing*) these operators into combinations of *cogroup* and *map* operators. The advantage of decomposing the joins in this way is that the result of the *cogroup* operation, which does the heavy-lifting of assembling groups of tuples from which the *map* will then build join results, can be shared across different kinds of joins. The *map* will be different in each case

[2]The class `pig.newplan.logical.relational.LOForEach`, representing the `FOREACH` operator, has a field called `innerPlan` which in our tests could contain another `LOForEach` and so on on several levels. The purpose of the language-level restriction may have been to prevent programmers from writing deeply-nested loops whose performance could be poor.

$$\frac{A_1 := cogroup\langle a_1, a_2, \ldots, a_n\rangle(\underline{\text{var}}_1, \underline{\text{var}}_2, \ldots, \underline{\text{var}}_n) \quad A_2 := map\langle\delta(\underline{\text{var}}_1) \times \delta(\underline{\text{var}}_2) \times \ldots \times \delta(\underline{\text{var}}_n)\rangle(A_1)}{\bowtie \langle a_1, a_2, \ldots, a_n\rangle(\underline{\text{var}}_1, \underline{\text{var}}_2, \ldots, \underline{\text{var}}_n) = A_2} \quad \text{(IJ)}$$

$$\frac{A_1 := cogroup\langle a_1, a_2\rangle(\underline{\text{var}}_1, \underline{\text{var}}_2) \quad A_2 := map\langle\delta(\underline{\text{var}}_1) \times \delta(empty(\underline{\text{var}}_2)?\{\{\bot\}\} : \underline{\text{var}}_2)\rangle(A_1)}{⟕ \langle a_1, a_2\rangle(\underline{\text{var}}_1, \underline{\text{var}}_2) = A_2} \quad \text{(LOJ)}$$

$$\frac{A_1 := cogroup\langle a_1, a_2\rangle(\underline{\text{var}}_1, \underline{\text{var}}_2) \quad A_2 := map\langle\delta(empty(\underline{\text{var}}_1)?\{\{\bot\}\} : \underline{\text{var}}_1) \times \delta(\underline{\text{var}}_2)\rangle(A_1)}{⟖ \langle a_1, a_2\rangle(\underline{\text{var}}_1, \underline{\text{var}}_2) = A_2} \quad \text{(ROJ)}$$

$$\frac{A_1 := cogroup\langle a_1, a_2\rangle(\underline{\text{var}}_1, \underline{\text{var}}_2) \quad A_2 := map\langle\delta(empty(\underline{\text{var}}_1)?\{\{\bot\}\} : \underline{\text{var}}_1)\times \delta(empty(\underline{\text{var}}_2)?\{\{\bot\}\} : \underline{\text{var}}_2)\rangle(A_1)}{⟗ \langle a_1, a_2\rangle(\underline{\text{var}}_1, \underline{\text{var}}_2) = A_2} \quad \text{(FOJ)}$$

Figure 9: Decomposing JOIN operators.

depending on the join type, but the most expensive component of computing the join, namely the *cogroup*, will be factorized. Further, there is no noticeable performance difference between executing a certain join or its decomposed rewritten version, as the overhead introduced by the *map* operators is negligible.

Figure 9 shows the decomposition rules that are applied on the input NRAB DAGs. Rule (IJ) rewrites an inner equi-join ⋈ into two operators. The first one is a *cogroup* on the attributes used by the join predicate. The second one is a *map* that does the following for each input tuple: (*i*) project each bag of tuples corresponding to the *cogroup* input relations; (*ii*) apply a δ operation on each of those bags; and (*iii*) perform a cartesian product among the tuples resulting from unnesting those bags. Observe that if a bag is empty, e.g., the input relation did not contain any value for the given grouping value, the δ operator does not produce any tuple, and thus the tuples from the other bags for the given tuple are discarded. Thus, this rewriting produces the exact same result as the original ⋈ operator.

The rest of the rules use the aggregation function *empty*, that checks if an input bag is empty. For instance, the expression $empty(\underline{\text{var}})?\{\{\bot\}\} : \underline{\text{var}}$ is a conditional assignment, that is: if var is empty, a bag with a null tuple ($\bot$), i.e., a tuple whose values are bound to null values, conforming to var schema is assigned, otherwise the bag var is assigned.

Rule (LOJ) rewrites a left outer join ⟕ into a *cogroup* on the attributes used by the join predicate, followed by a *map* operator that (*i*) unnests the bag associated to the left input of the *cogroup*; (*ii*) if the bag associated to the right input ($\underline{\text{var}}_2$) is empty, it replaces it with a bag with a null tuple, otherwise it keeps the bag as it is; (*iii*) unnests the bag resulting from the previous operation; and (*iv*) performs a cartesian product on the tuples resulting from the δ operations in order to generate the ⟕ result. Rule (ROJ) rewrites a right outer join ⟖ in a similar fashion.

Finally, rule (FOJ) rewrites a full outer join ⟗ following the same principle as for the two previous operators. The difference is that in (FOJ) we check the bags from both inputs by means of the *empty* function.

Figure 10 shows the EG generated by PigReuse after applying *normalization and decomposition* to the NRAB DAGs q_1 to q_4. One can observe that the decomposition of the ⋈ operators from q_1 and q_2, and the ⟕ operator from q_3 leads to an additional sharing opportunity, as the result of the

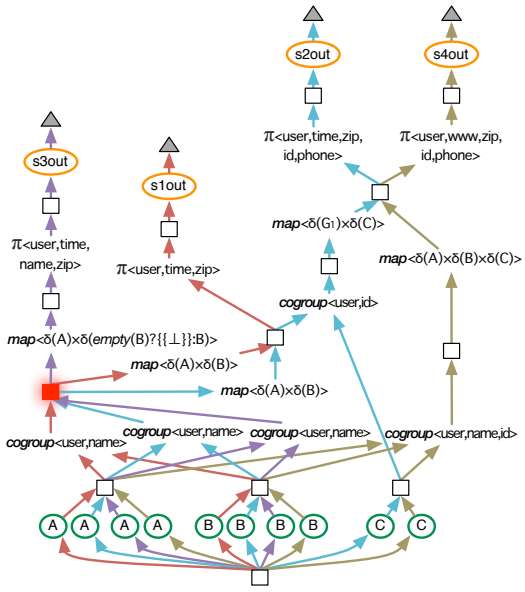


Figure 10: EG generated by PigReuse on the *normalized* and *decomposed* NRAB DAGs q_1-q_4.

cogroup on attributes *user* and *name* can be shared by the subsequent *map* operations (highlighted equivalence node).

Aggressive merge. This optimization is based on the observation that it is possible to derive the results of a ⋈ or *cogroup* operator from the results of a *cogroup*′ operator, as long as the former relies on *a subset* of the input relations and attributes of *cogroup*′. This means that these rewritings rely on the notion of *cogroup containment*. In particular, this entails checking the containment relationship between respective sets of input relations and attributes. Then, in order to generate the result of the original ⋈ or *cogroup* operator, we add the appropriate operator on top of *cogroup*′; this can be seen as a limited instance of query rewriting using views, where *cogroup*′ plays the role of a view. In contrast to the previous extensions that are applied on the input NRAB DAGs, *aggressive merge* is applied while creating the EG.

Figure 11 shows the rewritings considered by our aggressive merge algorithm. Rule (CG-CG) states that if a query contains a *cogroup*′ operator with two or more input relations, any other *cogroup* (with at least one input relation, part of the *cogroup*′ input) can be derived from the previous one in the following fashion. First, a π operator projects the attributes needed for the result of the *cogroup* operator. Then, a σ operator discards the tuples where *all* the bags associated to each input relation are empty.

Rules (IJ-CG), (LOJ-CG), and (ROJ-CG) are similar to those shown in Figure 9; the only difference is that the *map* operators take only a subset of the bag attributes in the original *cogroup*. Note that we do not have a rule for the ⟗ operator since we are able to generate its output directly from the result of the *cogroup*.

Figure 12 depicts the EG produced by PigReuse using the aggressive merge extensions, when normalization and decomposition has been applied to the NRAB plans q_1-q_4. The new connections created by aggressive merge are highlighted. The figure shows how the results for the *cogroup*, ⋈, and ⟕ operators on A and B relations are derived from the *cogroup* operator on A, B, and C.

$$\frac{\begin{array}{c}\underline{\mathsf{var}}_1, \ldots, \underline{\mathsf{var}}_k \subset \underline{\mathsf{var}}'_1, \underline{\mathsf{var}}'_2, \ldots, \underline{\mathsf{var}}'_n \qquad a_1, \ldots, a_k \subset a'_1, a'_2, \ldots, a'_n \\ A_1 := cogroup\langle a'_1, a'_2, \ldots, a'_n\rangle(\underline{\mathsf{var}}'_1, \underline{\mathsf{var}}'_2, \ldots, \underline{\mathsf{var}}'_n) \\ A_2 := \pi\langle group, \underline{\mathsf{var}}_1, \ldots, \underline{\mathsf{var}}_k\rangle(A_1) \qquad A_3 := \sigma\langle\neg(empty(\underline{\mathsf{var}}_1) \wedge \ldots \wedge empty(\underline{\mathsf{var}}_k))\rangle(A_2)\end{array}}{cogroup\langle a_1, \ldots, a_k\rangle(\underline{\mathsf{var}}_1, \ldots, \underline{\mathsf{var}}_k) = A_3} \quad \text{(CG-CG)}$$

$$\frac{\begin{array}{c}\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2, \ldots, \underline{\mathsf{var}}_k \subset \underline{\mathsf{var}}'_1, \underline{\mathsf{var}}'_2, \underline{\mathsf{var}}'_3, \ldots, \underline{\mathsf{var}}'_n \qquad a_1, a_2, \ldots, a_k \subset a'_1, a'_2, a'_3, \ldots, a'_n \\ A_1 := cogroup\langle a'_1, a'_2, a'_3, \ldots, a'_n\rangle(\underline{\mathsf{var}}'_1, \underline{\mathsf{var}}'_2, \underline{\mathsf{var}}'_3, \ldots, \underline{\mathsf{var}}'_n) \qquad A_2 := map\langle\delta(\underline{\mathsf{var}}_1) \times \delta(\underline{\mathsf{var}}_2) \ldots \times \delta(\underline{\mathsf{var}}_k)\rangle(A_1)\end{array}}{\bowtie \langle a_1, a_2, \ldots, a_k\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2, \ldots, \underline{\mathsf{var}}_k) = A_2} \quad \text{(IJ-CG)}$$

$$\frac{\begin{array}{c}\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2 \subset \underline{\mathsf{var}}'_1, \underline{\mathsf{var}}'_2, \underline{\mathsf{var}}'_3, \ldots, \underline{\mathsf{var}}'_n \qquad a_1, a_2 \subset a'_1, a'_2, a'_3, \ldots, a'_n \\ A_1 := cogroup\langle a'_1, a'_2, a'_3, \ldots, a'_n\rangle(\underline{\mathsf{var}}'_1, \underline{\mathsf{var}}'_2, \underline{\mathsf{var}}'_3, \ldots, \underline{\mathsf{var}}'_n) \qquad A_2 := map\langle\delta(\underline{\mathsf{var}}_1) \times \delta(empty(\underline{\mathsf{var}}_2)?\{\{\perp\}\} : \underline{\mathsf{var}}_2)\rangle(A_1)\end{array}}{⟕ \langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2) = A_2} \quad \text{(LOJ-CG)}$$

$$\frac{\begin{array}{c}\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2 \subset \underline{\mathsf{var}}'_1, \underline{\mathsf{var}}'_2, \underline{\mathsf{var}}'_3, \ldots, \underline{\mathsf{var}}'_n \qquad a_1, a_2 \subset a'_1, a'_2, a'_3, \ldots, a'_n \\ A_1 := cogroup\langle a'_1, a'_2, a'_3, \ldots, a'_n\rangle(\underline{\mathsf{var}}'_1, \underline{\mathsf{var}}'_2, \underline{\mathsf{var}}'_3, \ldots, \underline{\mathsf{var}}'_n) \qquad A_2 := map\langle\delta(empty(\underline{\mathsf{var}}_1)?\{\{\perp\}\} : \underline{\mathsf{var}}_1) \times \delta(\underline{\mathsf{var}}_2)\rangle(A_1)\end{array}}{⟖ \langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2) = A_2} \quad \text{(ROJ-CG)}$$

Figure 11: Rules for aggressive merge.

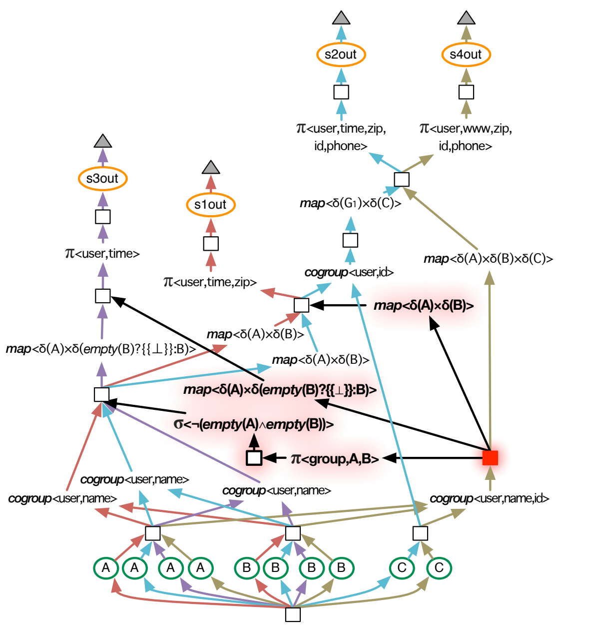


Figure 12: EG generated by PigReuse applying *aggressive merge* on the *normalized* and *decomposed* NRAB DAGs q_1-q_4.

5. EXPERIMENTAL EVALUATION

We have implemented PigReuse, our reuse-based optimization approach, in Java 1.6. The source code amounts to about 8000 lines and 50 classes. It works on top of Apache Pig 0.12.1 [22], which relied on the Hadoop platform 1.1.2 [11]. The cost-based plan selection algorithm (Section 3.2) uses the Gurobi BIP solver 5.6.2 (www.gurobi.com).

Section 5.1 describes our experimental setup. Then, Section 5.2 presents the two alternative cost functions that we have implemented and experimented with. Finally, Section 5.3 presents our experimental results.

5.1 Experimental setup

Deployment. All our experiments run in a cluster of 8 nodes connected by a 1GB Ethernet. Each node has a 2.93GHz Quad Core Xeon processor and 16GB RAM. The nodes run Linux CentOS 6.4. Each node has two 600GB SATA hard disks where HDFS is mounted.

Setup. For validation, we used data sets and scripts provided by the PigMix [23] PigLatin performance benchmark. We created a `page_views` input file of 250 million rows; the benchmark includes other input files, which are based on the `page_views` file, and are much smaller than this one. The total size of the data set amounted to approximately **400 GB** before the 3-way replication applied by HDFS.

We run our algorithm with two different workloads. The first one (denoted W_1) comprises 12 scripts taken directly from the PigMix benchmark, namely l_2-l_7 and l_{11}-l_{16}); these only use operators supported by our current implementation, e.g., `JOIN`, `COGROUP`, `FILTER` etc. Each script has on average 7 operators. The second workload (W_2) includes W_1, to which we add 8 extra scripts which feature many `JOIN` flavours, `COGROUP` on many relations etc. These scripts are added created to give opportunities to validate our algorithm on a wider variety of operators. Further details about these workloads can be found in Appendix E.

5.2 Cost functions and experiment metrics

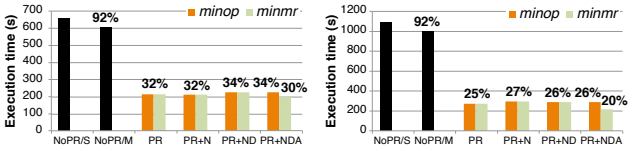
We now present the two cost functions that are implemented currently in PigReuse, focusing on the number of logical operators, and the number of MapReduce jobs, respectively. Although more elaborated cost functions can be envisioned [13], these two already lead to considerable gains due to reuse, as our experiments shortly show.

Operator-based cost function A first cost function characterizing the effort required by the evaluation of a batch of Pig Latin scripts is the number of operators in the equivalent NRAB expression eventually evaluated, that is:

$$\mathcal{C}_e = 1 \;\; \forall e \in E_a^{out}, \forall a \in A \qquad \mathcal{C}_e = 0 \quad \text{for all the rest}$$

Above, we assign a cost of 1 to the execution of every algebraic operator a, and we attach this cost to its outgoing edge. All the other edges, i.e., incoming edges to an operator node, have a cost of 0.

MapReduce jobs-based cost function Our second cost function is closely related to the Pig execution engine on top of MapReduce. The function minimizes the MapReduce jobs needed to compute the results of the input Pig Latin scripts, as some groups of operators are executed by Pig as part of the same job. For instance, σ, π, and *map* do not generate



(a) Execution time

(b) Total work

Figure 13: PigReuse evaluation using workload W_1 (left) and W_2 (right).

a new MapReduce job, which is very convenient for our *decomposition* and *aggressive merge* extension techniques that introduce these operators quite aggressively when rewriting.

Beyond these two cost functions used by our PigReuse algorithm, we also quantify the performance of executing a PigLatin workload through the following standard metrics: the **Execution time** is the wall-clock time measured from the moment when the scripts are submitted to the Pig engine, until the moment their execution is completely finished; the **Total work** is the sum of the effort made on all the nodes, i.e., the total CPU time as returned by logs of the MapReduce execution engine.

5.3 Experimental results

We now study the benefits brought by the optimizations proposed in this work. The reported results are averaged over three runs.

Figure 13 shows the effectiveness of our baseline PigReuse algorithm (PR), PigReuse with *normalization* (PR+N), PigReuse with *normalization* and *decomposition* (PR+ND), and PigReuse applying all our extensions including *aggressive merge* (PR+NDA). The figure shows relative values for the execution time and total work metrics. The cost function that minimizes the total number of operators in the EG is denoted by *minop*, while the cost function that minimizes the total number of MapReduce jobs is denoted by *minmr*.

In Figure 13.a, we notice that the total execution time is reduced by more than 70% on average among our PigReuse algorithms. Two alternative executions without PigReuse are shown. In the first one (NoPR/S), we execute *sequentially* every script in each workload using a single Pig client. In the second one (NoPR/M), we use multiple Pig clients that send *concurrently* the jobs resulting from the scripts to MapReduce. As it can be seen, the execution time for the second variant is lower as jobs resulting from multiple scripts are scheduled together, and thus the cluster usage is maximized. However, observe that the total work (Figure 13.b) increases for the multi-client alternative. This is because the number of slots needed for map tasks is very large, so the scheduler cannot overlap significantly the map phases of multiple queries. Thus, their execution remains quite sequential.

For the workloads we considered, our extensions reduced the total work over the baseline PigReuse algorithm (Figure 13.b). However, this was not always the case for the execution time (Figure 13.a). The reason is that some of the requiring more effort, had less execution steps, thus they could be parallelized easier by the MapReduce engine.

	PR	PR+N	PR+ND	PR+NDA
W_1 - EG equivalent nodes (#)	58	59	60	62
W_1 - EG operator nodes (#)	83	79	83	87
W_1 - REG (*minop*) operator nodes (#)	57	58	59	59
W_1 - REG (*minmr*) operator nodes (#)	57	58	59	60
W_2 - EG equivalent nodes (#)	74	82	83	88
W_2 - EG operator nodes (#)	135	125	131	143
W_2 - REG (*minop*) operator nodes (#)	73	81	82	82
W_2 - REG (*minmr*) operator nodes (#)	73	81	82	85

Table 2: Optimization details for workloads W_1/W_2.

When *aggressive merge* was applied, the execution time and the total work decreased only if the *minmr* cost function was used. The reason is that if the *minop* function is used, PigReuse generates the same REG for PR+ND and PR+NDA, namely, the REG with the minimum number of operators. However, if the *minmr* cost function is used, PigReuse chooses an alternative plan that executes faster even though it has more operators.

Table 2 provides some important metrics concerning the EGs and REGs created by PigReuse algorithm. PigReuse reduces the total number of logical operators by an average of 30%, using any of the two cost functions. The REGs generated PigReuse using the *minop* or *minmr* cost functions have the same number of operators, except when *aggressive merge* is used (PR+NDA). The reason is that all the connections that we establish through the aggressive merge strategy do not result in extra MapReduce jobs. Thus, using that strategy and the *minmr* cost function, a plan that contains more nodes but translates into less MapReduce jobs is selected. As we have seen before, this alternative plan leads to considerable execution time savings.

Concerning the total compile time overhead of using PigReuse (i.e. the time needed to generate the optimal set of scripts starting from the input workload), it stays below 125ms in all considered cases. So compile time is negligible compared to running time of the workloads, ranging from 28 minutes to 2 hours 35 minutes. Fast compile time is ensured by the adoption of a fast BIP solver, and by the fact that techniques we have devised to detect common subexpressions admit fast implementation.

6. RELATED WORK

Relational multi-query optimization. Our work directly relates to multi-query optimization (MQO), seeking to improve the performance of query batches with common sub-expressions. The early works [14, 28] proposed exhaustive, expensive algorithms which were not integrated with existing system optimizers. The technique presented in [27] was the first to integrate MQO into a Volcano-style optimizer, while [34] presents a completely integrated MQO solution accounting also for the usage and maintenance of materialized views. The approach of [29] takes into account the physical requirements (e.g., data partitioning) of the consumers of common sub-expressions in order to propose globally optimal execution plans. While all of these works

deals with the relational algebra, our approach optimises workloads expressed in terms of the richer NRAB algebra. As seen in Section 4, the presence of nested expressions involving operators like *c*ogroup and *m*ap, introduces issues that are typical of NRAB. Also, differently from [27, 29] our approach does not need fundamental modifications to the query optimiser ([27]) nor it needs to rely on assumptions at the physical level of the query engine [29]. As a consequence our approach has the advantage to be able to be directly applied to alternative implementations of Pig Latin (or of any other language based on NRAB).

The above considerations still hold for the Shared Workload optimization (SWO) approach proposed in [7], which relies on sharing *physical* operators (such as *scan*, *build*, *probe*, and several flavours of *join*) in large SQL workloads. Unlike PigReuse, this work *both* identifies sharing opportunities *and* optimizes the queries in order to improve global performance. To this end it deeply depends on the cost model of the query engine and on statistics about data (in order to estimate selectivity in join operations). As pointed out in [7], the global optimization + sharing problem can not be expressed by a linear program and thus a branch-and-bound heuristic solution is proposed, whereas our sharing problem can be solved optimally through BIP (although this does not apply other optimizations such as join reordering etc.). The approach presented in [18] also addresses both global optimisation and sharing possibilities at once, but it aims at optimising a single query, while extensions to multi-query are not trivial and not explored so far. Addressing simultaneously the optimization and reordering problem for Pig Latin is an interesting area of future work for which we laid foundations by formalizing the translation from Pig Latin, a language strictly more expressive than the SQL considered in [7, 18], to NRAB. Another interesting note is: while, unlike [7, 18], we do not explore operator reordering (other than σ and π and strictly for the needs of factorization), we shared with these works the need for quickly determining which operators are *not* likely to be equivalent; along the lines of [18], we used a set of *interesting operator properties*, e.g., the relations they join and the predicates they apply, to quickly prune out comparisons when looking for sharing opportunities.

Recycling techniques for a pipelined query engine are presented in [17], which represents dynamic SQL workloads as AND-DAGs. PigReuse DAGs are more complex as they include OR nodes, and our rewriting rules are more sophisticated.

Reuse-based optimizations on MapReduce. Recent works have sought to avoid redundant processing for a batch of MapReduce jobs by sharing their scans or intermediary results. Since the semantics of the computation is not visible at the level of MapReduce programs, these works are either limited to detecting identical inputs and outputs of MapReduce tasks (without being able to reason on task equivalence) [1, 19, 32], or need some annotations to the jobs to inform about sharing opportunities [6, 16]. Our PigReuse algorithm works on the higher-level semantic representation of Pig Latin scripts. This enables more complex reuse-based optimizations, e.g., through algebraic expression rewriting.

MQO for higher-level languages based on MapReduce has been considered in [2, 20]. For Hive workloads, [2] shows by example that improving replication of frequently used data, re-ordering queries in a workload, and scheduling queries in parallel can improve performance. Pig Latin optimization is discussed in [20]. Partial result sharing is considered especially from a scheduling perspective, that is: how to schedule programs in order to best profit from the shared computations. In our work, we assume the complete workload is examined and optimized, and then turned to the Pig Latin engine which schedules it independently for execution. The core of our work thus is concerned with identifying common sub-expression and examining the global sharing problem, which are not addressed in [20]. Approaches presented in [2, 20] are complementary to PigReuse and could be combined with it for better performance.

7. CONCLUSIONS AND FUTURE WORK

We have presented a novel approach for identifying and reusing common subexpressions occurring in Pig Latin scripts. Our PigReuse algorithm identifies sub-expression merging opportunities, and selects the best ones to merge based on a cost-based search process implemented with the help of a linear program solver. Our algorithm allows plugging any cost function and its output is a merged script reducing its value. Our experimental results demonstrate the value of our reuse-based algorithms and optimization strategies.

We see several interesting extensions to this work. First, adding better support for the optimization of Pig Latin scripts that contain calls to user-defined functions (UDFs). Our preliminary investigation (see Appendix C for details) revealed that the extension is feasible, and we postpone to future work its implementation. Second, we would like to add more (complex) cost functions in order to identify the ones leading to the most interesting total work reductions.

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APPENDIX

A. EXTENDED NESTED RELATIONAL ALGEBRA FOR BAGS

First, we recall the NRAB [10] data model in Section A.1, while we present the subset of its operators that we use to represent Pig Latin semantics in Section A.2. Then, Section A.3 extends NRAB with the Pig Latin operators, whose semantics are defined using the subset of NRAB operators that we introduce previously.

A.1 Data model

Let us assume the existence of a set of domain names $\widehat{D}_1, \ldots, \widehat{D}_n$ and an infinitive set of attributes $a_1, a_2, \ldots$. Further, the domain names are associated with domains $D_1, \ldots, D_n$. The elements of the domains can be of either atomic type or complex type. A type is associated with each instance of a domain. Formally, *types* and *values* are defined as follows:

- If $\widehat{D}_i \in \widehat{D}$ is a domain name, then $\widehat{D}_i$ denotes the *domain type*. For each database relation R in domain $\widehat{D}$, the type of R is $\widehat{D}_i$.
- If $T_1, \ldots, T_n$ are types and $a_1, \ldots, a_n$ are distinct attribute names for tuples in a database relation R, then R=$\{\{[a_1 : T_1, \ldots, a_n : T_n]\}\}$ is a bag of tuples in which $[a_1 : T_1, \ldots, a_n : T_n]$ is a *tuple* type. If v_1, ..., v_n are values of types T_1, ..., T_n, respectively, then $[a_1 : v_1, \ldots, a_n : v_n]$ is value of the *tuple* type. We also include $T_{[]}$ as a type; the only value of this type is [], the empty tuple.
- A *bag* is a (homogeneous) collection of tuples that may contain duplicates. If T is a tuple type, then $\{\{T\}\}$ is a *bag* type, whose domain is a set of bags containing homogeneous tuples of type T. We say that an element *o n-belongs* to a bag, if element o has n occurrences in that bag.
- A *bag database* is a set of named bags. A *bag schema* is an expression $B : T$, where B is a bag name and T is a bag type. An instance of B is a bag of type T.

A.2 Basic operators

NRAB operators. We now describe the NRAB operators [10] that we use to express Pig Latin sementics. The input and output types of all these operators are *bag* type.

- Duplicate elimination (ϵ). This operator extracts the distinct tuples in a relation. $\epsilon(R)$ is a bag containing exactly one occurrence of each tuple in R i.e., an element *o 1-belongs* to $\epsilon(R)$ iff *o p-belongs* to R for some $p > 0$, and *0-belongs* to $\epsilon(R)$ otherwise.
- Restructuring (*map*). $map\langle\varphi\rangle(R)$ returns a bag of type $\{\{T\}\}$, constructed by applying a function φ on each element of R. This operation is introduced for performing restructuring of complex values, which may include the application of functions to substructures of the values. *map* is a higher order operation with a function parameter φ that describes the restructuring.
- Selection (σ). Given a bag R and a boolean valued predicate condition p, $\sigma\langle p\rangle(R)$ denotes the select operation that returns a bag containing all the elements of R that satisfy the condition p. Only unary predicates

can be used as parameters for the select; we refer to them as *select specifications*.

- Additive union ($\uplus$). This operator deals with the union of bags with possibly duplicate elements. If R and S are two input relations of *bag* type $\{\{T\}\}$, then $R \uplus S$ is a bag of type $\{\{T\}\}$, such that a tuple t of type T *n-belongs* to $R \uplus S$, iff t *p-belongs* to R and *q-belongs* to S and $n = p + q$.
- Substraction ($-$). If R and S are two input relations of *bag* type $\{\{T\}\}$, then $R-S$ is a bag of type $\{\{T\}\}$, such that a tuple t of type T *n-belongs* to $R-S$, iff t *p-belongs* to R, *q-belongs* to S and $n = max(0, p - q)$, where function *max* returns the highest among the input values 0 and $p - q$.
- Cartesian product ($\times$). If R and S are bags containing tuples of arity k and k' respectively, then $R \times S$ is a bag containing tuples of arity $k + k'$, such that the new relation X becomes, $X = R \times S = \{[a_1, \ldots, a_k, a_{k+1}, \ldots, a_{k+k'}]\}$, where $[a_1, \ldots, a_k, a_{k+1}, \ldots, a_{k+k'}]$ is a tuple type. Tuple t $=[a_1, \ldots, a_k, a_{k+1}, \ldots, a_{k+k'}]$ *n-belongs* to $R \times S$ iff $t_1 = [a_1, \ldots, a_k]$ *p-belongs* to R and $t_2 = [a_{k+1}, \ldots, a_{k+k}]$ *q-belongs* to S and $n = pq$.
- Bag-destroy function (δ). δ unnests one level of bag nesting. If R is a bag of type $\{\{S : \{\{T\}\}\}\}$, then $map\langle\delta(S)\rangle(R)$ results a bag of type {{T}}.

NRAB functions. Function definition in NRAB has two parts: a class of base functions and function constructors that are used for constructing more complex function expressions.

First, we describe the base functions. In our algebra, constants c, and database relation names $\widehat{R}$ are considered as functions. Additionally, each attribute of the input relation is also considered as a function expression. We use **id** for denoting the identity function. For example, $map\langle R \uplus \mathbf{id}\rangle(S)$, denotes that additive union of R's element is performed recursively on each of S's elements, where S is a bag of tuples. Here, **id** indicates each element in S. The algebraic operations, except *select* and *restructuring*, are function expressions. *Select* and *restructuring* are function constructors, which are discussed next.

In our algebra, complex functions are constructed by using one of the function construction operators (*select* and *restructuring*). If φ is a unary function, then $map\langle\varphi\rangle(R)$ is a function. Similarly, if p is a unary boolean-valued function then $\sigma\langle p\rangle(R)$ is also a function. We use tuple construction as a function constructor i.e., if $f_1, \ldots, f_n$ are unary functions, then $[f_1, \ldots, f_n]$ is a unary function, whose meaning is defined by $[f_1, \ldots, f_n](x) = [f_1(x), \ldots, f_n(x)]$. Our algebra supports labeled tuple construction as a function constructor too, i.e., formation of expressions like $[A_1 = f_1, \ldots, A_n = f_n]$ is allowed; note that the A_is here are not functions but labels. The semantics is given by $[A_1 = f_1, \ldots, A_n = f_n](x)$ $= [A_1 : f_1(x), \ldots, A_n : f_n(x)]$. This implies that every function is unary, where its input is a tuple.

A.3 Additional operators and functions

In the following, we extend the basic NRAB set of operators to encapsulate the semantics of more complex operations that are supported by the Pig Latin language.

- Scan (*scan*). $scan\langle fileID\rangle$ is an operator introduced to represent a data source that reads a file *fileID*.
- Store (*store*). $store\langle dir\rangle(R)$ is an operator introduced to represent a data sink that writes the bag R to directory *dir*.
- Projection (π). $\pi\langle a_1, \ldots, a_n\rangle(R)$ projects attributes with names $a_1, \ldots, a_n$ from the tuples in bag R. Formally:

$$\pi\langle a_1, \ldots, a_n\rangle(R) \equiv map\langle[a_1, \ldots, a_n]\rangle(R)$$

- Cogroup (*cogroup*). In order to define the semantics of the *cogroup* operator, we first define a G operator that works on a single bag. In particular, $G\langle a\rangle(R)$ groups the tuples in R by the value bound to a. The result of the expression is a bag with tuples containing two elements: a *group* attribute associated to the grouping value, and a R attribute associated to the bag of tuples whose attribute a was bound to that value. Formally:

$$G\langle a\rangle(R) \equiv map\langle map\langle\sigma\langle group{=}a\rangle(id)\rangle(R)\rangle (map\langle[group = a, R = R]\rangle(R))$$

$cogroup\langle a_1, \ldots, a_n\rangle(R_1, \ldots, R_n)$ groups together tuples from multiple bags $R_1, \ldots, R_n$, based on the values of their attributes $a_1, \ldots, a_n$, respectively. The result of a *cogroup* operation is a bag containing a *group* attribute, bound to values of attributes $a_1, \ldots, a_n$, followed by one bag of grouped tuples for each relation in $R_1, \ldots, R_n$. Without loss of generality, we define it formally for two input relations; the extension for more than two inputs is straightforward. Thus:

$$cogroup\langle a_1, a_2\rangle(R_1, R_2) \equiv A_9$$

where:

$$A_1 := G\langle a_1\rangle(R_1) \qquad A_2 := G\langle a_2\rangle(R_2)$$
$$A_3 := \bowtie \langle group{=}group\rangle(A_1, A_2) \quad A_4 := \pi\langle group\rangle(A_3)$$
$$A_5 := \pi\langle group\rangle(A_1)$$
$$A_6 := \bowtie \langle group{=}group\rangle(A_5{-}A_4, A_1)$$
$$A_7 := \pi\langle group\rangle(A_2)$$
$$A_8 := \bowtie \langle group{=}group\rangle(A_7{-}A_4, A_2)$$
$$A_9 := A_3 \uplus A_6 \uplus A_8$$

- Inner join ($\bowtie$). $\bowtie \langle a_1, a_2, \ldots, a_n\rangle(R_1, R_2, \ldots, R_n)$ creates the cartesian product between the tuples in bags $R_1, R_2, \ldots, R_n$, and filters the resulting tuples based on condition $a_1{=}a_2{=}\ldots{=}a_n$. Thus, $\bowtie$ is formalized as:

$$\bowtie \langle a_1, a_2, \ldots, a_n\rangle(R_1, R_2, \ldots, R_n) \equiv \sigma\langle a_1{=}a_2{=}\ldots{=}a_n\rangle(R_1 \times R_2 \times \ldots \times R_n)$$

- Left outer join ($\rtimes$). $\rtimes \langle a_1{=}a_2\rangle(R_1, R_2)$ returns the cartesian product of tuples from input relations R_1 and R_2 for which boolean condition $a_1{=}a_2$ is true, and the tuples in R_1 without a matching right tuple. Formally:

$$\rtimes \langle a_1, a_2\rangle(R_1, R_2) \equiv A_5$$

where:

$$A_1 := \bowtie\langle a_1, a_2\rangle(R_1, R_2) \qquad A_2 := \pi\langle a_1\rangle(A_1)$$
$$A_3 := \pi\langle a_1\rangle(R_1) \quad A_4 := \bowtie\langle a_1, a_1\rangle(A_3 - A_2, A_1)$$
$$A_5 := A_1 \uplus A_4$$

- Right outer join ($\bowtie$). $\bowtie\langle a_1{=}a_2\rangle(R_1, R_2)$ returns the cartesian product of tuples from input relations R_1 and R_2 for which boolean condition $a_1{=}a_2$ is true, and the tuples in R_2 without a matching right tuple. Formally:

$$\bowtie\langle a_1, a_2\rangle(R_1, R_2) \equiv A_5$$

where:

$$A_1 := \bowtie\langle a_1, a_2\rangle(R_1, R_2) \qquad A_2 := \pi\langle a_2\rangle(A_1)$$
$$A_3 := \pi\langle a_2\rangle(R_2) \quad A_4 := \bowtie\langle a_2, a_2\rangle(A_3 - A_2, A_1)$$
$$A_5 := A_1 \uplus A_4$$

- Full outer join ($\bowtie$). $\bowtie\langle a_1{=}a_2\rangle(R_1, R_2)$ returns the cartesian product of tuples from input relations R_1 and R_2 for which boolean condition $a_1{=}a_2$ is true, the tuples in R_1 without a matching right tuple, and the tuples in R_2 without a matching left tuple. Formally:

$$\bowtie\langle a_1, a_2\rangle(R_1, R_2) \equiv A_8$$

where:

$$A_1 := \bowtie\langle a_1, a_2\rangle(R_1, R_2)$$
$$A_2 := \pi\langle a_1\rangle(A_1) \quad A_3 := \pi\langle a_1\rangle(R_1)$$
$$A_4 := \bowtie\langle a_1, a_1\rangle(A_3 - A_2, A_1)$$
$$A_5 := \pi\langle a_2\rangle(A_1) \quad A_6 := \pi\langle a_2\rangle(R_2)$$
$$A_7 := \bowtie\langle a_2, a_2\rangle(A_6 - A_5, A_1)$$
$$A_8 := A_1 \uplus A_4 \uplus A_7$$

- Restructuring and concatenation (*mapconcat*). The operation $mapconcat\langle\varphi\rangle(R)$ applies $map\langle\varphi\rangle(R)$ and concatenates its result to the original tuple. Thus:

$$mapconcat\langle\varphi\rangle(R) \equiv map\langle[id, \varphi]\rangle(R)$$

- Empty (*empty*) and aggregate functions (*aggr*). The boolean function $empty(R)$ returns true iff R is empty. In turn, aggregate functions *aggr* include *count*, *max*, *min* and *sum*. $count(R)$ calculates the number elements in a bag of tuples R. $max\langle a\rangle(R)$ returns the maximum integer value of an element a in a bag of tuples R. $min\langle a\rangle(R)$ returns the minimum integer value of an element a in a bag of tuples R. $sum\langle a\rangle(R)$ returns the sum of integer values for an element a in a bag of tuples R. Each of these functions can be described in NRAB.

B. Pig Latin - TO - NRAB TRANSLATION

Along the lines of [26], we define our Pig Latin to NRAB translation by means of deduction (or *translation*) *rules*. In a nutshell, a rule describes *how the translation is performed when some conditions are met over the input*. Our rules rely on *translation judgments*, noted as J, J_i, and are of the form:

$$\frac{J_1 \ \ldots \ J_n}{J}$$

stating that the translation J (conclusion) is recursively made in terms of translations $J_1 \ \ldots \ J_n$ (premises). The translation judgments J_i are optional.

For ease of presentation, we split the rules in two sets: the first one deals with the translation of programs as ordered sequences of expressions, while the second set details the translation of a single Pig Latin operation. Below, we present the rule sets in turn.

Pig Latin scripts translation. Rules in the first set are presented in Figure 14. They rely on judgments of the form $[\![P]\!]_\Gamma \rightsquigarrow \Gamma'$, meaning that a Pig Latin program P is translated to a set of named NRAB expressions Γ', in the context of a given set of named NRAB expressions Γ. By rules definition, it easily follows that Γ' always includes Γ. A named NRAB expression is a binding of the form $\{\underline{\mathsf{var}} = A\}$ where $\underline{\mathsf{var}}$ is a name given to the algebraic expression A. During the application of the translation rules, every binding expression $\{\underline{\mathsf{var}} = \mathsf{op}\}$ belonging to the Pig Latin program is translated into a named algebraic expression $\{var = A\}$, where A is the NRAB expression corresponding to the operation op (and obtained by applying the second set of translation rules).

Binding expressions in the Pig Latin program are translated one after the other, according to their order in the program. Each time a named algebraic expression $\{var = A\}$ is created, it is added to the context Γ. The context holds all variables which may be encountered while translating subsequent Pig Latin binding expressions of the program; we assume that *var* is a fresh variable, i.e., it is not already bound in the context.

Figure 14 shows the rules used by the high-level translation process outlined above. The rules are rather simple; note that the rule corresponding to `STORE` adds to the context a dummy binding. This rule records the fact that a bag has been saved on the disk, thus the symbol $\top$ is used instead of a variable symbol, which is not needed in this case.

Pig Latin operations translation. The second set of rules translates the operator op from a binding expression $\underline{\mathsf{var}} = \mathsf{op}$ into a NRAB expression A. These rules are defined over judgements of the form $\mathsf{op} \Rightarrow A$, meaning that the Pig Latin operation op is translated to the NRAB expression A.

A special case is the `FOREACH` operator, whose translation is not trivial as it is the main way to write complex programs in Pig Latin, e.g., it allows applying nested operations. The translation rules for this operator are shown in Figure 15. We use three different rules depending on the form of the `FOREACH` expression:

- The first rule (Projection ForEach) deals with the case of an iteration simply projecting n fields of the input relation. The rule specific to this case enables the generation of NRAB projections, playing an important role in our optimization technique. In Figure 15, $\underline{\mathsf{var}}_1$,$\underline{\mathsf{var}}_2$,...,$\underline{\mathsf{var}}_n$ are the fields to be projected from the input relation denoted by the name $\underline{\mathsf{var}}$.
- If the previous rule does not apply, and if the `FOREACH` operator contains a `GENERATE` clause with functions applied on the input relation $\underline{\mathsf{var}}$, the second rule (Simple ForEach) is applied. In this rule, every function definition f_i inside the `GENERATE` clause is translated to an algebraic expression A'_i and these expressions are applied with a *map* operator on each tuple in $\underline{\mathsf{var}}_1$ (recall Table 1).

- Rule (Complex ForEach) in Figure 15 considers `FOREACH` expressions containing one or more binding expressions before the `GENERATE` clause. Each Pig Latin operator op_i is translated first into an algebraic expression A'_i. These algebraic expressions are then used by a *mapconcat* operator, which applies A'_i on each tuple in A'_{i-1} (or $\underline{\mathsf{var}}_1$ initially) and appends the result to the input tuple; the use of *mapconcat* is necessary to use local contextual information that is visible only in the scope of the translated `FOREACH` expression. Every function definition $\underline{\mathsf{f}}_i$ inside the `GENERATE` clause is then translated to an algebraic expression A''_i, which are applied on each of the resulting tuples from the algebraic expression A_n.

We provide below an example that illustrates the (Simple ForEach) and (Complex ForEach) translation rules depicted in Figure 15. Recall that a complex `FOREACH` operator consists of one or more binding expressions before the `GENERATE` clause.

Consider the following Pig Latin script:

```
1  A = LOAD 'page_views' AS (user, time, www);
2  B = LOAD 'users' AS (name, zip);
3  R = COGROUP A BY user, B BY name;
4  S = FOREACH R {
5      X = FILTER A BY time > 300;
6      Y = FOREACH X GENERATE max(time);
7      Z = FILTER B BY zip == 9000;
8      GENERATE group, Y, count(Z);
9  }
10 STORE S INTO 's1out';
```

Line 1 loads data from a file `page_views` and creates a bag of tuples that is bound to variable `A`; in turn, line 2 loads data from a second file, and binds the resulting tuple bag to `B`. Line 3 groups together the tuples of `A` and `B` based on the equality of the values bound to attributes `user` and `name`; recall that the tuples output by the `COGROUP` operator consist of attributes `group`, `A`, and `B`. Lines 4-9 contain a complex `FOREACH` expression. In particular, for each tuple in `R`, line 5 creates a nested bag `X` with the tuples in `A` with a value bound to `time` that is greater than 300; then, line 6 projects the maximum value bound to `time` and binds it to variable `Y`; line 7 creates a nested bag `Z` with the tuples in `B` with a value bound to `zip` that is equal to 9000; finally, in line 8 the attributes `group`, `Y`, and the number of tuples in bag `Z` are generated. The result is stored in `s1out`.

The translation of the previous script yields:

$$
\begin{aligned}
\Gamma = \{\ A &= scan\langle \text{`}page\_views\text{'}\rangle,\\
B &= scan\langle \text{`}users\text{'}\rangle,\\
R &= cogroup\langle user, name\rangle(A, B),\\
S &= map\langle group, Y, count(Z)\rangle(\\
&\quad mapconcat\langle Z = \sigma\langle zip == 9000\rangle(B)\rangle(\\
&\quad\ mapconcat\langle Y = map\langle max\langle time\rangle(X)\rangle(\\
&\quad\quad mapconcat\langle X = \sigma\langle time > 300\rangle(A)\rangle(R)))),\\
&store\langle \text{`}s1out\text{'}\rangle(S)\ \}
\end{aligned}
$$

In the resulting context, S has been generated by the (Complex ForEach) translation rule; in turn, Y inside S has been generated by the (Simple ForEach) rule.

Other Pig Latin operators have a one-to-one correspondence with NRAB operators, and their translation (Figure 16) is commented in the sequel.

Rule (Load) translates a `LOAD` expression into a *scan* that generating a new bag that satisfies the schema description in the input expression.

Rule (Distinct) translates `DISTINCT` into a ϵ operator on the input relation $\underline{\mathsf{var}}_1$.

$$\frac{[\![\mathsf{expr}_1]\!]_{\Gamma_0} \rightsquigarrow \Gamma_1 \quad \ldots \quad [\![\mathsf{expr}_n]\!]_{\Gamma_{n-1}} \rightsquigarrow \Gamma_n}{[\![\mathsf{expr}_1; \ldots; \mathsf{expr}_n;]\!]_{\Gamma_0} \rightsquigarrow \Gamma_n} \quad \text{(Script)}$$

$$\frac{\mathsf{op} \Rightarrow A \qquad \Gamma_1 := \Gamma_0 \cup \{var = A\}}{[\![\underline{\mathsf{var}} = \mathsf{op}]\!]_{\Gamma_0} \rightsquigarrow \Gamma_1} \quad \text{(Bind)}$$

$$\frac{A := store\langle dir\rangle(var) \qquad \Gamma_1 := \Gamma_0 \cup \{\top = A\}}{[\![\texttt{STORE}\ \underline{\mathsf{var}}\ \texttt{INTO}\ \underline{\mathsf{dir}}]\!]_{\Gamma_0} \rightsquigarrow \Gamma_1} \quad \text{(Store)}$$

Figure 14: Translation rules for Pig Latin scripts and basic Pig Latin constructs.

Rule (Filter) translates a Pig Latin `FILTER` operator into a selection σ with a condition p on $\underline{\mathsf{var}}_1$.

Rule (Flatten Function) translates `FLATTEN` into a δ function that unnests the bag $\underline{\mathsf{var}}$. Rule (Empty Function) translates `IsEmpty` Pig Latin function, while rule (Aggregation Function) translates Pig Latin aggregation functions into their NRAB operators counterparts. Finally, rule (Attribute Function) translates a Pig Latin attribute name into its corresponding NRAB function expression.

The functions introduced in the last four rules are blocks that need to be used in the algebra in conjunction with one of the algebra construction operators, e.g., restructuring (*map*) or select (σ).

Rule (Cross) translates a `CROSS` into a cartesian product between $\underline{\mathsf{var}}_1, \ldots, \underline{\mathsf{var}}_n$.

Rule (Cogroup) translates a Pig Latin `COGROUP` operation to its algebraic equivalence *cogroup* that groups the tuples in $\underline{\mathsf{var}}_1, \ldots, \underline{\mathsf{var}}_n$ based on the values of attributes bound to $a_1, \ldots, a_n$.

Rule (Inner Join) translates an inner join `JOIN` operator into its algebraic counterpart $\bowtie$. Rule (Left Outer Join) translates a Pig Latin left outer join expression into a $\mathbin{⟕}$ operator, while rule (Right Outer Join) translates a Pig Latin right outer join expression into a $\mathbin{⟖}$ operator. Finally, rule (Full Outer Join) translates a Pig Latin full outer join expression into a $\mathbin{⟗}$ operator. Observe that outer joins can only be binary in Pig Latin.

C. EXTENSION TO UDFS

User-defined functions (UDFs) are extensively used in Pig Latin. These are functions that can be defined by users, implementing specific interfaces of the Pig Latin framework. Two common types of custom functions are *aggregate functions* that are applied to bags of tuples and return a scalar value, and *filter functions* that are applied to one or many attributes and return a boolean value.

Currently, PigReuse does not support UDFs; however, in future work we envision extensions to our technique to enable UDFs in PigReuse. We briefly sketch next the main points behind these extensions.

Our approach relies on distinguishing *functional* UDFs from *non functional*. Functional UDFs are those whose invocation does not have side effects, and whose result only depends on the input. This ensures that the result of the function call on a given input does not depend on when, and the context in which, the function is called. If an UDF has side effects or depends on values out of the input (i.e., current time or date provided by the system) then the UDF is not functional.

In the extension of NRAB, we assume that functions have associated a label to indicate whether they are functional

$$\frac{}{\texttt{FOREACH } \underline{\text{var}} \texttt{ GENERATE } \underline{\text{var}}_1 \ \ldots, \underline{\text{var}}_n \Rightarrow \pi\langle \underline{\text{var}}_1, \ldots, \underline{\text{var}}_n \rangle(\underline{\text{var}})} \quad \text{(Projection ForEach)}$$

$$\frac{\underline{\text{f}}_1 \Rightarrow A'_1, \ldots, \underline{\text{f}}_m \Rightarrow A'_m \qquad A_2 := map\langle [A'_1, \ldots, A'_m] \rangle (var_1)}{\texttt{FOREACH } \underline{\text{var}} \texttt{ GENERATE } \underline{\text{f}}_1, \ldots, \underline{\text{f}}_m \Rightarrow A_2} \quad \text{(Simple ForEach)}$$

$$\frac{\begin{array}{c} \text{op}_1 \Rightarrow A'_1 \qquad A_1 := mapconcat\langle [nvar_1 = A'_1] \rangle (var_1) \\ \text{op}_i \Rightarrow A'_i \qquad A_i := mapconcat\langle [nvar_i = A'_i] \rangle (A_{i-1}) \qquad 2 \leq i \leq n \\ \underline{\text{f}}_1 \Rightarrow A''_1, \ldots, \underline{\text{f}}_m \Rightarrow A''_m \qquad A_{n+1} := map\langle [A''_1, \ldots, A''_m] \rangle (A_n) \end{array}}{\texttt{FOREACH } \underline{\text{var}}_1 \ \{\underline{\text{nvar}}_1 = \text{op}_1; \ldots; \underline{\text{nvar}}_n = \text{op}_n; \texttt{ GENERATE } \underline{\text{f}}_1, \ldots, \underline{\text{f}}_m\} \Rightarrow A_{n+1}} \quad \text{(Complex ForEach)}$$

Figure 15: Translation rules for `foreach` operator.

$$\frac{A := scan\langle fileID \rangle}{\texttt{LOAD } fileID \Rightarrow A} \quad \text{(Load)}$$

$$\frac{A := \epsilon(\underline{\text{var}}_1)}{\texttt{DISTINCT } \underline{\text{var}}_1 \Rightarrow A} \quad \text{(Distinct)}$$

$$\frac{A := \sigma\langle p \rangle(\underline{\text{var}}_1)}{\texttt{FILTER } \underline{\text{var}}_1 \texttt{ BY } p \Rightarrow A} \quad \text{(Filter)}$$

$$\frac{A := \delta(\underline{\text{var}})}{\texttt{FLATTEN}(\underline{\text{var}}) \Rightarrow A} \quad \text{(Flatten Function)}$$

$$\frac{A := empty(\underline{\text{var}})}{\texttt{IsEmpty}(\underline{\text{var}}) \Rightarrow A} \quad \text{(Empty Function)}$$

$$\frac{A := aggr(\underline{\text{var}})}{\texttt{AGGR}(\underline{\text{var}}) \Rightarrow A} \quad \text{(Aggregation Function)}$$

$$\frac{}{\underline{\text{var}} \Rightarrow \underline{\text{var}}} \quad \text{(Attribute Function)}$$

$$\frac{A := \underline{\text{var}}_1 \uplus \ldots \uplus \underline{\text{var}}_n}{\texttt{UNION } \underline{\text{var}}_1, \ldots, \underline{\text{var}}_n \Rightarrow A} \quad \text{(Union)}$$

$$\frac{A := \underline{\text{var}}_1 \times \ldots \times \underline{\text{var}}_n}{\texttt{CROSS } \underline{\text{var}}_1, \ldots, \underline{\text{var}}_n \Rightarrow A} \quad \text{(Cross)}$$

$$\frac{A := cogroup\langle a_1, \ldots, a_n \rangle(\underline{\text{var}}_1, \ldots, \underline{\text{var}}_n)}{\texttt{COGROUP } \underline{\text{var}}_1 \texttt{ BY } a_1, \ldots, \underline{\text{var}}_n \texttt{ BY } a_n \Rightarrow A} \quad \text{(Cogroup)}$$

$$\frac{A_1 := \bowtie \langle a_1, \ldots, a_n \rangle(\underline{\text{var}}_1, \ldots, \underline{\text{var}}_n)}{\texttt{JOIN } \underline{\text{var}}_1 \texttt{ BY } a_1, \ldots, \underline{\text{var}}_n \texttt{ BY } a_n \Rightarrow A_1} \quad \text{(Inner Join)}$$

$$\frac{A_1 := \bowtie \langle a_1, a_2 \rangle(\underline{\text{var}}_1, \underline{\text{var}}_2)}{\texttt{JOIN } \underline{\text{var}}_1 \texttt{ BY } a_1 \texttt{ LEFT}, \underline{\text{var}}_2 \texttt{ BY } a_2 \Rightarrow A_1} \quad \text{(Left Outer Join)}$$

$$\frac{A_1 := \bowtie \langle a_1, a_2 \rangle(\underline{\text{var}}_1, \underline{\text{var}}_2)}{\texttt{JOIN } \underline{\text{var}}_1 \texttt{ BY } a_1 \texttt{ RIGHT}, \underline{\text{var}}_2 \texttt{ BY } a_2 \Rightarrow A_1} \quad \text{(Right Outer Join)}$$

$$\frac{A_1 := \bowtie \langle a_1, a_2 \rangle(\underline{\text{var}}_1, \underline{\text{var}}_2)}{\texttt{JOIN } \underline{\text{var}}_1 \texttt{ BY } a_1 \texttt{ FULL}, \underline{\text{var}}_2 \texttt{ BY } a_2 \Rightarrow A_1} \quad \text{(Full Outer Join)}$$

Figure 16: Rules for translating Pig Latin operators to corresponding NRAB representations.

(this information can be provided by the programmer). In the search of common sub-expressions, two function calls are deemed as the same only if they refer to the *same* function name *and* this name is associated to a functional function. Like previously introduced functions, UDFs are blocks that need to be used in the algebra in conjunction with a construction operator e.g., *map*.

Additional equivalence rules. To better integrate within our framework the reutilization of results comprising *map* operators, including those containing *udf* functions, new equivalence rules could be added to the existing set, as the following two ones, where we assume the function φ being functional. The first rule comes from commutativity of projection and restructuring

$$\pi\langle a_1, \ldots, a_i \rangle(map\langle \varphi \rangle(\underline{\text{var}})) \equiv map\langle \varphi \rangle(\pi\langle a_1, \ldots, a_i \rangle(\underline{\text{var}}))$$

where $a_1, \ldots, a_i$ includes all the attributes on which φ depends. A second rule comes from commutativity of selection and restructuring:

$$\sigma\langle p \rangle(map\langle \varphi \rangle(\underline{\text{var}})) \equiv map\langle \varphi \rangle(\sigma\langle p \rangle(\underline{\text{var}}))$$

where p and φ depends on two disjoint sets of attributes, and φ preserves all attributes used by p.

Changes to PigReuse normalization. Given that the information about the fields that a UDF accesses is available to PigReuse, accommodating e.g., an *map* operator containing a UDF *udf* in the normalization step is straightforward.

In particular, as it happens with *built-in* functions, a child π operator can be swapped with the parent operator *map* operator containing a UDF *udf* if and only if none of the fields used by the parent operator is projected by π.

A special case of syntactic dependency arises when the given UDF *consults tuple metadata*, e.g., counting the number of fields in a tuple, which is not possible in the traditional algebraic context. In this case, we could consider that all fields in the tuple are accessed, and thus, the child π operator cannot be swapped with the parent operator.

D. ALGEBRA EQUIVALENCES

To detect algebra expressions equivalences, PigReuse relies on the *logical properties* of these expressions [18]. In the following, we enumerate the different laws that PigReuse uses to set these logical properties, which have been extensively studied previously [3, 9, 24, 25].

Equivalence 1. *Cascading of selections:*

$$\sigma\langle p_1 \rangle(\sigma\langle p_2 \rangle(\ldots(\sigma\langle p_n \rangle(\underline{\text{var}}))\ldots)) \equiv \sigma\langle p_1 \wedge p_2 \wedge \ldots \wedge p_n \rangle(\underline{\text{var}})$$

Equivalence 2. *Commutativity of selection:*

$$\sigma\langle p_1 \rangle(\sigma\langle p_2 \rangle(\underline{\text{var}})) \equiv \sigma\langle p_2 \rangle(\sigma\langle p_1 \rangle(\underline{\text{var}}))$$

Equivalence 3. *Cascading of projections:*

$$\pi\langle C_1 \rangle(\pi\langle C_2 \rangle(\ldots(\pi\langle C_n \rangle(\underline{\text{var}}))\ldots)) \equiv \pi\langle C_1 \rangle(\underline{\text{var}})$$

where C_i is a set of columns such that $C_i \subseteq C_{i+1}$, $\forall i = 1, \ldots, n-1$.

EQUIVALENCE 4. *Cascading of additive union:*

$$\underline{\mathsf{var}}_1 \uplus (\underline{\mathsf{var}}_2 \uplus (\ldots \uplus (\underline{\mathsf{var}}_{n-1} \uplus \underline{\mathsf{var}}_n)\ldots)) \equiv \underline{\mathsf{var}}_1 \uplus \underline{\mathsf{var}}_2 \uplus \ldots \uplus \underline{\mathsf{var}}_n$$

EQUIVALENCE 5. *Commutativity of additive union:*

$$\underline{\mathsf{var}}_1 \uplus \underline{\mathsf{var}}_2 \equiv \underline{\mathsf{var}}_2 \uplus \underline{\mathsf{var}}_1$$

EQUIVALENCE 6. *Associativity of additive union:*

$$\underline{\mathsf{var}}_1 \uplus (\underline{\mathsf{var}}_2 \uplus \underline{\mathsf{var}}_3) \equiv (\underline{\mathsf{var}}_1 \uplus \underline{\mathsf{var}}_2) \uplus \underline{\mathsf{var}}_3$$

EQUIVALENCE 7. *Cascading of cross:*

$$\underline{\mathsf{var}}_1 \times (\underline{\mathsf{var}}_2 \times (\ldots \times (\underline{\mathsf{var}}_{n-1} \times \underline{\mathsf{var}}_n)\ldots)) \equiv \underline{\mathsf{var}}_1 \times \underline{\mathsf{var}}_2 \times \ldots \times \underline{\mathsf{var}}_n$$

EQUIVALENCE 8. *Commutativity of cross:*

$$\underline{\mathsf{var}}_1 \times \underline{\mathsf{var}}_2 \equiv \underline{\mathsf{var}}_2 \times \underline{\mathsf{var}}_1$$

EQUIVALENCE 9. *Associativity of cross:*

$$(\underline{\mathsf{var}}_1 \times \underline{\mathsf{var}}_2) \times \underline{\mathsf{var}}_3 \equiv (\underline{\mathsf{var}}_1 \times \underline{\mathsf{var}}_3) \times \underline{\mathsf{var}}_2$$

EQUIVALENCE 10. *Commutativity of cogroup:*

$$\mathit{cogroup}\langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2) \equiv \mathit{cogroup}\langle a_2, a_1\rangle(\underline{\mathsf{var}}_2, \underline{\mathsf{var}}_1)$$

EQUIVALENCE 11. *Cascading of inner join:*

$$\bowtie \langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, \bowtie \langle a_2, a_3\rangle(\underline{\mathsf{var}}_2, \ldots, \bowtie \langle a_{n-1}, a_n\rangle(\underline{\mathsf{var}}_{n-1}, \underline{\mathsf{var}}_n)\ldots)) \equiv \bowtie \langle a_1, a_2, \ldots, a_n\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2, \ldots, \underline{\mathsf{var}}_n)$$

EQUIVALENCE 12. *Commutativity of inner join:*

$$\bowtie \langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2) \equiv \bowtie \langle a_2, a_1\rangle(\underline{\mathsf{var}}_2, \underline{\mathsf{var}}_1)$$

EQUIVALENCE 13. *Associativity of inner join:*

$$\bowtie \langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, \bowtie \langle a_2, a_3\rangle(\underline{\mathsf{var}}_2, \underline{\mathsf{var}}_3)) \equiv \bowtie \langle a_2, a_3\rangle(\bowtie \langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2), \underline{\mathsf{var}}_3)$$

EQUIVALENCE 14. *Cascading of full outer join:*

$$⟗ \langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, ⟗ \langle a_2, a_3\rangle(\underline{\mathsf{var}}_2, \ldots, ⟗ \langle a_{n-1}, a_n\rangle(\underline{\mathsf{var}}_{n-1}, \underline{\mathsf{var}}_n)\ldots)) \equiv ⟗ \langle a_1, a_2, \ldots, a_n\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2, \ldots, \underline{\mathsf{var}}_n)$$

EQUIVALENCE 15. *Commutativity of full outer join:*

$$⟗ \langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2) \equiv ⟗ \langle a_2, a_1\rangle(\underline{\mathsf{var}}_2, \underline{\mathsf{var}}_1)$$

EQUIVALENCE 16. *Associativity of full outer join:*

$$⟗ \langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, ⟗ \langle a_2, a_3\rangle(\underline{\mathsf{var}}_2, \underline{\mathsf{var}}_3)) \equiv ⟗ \langle a_2, a_3\rangle(⟗ \langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2), \underline{\mathsf{var}}_3)$$

EQUIVALENCE 17. *Commutativity of selection and projection:*

$$\sigma\langle p\rangle(\pi\langle a_1, \ldots, a_n\rangle(\underline{\mathsf{var}})) \equiv \pi\langle a_1, \ldots, a_n\rangle(\sigma\langle p\rangle(\underline{\mathsf{var}}))$$

where every attribute mentioned in p must be included in $a_1, \ldots, a_n$.

EQUIVALENCE 18. *Commutativity of selection and cross:*

$$\sigma\langle p\rangle(\underline{\mathsf{var}}_1 \times \underline{\mathsf{var}}_2) \equiv \sigma\langle p\rangle(\underline{\mathsf{var}}_1) \times \underline{\mathsf{var}}_2$$

where all attributes in p belong to $\underline{\mathsf{var}}_1$. In general, a selection can be replaced by a cascade of selections, and then some of the resulting selections might commute with the cross operator.

EQUIVALENCE 19. *Commutativity of selection and inner join:*

$$\sigma\langle p\rangle(\bowtie \langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2)) \equiv \bowtie \langle a_1, a_2\rangle(\sigma\langle p\rangle(\underline{\mathsf{var}}_1), \underline{\mathsf{var}}_2)$$

where all attributes in p belong to $\underline{\mathsf{var}}_1$. In general, a selection can be replaced by a cascade of selections, and then some of the resulting selections might commute with the join operator.

EQUIVALENCE 20. *Commutativity of selection and left outer join:*

$$\sigma\langle p\rangle(⟕ \langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2)) \equiv ⟕ \langle a_1, a_2\rangle(\sigma\langle p\rangle(\underline{\mathsf{var}}_1), \underline{\mathsf{var}}_2)$$

where all attributes in p belong to $\underline{\mathsf{var}}_1$. A selection can only be pushed to the left input of a left outer join operator.

EQUIVALENCE 21. *Commutativity of selection and right outer join:*

$$\sigma\langle p\rangle(⟖ \langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2)) \equiv ⟖ \langle a_1, a_2\rangle(\underline{\mathsf{var}}_1, \sigma\langle p\rangle(\underline{\mathsf{var}}_2))$$

where all attributes in p belong to $\underline{\mathsf{var}}_2$. A selection can only be pushed to the right input of a right outer join operator.

EQUIVALENCE 22. *Commutativity of projection and inner join:*

$$\pi\langle a_1, \ldots, a_i, a_{i+1}, \ldots, a_n\rangle(\bowtie \langle a_x, a_y\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2)) \equiv \bowtie \langle a_x, a_y\rangle(\pi\langle a_1, \ldots, a_i\rangle(\underline{\mathsf{var}}_1), \pi\langle a_{i+1}, \ldots, a_n\rangle(\underline{\mathsf{var}}_2))$$

where attributes $a_1, \ldots, a_i$ belong to $\underline{\mathsf{var}}_1$, while attributes $a_{i+1}, \ldots, a_n$ belong to $\underline{\mathsf{var}}_2$. Note that the attributes a_x, a_y must be contained in $a_1, \ldots, a_i, a_{i+1}, \ldots, a_n$.

EQUIVALENCE 23. *Commutativity of projection and left outer join:*

$$\pi\langle a_1, \ldots, a_i, a_{i+1}, \ldots, a_n\rangle(⟕ \langle a_x, a_y\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2)) \equiv ⟕ \langle a_x, a_y\rangle(\pi\langle a_1, \ldots, a_i\rangle(\underline{\mathsf{var}}_1), \pi\langle a_{i+1}, \ldots, a_n\rangle(\underline{\mathsf{var}}_2))$$

where attributes $a_1, \ldots, a_i$ belong to $\underline{\mathsf{var}}_1$, while attributes $a_{i+1}, \ldots, a_n$ belong to $\underline{\mathsf{var}}_2$. Note that the attributes a_x, a_y must be contained in $a_1, \ldots, a_i, a_{i+1}, \ldots, a_n$.

EQUIVALENCE 24. *Commutativity of projection and right outer join:*

$$\pi\langle a_1, \ldots, a_i, a_{i+1}, \ldots, a_n\rangle(⟖ \langle a_x, a_y\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2)) \equiv ⟖ \langle a_x, a_y\rangle(\pi\langle a_1, \ldots, a_i\rangle(\underline{\mathsf{var}}_1), \pi\langle a_{i+1}, \ldots, a_n\rangle(\underline{\mathsf{var}}_2))$$

where attributes $a_1, \ldots, a_i$ belong to $\underline{\mathsf{var}}_1$, while attributes $a_{i+1}, \ldots, a_n$ belong to $\underline{\mathsf{var}}_2$. Note that the attributes a_x, a_y must be contained in $a_1, \ldots, a_i, a_{i+1}, \ldots, a_n$.

EQUIVALENCE 25. *Commutativity of projection and full outer join:*

$$\pi\langle a_1, \ldots, a_i, a_{i+1}, \ldots, a_n\rangle(⟗ \langle a_x, a_y\rangle(\underline{\mathsf{var}}_1, \underline{\mathsf{var}}_2)) \equiv ⟗ \langle a_x, a_y\rangle(\pi\langle a_1, \ldots, a_i\rangle(\underline{\mathsf{var}}_1), \pi\langle a_{i+1}, \ldots, a_n\rangle(\underline{\mathsf{var}}_2))$$

where attributes $a_1, \ldots, a_i$ belong to $\underline{\mathsf{var}}_1$, while attributes $a_{i+1}, \ldots, a_n$ belong to $\underline{\mathsf{var}}_2$. Note that the attributes a_x, a_y must be contained in $a_1, \ldots, a_i, a_{i+1}, \ldots, a_n$.

E. EXPERIMENTAL QUERY WORKLOADS

Workload W_1 consists of scripts 1-12, while workload W_2 consists of the 20 scripts that we introduce below.

SCRIPT 1. *l2.pig. Extract the estimated revenue for the pages visited by registered users.*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, estimated_revenue;
alpha = LOAD 'users' AS (name, phone, address, city, state,
     zip);
beta = FOREACH alpha GENERATE name;
C = JOIN B BY user, beta BY name;
STORE C INTO 'l2out';
```

SCRIPT 2. *l3.pig. Extract the total estimated revenue per registered user.*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, estimated_revenue;
alpha = LOAD 'users' AS (name, phone, address, city, state,
     zip);
beta = FOREACH alpha GENERATE name;
C = JOIN B BY user, beta BY name;
D = GROUP C BY user;
E = FOREACH D GENERATE group, SUM(C.estimated_revenue);
STORE E INTO 'l3out';
```

SCRIPT 3. *l4.pig. How many different actions has each registered user done?*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, action;
C = GROUP B BY user ;
D = FOREACH C {
    aleph = B.action;
    beth = DISTINCT aleph;
    GENERATE group, COUNT(beth);
}
STORE D INTO 'l4out';
```

SCRIPT 4. *l5.pig. List the page visitors that are not registered users.*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user;
alpha = LOAD 'users' AS (name, phone, address, city, state,
     zip);
beta = FOREACH alpha GENERATE name;
C = COGROUP B BY user, beta BY name;
D = FILTER C BY COUNT(beta) == 0;
E = FOREACH D GENERATE group;
STORE E INTO 'l5out';
```

SCRIPT 5. *l6.pig. How long did visitors that queried for a certain term stayed in the page?*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, action, timespent, query_term,
     ip_addr, timestamp;
C = GROUP B BY query_term;
D = FOREACH C GENERATE group, SUM(B.timespent);
STORE D INTO 'l6out';
```

SCRIPT 6. *l7.pig. How many visits did each user do during the morning/afternoon?*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, timestamp;
C = GROUP B BY user;
D = FOREACH C {
    morning = FILTER B BY timestamp < 43200;
    afternoon = FILTER B BY timestamp >= 43200;
    GENERATE group, COUNT(morning), COUNT(afternoon);
}
STORE D INTO 'l7out';
```

SCRIPT 7. *l11.pig. List all the users in the dataset (without repetitions).*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user;
C = DISTINCT B;
alpha = LOAD 'users' AS (name, phone, address, city, state,
     zip);
beta = FOREACH alpha GENERATE name;
gamma = DISTINCT beta;
D = UNION C, gamma;
E = DISTINCT D;
STORE E INTO 'l11out';
```

SCRIPT 8. *l12.pig. Extract the highest revenue page per user, the total timespent in the page, and the number of queries per action.*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, action, timespent, query_term,
     estimated_revenue;
C = FILTER B BY user IS NOT null;
alpha = FILTER B BY user IS null;
D = FILTER C BY query_term IS NOT null;
aleph = FILTER C BY query_term IS null;
E = GROUP D BY user;
F = FOREACH E GENERATE group, MAX(D.estimated_revenue);
STORE F INTO 'l12out/highest_value_page_per_user';
beta = GROUP alpha BY query_term;
gamma = FOREACH beta GENERATE group, SUM(alpha.timespent);
STORE gamma INTO 'l12out/total_timespent_per_term';
beth = GROUP aleph BY action;
gimel = FOREACH beth GENERATE group, COUNT(aleph);
STORE gimel INTO 'l12out/queries_per_action';
```

SCRIPT 9. *l13.pig. List all the page views together with their associated advanced user (if any).*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, estimated_revenue;
alpha = LOAD 'power_users' AS (pname, pphone, paddress, pcity,
     pstate, pzip);
beta = FOREACH alpha GENERATE pname, pphone;
C = JOIN B BY user LEFT, beta BY pname;
STORE C INTO 'l13out';
```

SCRIPT 10. *l14.pig. Extract the estimated revenue for the pages visited by registered users.*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, estimated_revenue;
alpha = LOAD 'users' AS (name, phone, address, city, state,
     zip);
beta = FOREACH alpha GENERATE name;
C = JOIN B BY user, beta BY name;
STORE C INTO 'l14out';
```

SCRIPT 11. *l15.pig. Extract the number of different actions, the average spent time, and the generated revenue, per registered user.*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, action, timespent,
     estimated_revenue;
C = GROUP B BY user;
D = FOREACH C {
    beth = DISTINCT B.action;
    ts = DISTINCT B.timespent;
    rev = DISTINCT B.estimated_revenue;
    GENERATE group, COUNT(beth), AVG(ts), SUM(rev);
}
STORE D INTO 'l15out';
```

SCRIPT 12. *l16.pig. How much revenue did each registered user generate?*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, estimated_revenue;
C = GROUP B BY user;
D = FOREACH C {
    F = B.estimated_revenue;
    GENERATE group, SUM(F);
}
STORE D INTO 'l16out';
```

SCRIPT 13. *e1.pig. List all the registered users together with their associated page views (if any).*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, estimated_revenue;
alpha = LOAD 'users' AS (name, phone, address, city, state,
     zip);
beta = FOREACH alpha GENERATE name;
C = JOIN B BY user RIGHT, beta BY name;
STORE C INTO 'e1out';
```

SCRIPT 14. *e2.pig. List all the page views and all the registered users, associating them if possible.*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, estimated_revenue;
alpha = LOAD 'users' AS (name, phone, address, city, state,
     zip);
beta = FOREACH alpha GENERATE name;
C = JOIN B BY user FULL, beta BY name;
STORE C INTO 'e2out';
```

SCRIPT 15. *e3.pig. How many different actions has each registered user done?*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, action;
C = GROUP B BY user ;
D = FOREACH C {
    aleph = B.action;
    beth = DISTINCT aleph;
    GENERATE group, COUNT(beth);
}
STORE D INTO 'e3out';
```

SCRIPT 16. *e4.pig. List the page views per registered user, together with their information as advanced users (if any).*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user;
alpha = LOAD 'users' AS (name, phone, address, city, state,
     zip);
beta = FOREACH alpha GENERATE name;
X = LOAD 'power_users' AS (pname, pphone, paddress, pcity,
     pstate, pzip);
Y = FOREACH X GENERATE pname, pphone;
C = COGROUP B BY user, beta BY name, Y BY pname;
D = FILTER C BY COUNT(beta) == 0;
E = FOREACH D GENERATE group;
STORE E INTO 'e4out';
```

SCRIPT 17. *e5.pig. How long did visitors with the same IP address stayed in the page?*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, action, timespent, query_term,
     ip_addr, timestamp;
C = GROUP B BY ip_addr;
D = FOREACH C GENERATE group, SUM(B.timespent);
STORE D INTO 'e5out';
```

SCRIPT 18. *e6.pig. Extract the estimated revenue for the pages visited per registered user.*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, estimated_revenue;
alpha = LOAD 'users' AS (name, phone, address, city, state,
     zip);
beta = FOREACH alpha GENERATE name;
C = COGROUP B BY user, beta BY name;
STORE C INTO 'e6out';
```

SCRIPT 19. *e7.pig. List all the users in the dataset (without repetitions).*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user;
C = DISTINCT B;
alpha = LOAD 'users' AS (name, phone, address, city, state,
     zip);
beta = FOREACH alpha GENERATE name;
gamma = DISTINCT beta;
D = UNION C, gamma;
E = DISTINCT D;
STORE E INTO 'e7out';
```

SCRIPT 20. *e8.pig. Extract the number of different actions, the average spent time, and the generated revenue, per registered user.*

```
A = LOAD 'page_views' AS (user, action, timespent, query_term,
     ip_addr, timestamp, estimated_revenue, page_info,
     page_links);
B = FOREACH A GENERATE user, action, timespent,
     estimated_revenue;
C = GROUP B BY user;
D = FOREACH C {
    beth = DISTINCT B.action;
    ts = DISTINCT B.timespent;
    rev = DISTINCT B.estimated_revenue;
    GENERATE group, COUNT(beth), AVG(ts), SUM(rev);
}
STORE D INTO 'e8out';
```