Processing Analytical Queries in the AWESOME Polystore

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ABSTRACT
Modern big data applications usually involve heterogeneous data sources and analytical functions, leading to increasing demand for polystore systems, especially analytical polystore systems. This paper presents AWESOME system along with a domain-specific language ADIL. ADIL is a powerful language which supports 1) native heterogeneous data models such as Corpus, Graph, and Relations; 2) a rich set of analytical functions; and 3) clear and rigorous semantics. AWESOME is an efficient tri-store middleware which 1) is built on the top of three heterogeneous DBMSs (Postgres, Solr, and Neo4j) and is easy to be extended to incorporate other systems; 2) supports the in-memory query engines and is equipped with a rich set of analytical functions; 3) applies a cost model to efficiently execute workloads written in ADIL; 4) fully exploits machine resources to improve scalability. A set of experiments on real workloads demonstrate the capability, efficiency, and scalability of AWESOME.

1 INTRODUCTION
Since their inception in 2015 [9], polystore systems [12, 14, 16, 22] have become a significant area of data management research. In a polystore, a common query processing facility is constructed over a number of data management systems, enabling a user to specify queries across stores. As polystores started getting applied to different application domains, it became clear that polystore system must not only support cross-model queries across data stores, but also support analytical operations, a term we use to loosely refer to operations that perform a computation instead of data manipulation and are typically not natively provided by a DBMS but by external software libraries. The example analytical operators include tasks like centrality computation on graphs, entity extraction from text, and classification tasks on relational data.

This work is motivated by our longstanding and ongoing collaboration with social and political scientists [8, 25, 26]. The data sets used in these collaborations cover diverse forms of information including social media, news articles, court documents, and public records covering roles, responsibilities, political positions and voting records of congress members and so forth. To facilitate this collaborative research, we have set up an automated data ingestion mechanism from a wide variety of information sources. The collected data is used by social science researchers for various problems ranging from coordinated rumor spreading on social media to understanding societal issues in the judicial system. These pragmatic social science analyses have demonstrated that these social science inspired workflows have some interesting characteristics that can benefit from novel scalable data analytics approaches:

1) The heterogeneity nature of data. In general, a social science research task requires multiple forms of data that naturally reside in different stores with different formats. Political scientists who study the influence of Twitter on presidential election would like to store social network data in a graph database and store news related to politicians in a textual database. If a single platform or database engine is used for their analytical tasks, overhead caused by data movement among diverse stores can be inevitably significant.
2) The capabilities of different DB engines. In performing the analysis, we discovered that some operations can be much more efficiently processed by one store versus another. E.g., Solr is capable of document indexing and textual search, RDBMS like PostgreSQL is efficient for graph traversal and analytics, etc.
3) Difficulty to write efficient and scalable code. The standard practice today for social science researchers is to write the application entirely in Python or R. Even when the data is placed in a DBMS, it is painful and time consuming for them to express their workloads using a data processing pipeline that can efficiently manage and straddle through different forms of data. It would be highly expected if a system can expose easy-to-use polystore management functionalities and analytical operators to users such that they can easily assemble their applications involving complex analytics on heterogeneous data.

1.1 System Design Decisions
We first depict a motivating workload named PoliSci and use it as a running example to demonstrate our system design decisions.

Example 1.1 (PolySci Workload). As illustrated in Figure 1, given a set of keywords about Covid-19, recent news articles containing any of them are found out through text queries against a Solr [1] document database. Then, a named entity recognition algorithm (an analytical operator) is invoked on the collected documents to retrieve named entities (e.g., President Trump). The returned entity list is then joined with a Twitter handler table for the US senators, which is stored in a PostgreSQL [3] relational database, to obtain the Twitter users for named entities who are senators. Finally, the Twitter social network, stored in a Neo4j [2] graph, is queried to retrieve all the users who mentioned any of these Twitter users and all tweets which contain any of these senators’ names.

By investigating the workloads like PoliSci, we determine the following design choices for an analytical polystore system:
• **Tri-store Middle-ware.** A minimum of three underlying DB engines (i.e., Neo4j, PostgreSQL and Solr) can be seamlessly queried, and more importantly, the intermediate variables computed in the workload can be passed to a DBMS query. E.g., the detected named entities need to be joined with a table from PostreSQL, and the join result needs to be further passed to a Cypher query over a Neo4j graph.

• **Analytical Function Support.** A wide spectrum of frequently-used analytical operators, e.g., NLP algorithms on textual data, should be supported to meet the increasing demand of polystore analytical tasks. Besides, AWESOME should allow users to write UDFs to expand the family of support operators.

• **Native Data Types.** AWESOME should support basic data types such as List and String. Besides, it should support native property graph, relation and text data models so that some native analytic functions can be directly applied. E.g., in PoliSci workload, the result of the Solr query is passed to an NER operator.

• **Flexible Dataflow Language.** There should be an easy-to-use language to help users express their polystore workloads of great flexibility. Specifically, it should allow users to express native DBMS queries (e.g., SQL snippets) and control flows (e.g., foreach) like a generic programming language like Scala.

• **In-memory Execution.** Providing in-memory query engines enables more optimization opportunities. In the PoliSci workload, the NER function returns a table which is much larger than the senator table in PostgreSQL, and this case, materializing the senator table (a small table) to memory and processing the join operator in memory can be much more efficient than storing the NER result to PostgreSQL and performing join in PostgreSQL.

• **Strict Validation Mechanism.** Many analytical operations, e.g., PageRank, are time consuming, and run-time errors/exceptions (e.g., type mismatch) will incur unaffordable overhead. A rigorous semantics check mechanism at compile time can avoid run-time errors as much as possible.

Unfortunately, existing polystore systems cannot fully meet the aforementioned design requirements. Table 1 summarizes the major technical features of previous polystore systems. Besides, conventional DBMSs like PostgreSQL provides UDF support, which can be borrowed to process workloads involving analytical operations. However, we demonstrate that such an approach is neither easy-to-implement nor efficient-to-execute in Section 7).

### 1.2 Contribution

Inspired by the increasing analytical demands and based on the design decisions discussed above, we introduce AWESOME (as shown in Figure 2), an in-memory full-fledged analytical polystore system. In summary, we made the following technical contributions.

- We present a formal description of ADIL, a dataflow language with clear native data types and rigorous semantics that acts as the polyglot interface to the AWESOME polystore.

- We present the architecture of AWESOME system which is a tri-store middle-ware equipped with full-fledged analytical capability. To improve efficiency, the system 1) automates the handling of intermediate data and avoids unnecessary data movement by supporting in-memory query engines; 2) automates the optimization of the usage of machine resources; and 3) develops a cost model to choose the optimal execution plan at run-time.

- We present an extensive set of experiments to demonstrate that AWESOME can effectively express and efficiently execute complex workloads involving management and analysis over heterogeneous data sources.

### 2 ADIL: A DATAFLOW LANGUAGE

ADIL, the surface language for AWESOME, is designed as a dataflow language. The user expresses an analysis workload in ADIL as a sequence of assignment statements where the LHS of the assignment is a variable or multiple variables and the RHS is an expression. Figure 3 presents the ADIL script for the PoliSci workload.

#### 2.1 Data Types

ADIL supports the following data types in native. We annotate the data types for some variables in Figure 3.

- **Primitive types:** Integer, Double, String, and Boolean.
- **Relation and Record:** A Relation variable represents a relational table and a Record variable is a single tuple of a relation.
- **Property Graph and Graph Element:** Users can construct, query against, or apply analytical functions (e.g., PageRank) on property graphs. A GraphElement variable can be either a node or an edge with labels and properties.
- **Corpus and Document:** A Corpus is a collection of documents, and each document consists of document content (String), a document identifier (Integer) and tokens (List<String>).
- **Matrix:** We support Matrix data type and commonly-used matrix operators such as dot products on matrix-valued variables. In addition, an AWESOME matrix has optional row map and column.
An ADIL script starts by declaring a polystore instance registered in AWESOME system catalog:

```
USE newsDB;
create analysis politician as (...
```

AWESOME system catalog is a file that maintains the metadata for each user-defined polystore instance including the alias, connection detail, and schema of data stores in this instance. For underlying data store which admits a schema (e.g., PostgreSQL, Solr), a copy of the schema is maintained in the catalog. For stores that do not admit a schema (e.g., Neo4j), a set of schema-like information (e.g., node/edge labels/properties) is maintained. In the above example, the metadata of polystore instance newsDB will be retrieved from the system catalog which contains the information of all DBMSs used in the workload named NewsAnalysis.

The main code block contains a sequence of assignment statements (Section 2.3) and store statements (Section 2.4).

### 2.3 Assignment Statement

An ADIL assignment statement evaluates an RHS expression and assigns the result to one or more LHS variables. The grammar for assignment statement is shown as follows.

```
(assignment-statement) ::= (var1) '=' (var2) '...' '=' (assign) (assign) ::= (basic-expr) | (ho-expres)
```

The RHS expression ( assign ) can be “basic” or “higher-order” explained by the following grammar fragments.

```
(basic-expr) ::= (const) | (query) | (func)
(ho-expres) ::= (assign) '->' (assign) | (assign) '->' (assign) '->' (assign) ... '->' (assign)
```

2.3.1 Basic Expression. <basic-exp> includes three types:

Constant Expression (<const>): A constant expression evaluates to a constant of any allowed data type. The expression can itself be a constant, e.g., ['x', 'y', 'z'], or a prior constant variable, or an element of a prior collection variable, e.g., a[1].

Query Expression (<query>): A query expression executes a query against a data store or against an AWESOME variable with a constituent data model. It uses standard query languages: SQL-93 for relational queries, OpenCypher [10] for property graph queries, and Lucene [17] for retrieval from text indices. In Figure 3, three query expressions are marked in pink and they use executeSQLR, executeSQL, and executeCypher keywords respectively. The first argument of a query expression is the alias of target DBMS registered in the polystore instance. If the query is against a variable created in prior statements, the first argument is left empty. The
second argument is a standard Lucene/SQL/Cypher query with the exception of the $ followed by a variable name (highlighted by the rounded rectangles in the figure). ADIL uses $ as a prefix of the variable passed as a parameter to a query.

**Function Expression (<func>):** AWESOME supports a rich native library for common data analytical tasks. The expression includes function name with required positional parameters followed by optional and named parameters. A parameter can be a constant or a variable. The expression can return a single or multiple variables. The NER function expression marked as brown in Figure 3 takes a relation variable as parameter and returns a relation variable.

**2.3.2 Higher-Order Expression.** A higher-order expression is recursively defined where another expression serves as its sub-expression. The following snippet from NewsAnalysis workload shows an example statement where the RHS is a nested higher-order expression:

```plaintext
wtmPerTopic := topicID, map(i =>
    WTM where getValue(_:Row, i) > 0.00);
```

*topicID* is a list of Integers and *WTM* is word-topic matrix where each row presents a word’s weights on all topics. For each topic, it produces a word-topic matrix consisting of words with weights higher than 0 on this topic. This snippet contains map, filter and binary comparison which are explained as follows.

**Map Expression:** A map expression operates on a collection variable, evaluates a sub-expression for each element in the collection, and returns a new collection object. The sub-expression can be a constant, a query, a function or another higher-order expression. In this snippet, it takes a list of integers (*topicID*) as input and, for each, applies another higher-order expression (a filter expression) on the *WTM* matrix to generate a matrix. Thus the returned variable (*wtmPerTopic*) is a list of matrices.

**Filter Expression:** The filter expression is indicated by the where clause – its sub-expression is a predicate; it returns a new collection with values which satisfy the given predicate. Since a matrix can be iterated by rows or by columns, users need to specify the iteration mode: the underscore sign (_) is used to represent every single element in the matrix, and the colon (:) followed by the type specify the element type. In the example snippet, it applies a binary comparison predicate on each row of the matrix and returns a new matrix consists of the rows satisfying the predicate.

**Binary Comparison and Logical Operations:** A binary comparison accepts two expressions and compares their values to return a Boolean value. In the example above,

```plaintext
getValue(_,Row, i) > 0.00
```

checks whether the *i*-th element of a row vector is positive. More generally, ADIL supports any binary logical operators such as AND, OR and NOT over predicates.

**Reduce Expression:** A reduce operation aggregates results from a collection by passing a commutative and associative binary operator as its sub-expression. For example, the following snippet

```plaintext
R := relations.reduce((r1,r2) => join(r1,r2, on="id"))
```

takes a list of relations as input and then joins each two tables and returns a new table at the end.

**2.4 Store Statement**

A store statement specifies the variables to be stored to a persistent storage, which can be an underlying DBMS registered in the system catalog or the AWESOME file system; it also includes the instructions for how to store the variable. In Figure 3, the last two lines store *user* and *tweet* variables to relational DBMS, and specifies the DBMS alias (*dbName* parameter), table name (*tName* optional parameter) and mapping between the targeted column names to the relational variables’ column names (*cName* optional parameter).

**2.5 Some Properties of ADIL**

A full discussion of the formal properties of ADIL is beyond the scope of this paper. Here we provide a few properties that will be useful in validating and developing logical plans from ADIL scripts.

1. ADIL does not have a for loop or a while operation. Instead, it uses the map operation to iterate over a collection and apply function over each element, the filter operation to select out elements from a collection that satisfies predicates, the reduce operation to compute an aggregate function on a collection. In ADIL, the collection must be completely constructed before the map (resp. filter or reduce) operation can be performed. Therefore, these operations are guaranteed to terminate.
2. ADIL is strongly typed.
3. In an assignment where the RHS expression is a query in a schemaless language like OpenCypher, the user must specify a schema for the LHS variable in the current system.
4. The data type and some metadata information of any LHS variable can be uniquely and correctly determined by analyzing the RHS expression (see Section 3).

**3 VALIDATING ADIL SCRIPTS**

An ADIL script is usually complex with many expensive operations executed by internal and external engines and libraries. To reduce the risk of avoidable run-time errors, AWESOME implements a strict compile-time semantics check mechanism to detect as many errors as possible before the query planing and execution stages. Validation of ADIL plans includes not only syntax checks of each statement, but also semantic validation across multiple statements. For example, if an LHS variable produced in line 5 is used in line 9, the latter statement needs to verify that the operations performed on *v* are consistent with its type and metadata inferred while parsing line 5. We use the term validation to refer to the process of determining the semantic correctness of the RHS expression, type inference for the process of inferring the data type of the LHS variable and metadata inference for the process of inferring the statically determinable properties of the LHS variables.

**3.1 Validation**

The semantic validation is based on system catalog which holds the meta information of external databases, function catalog which records the parameters and output types of AWESOME registered functions and variable metadata map which stores the key properties of variables and is built through inference process. The information stored in the variable metadata map varies for variables with different data types, and the details will be introduced in Section 3.2.
Table 2: Metadata for different data types.

| Data Type     | Metadata                  |
|---------------|---------------------------|
| Relation      | Schema \( S = \{ \text{ColName} : \text{Type} \} \) |
| Property Graph| Node labels set NL; Node properties map \( NP = \{ \text{PropName} : \text{Type} \} \); Edge labels set EL; Edge properties map \( EP = \{ \text{PropName} : \text{Type} \} \) |
| List          | Element type, Element metadata, Size |
| Tuple         | Each element’s type and metadata, Size |
| Map           | Key type, Key metadata, Value type, Value metadata, Size |
| Matrix        | Row (and column) count, Element type |

System catalog based validation. To validate a query expression (=query=), the system catalog is used if the query is against external DBMSs. For a SQL query, the metadata of the RDBMS used in the query can be found from the system catalog, then it checks if the relations and columns in the query exist in the database; for a Cypher query, it checks if the nodes (resp. edge) properties and labels used in the query exist in the database by using the schema information of the graph stored in system catalog.

Function catalog based validation. For function expressions (=func=), ADIL checks if the data types of the input variables/constant values are consistent with the parameters information registered in the function catalog.

Validation with Variable Metadata. Variable metadata map is looked up for every type of statement containing a variable. For a query expression, if it queries on AWESOME relations (i.e., relation-valued variables), their schema is found from the variable metadata map instead of the system catalog. For a function expression, if an input parameter is a variable, the data type of the variable will also be found in the map.

Validation Example. Usually, more than one types of validation need to be used. We use the example snippet from Sec. 2.3.2 to show how to validate a nested higher-order expression. To validate the Map expression, it gets the data type and element type of \( \text{topicID} \) from the variable metadata map, then it checks if the variable has a collection type and the element type will be used to validate the sub-expression which is a Filter expression; to validate the Filter expression, similar to the Map expression, the data type of \( \text{WTM} \) is checked and the element type is used to validate the sub-expression which is a binary comparison expression, besides, it also checks if the return type of the sub-expression is a Boolean; to validate the binary comparison expression, it validates if the two operands have the same data type and the data type is comparable: in this example, the type of the left operand can be inferred based on the function catalog; At the end, it checks the \( \text{getValue} \) function using the element type information of \( \text{WTM} \) and \( \text{topicID} \).

### 3.2 Type and Metadata Inference

This section introduce the process of building variable metadata map. Table 2 shows the variable types and their corresponding metadata properties. For each statement in an ADIL analysis plan, after validating the correctness, the type and metadata information of the LHS variables will be inferred as much as possible and stored to the map.

For different types of expressions, the inference mechanisms are different. For a query expression, if it is a SQL query, the schema of the returned relation will be inferred by parsing the SELECT clause and looking up the system catalog or variable metadata map to get column types; if it is a Cypher or Solr query, the schema should be provided explicitly by users. For function expressions, the returned types are registered in the function catalog. For nested expressions, the inference is handled from the innermost expression to the outermost expression. Taking the snippet shown in Sec. 2.3.2 as an example, the LHS variable’s type and metadata is inferred by the following steps: 1) the Filter expression returns a matrix since \( \text{WTM} \) is a matrix; and 2) Map expression will return a list of matrices since its sub-expression returns a matrix.

### 4 LOGICAL PLAN

After validating the correctness of an ADIL script, a logical plan will be constructed. A logical plan is a DAG where each node represents a logical operator.

#### 4.1 Logical Plan Creation

The initial logical plan is directly translated from the parsing results. In most cases, each expression in the ADIL script corresponds to a single logical operator. For example, an \( \text{ExecuteSQL} \) query expression will be mapped to an \( \text{ExecuteSQL} \) logical operator. However, for specific functions expressions or higher-order expressions, extra processing steps are required to generate the initial logical plan.

**Input-based Function Translation.** For analytical functions, the corresponding logical operators can vary based on different function inputs. Table 3 presents some functions. For example, the function \( \text{LDA} \) can take either a \( \text{Matrix} \) variable or a \( \text{Corpus} \) variable as input, which corresponds to logical operators \( \text{LDAOnTextMatrix} \) and \( \text{LDAOnCorpus} \) respectively.

**Higher-order Expressions to Sub-plans.** For higher-order expressions (e.g., map expressions), a single expression will be translated to a sub-plan since it contains sub-expressions. For the nested higher order expression shown in Section 2.3.2, the logical plan is given in Figure 4. In Figure 4, there are two types of edges denoting data flow and sub-operator consumption, respectively. The \( \text{Filter} \) operator takes data from \( \text{LDA} \) and applies a binary comparison sub-operator. The \( \text{Map} \) operator takes data from \( \text{ListCreation} \) and applies the \( \text{Filter} \) sub-operator on each element of the data. Both \( \text{Map} \) and \( \text{Filter} \) create a local variable to denote each element of a collection, and the scope of such local variable is the sub-expression block of that higher-order expression.

#### 4.2 Logical rewriting

After creating the initial logical plan, a set of rewriting rules will be applied to generate an optimized logical plan.
Table 3: Some of ADIL functions and logical operators.

| ADIL Function | Input Parameter | Logical Operator(s) |
|---------------|-----------------|--------------------|
| Preprocess    | Column, List-String, Corpus | CreateCorpusFromColumn, CreateCorpusFromList, NLPAnnotator(tokenize), NLPAnnotator(split), NLPAnnotator(pos), NLPAnnotator(lemma), FilterStopWords |
| NER           | Column, List-String, Corpus, AnnotatedCorpus | CreateCorpusFromColumn, CreateCorpusFromList, NLPAnnotator(tokenize), NLPAnnotator(split), NLPAnnotator(pos), NLPAnnotator(lemma), NLPAnnotator(ner) |
| TopicModel    | TextMatrix, Corpus | TopicModelOnTextMatrix, TopicModelOnCorpus |
| LDA           | Matrix, Corpus   | LDAOnTextMatrix, LDAOnCorpus |
| SVD           | Matrix, Corpus   | SVDAOnTextMatrix, SVDAOnCorpus |
| Sum           | List, Column, Vector, Matrix, Index | GetVector, SumList, SumVector |

Figure 5: Illustration of map fusion.

(a) Before map fusion
(b) After map fusion

Rule 1: Function decomposition. Some functions can be decomposed to several logical operators to achieve a deeper level of optimization. For example, for NER function which recognizes named entities in corpus, it will be translated to a series of CoreNLPAnnotator operators with different annotation sub-operators.

Rule 2: Redundancy elimination. The same operators which take the same input data will only be executed once. As Table 3 shows, some functions may share common logical operators, and these common operators will be merged.

Rule 3: Operators fusion. There are two special operators which apply a sub-operator on each single element of a collection variable: Map and NLPAnnotator. For a series of Map or NLPAnnotator, they will be fused and the sub-operators of them will be connected, which are termed as Map Fusion and NLP annotation pipeline. Figure 5 shows an example that corresponds to a snippet of workload NewsAnalysis, the left plot is the initial logical plan, and the right one applies map fusion. This rewriting has two advantages: 1) the intermediate results will not be materialized which saves memory, 2) it will benefit the candidate physical plans generation which will be discussed in detail in the physical planning section (Section 5).

Supposing the following ADIL snippet,

\[ (\text{Preprocess}(doc)) \rightarrow (\text{NER}(doc)) \]

Figure 6 illustrates the aforementioned rewriting rules. The first part is the initial logical plan, and the second part shows the plan after applying the function decomposition rule. For the third part, functions Preprocess and NER share a series of common logical operators which are merged based on Rule 2. The final part applies Rule 3 to generate an NLP annotator pipeline, which is a common practice in NLP toolkits such as Stanford coreNLP.

5 PHYSICAL PLAN

Based on the optimized logical plan, we introduce the physical planning details of AWESOME. As shown in Algorithm 1, there are mainly three steps to generate the candidate physical plans, each of which will be introduced in the following sections.

5.1 Candidate Physical Plans Generation

We introduce the pattern based transform algorithm to generate a set of candidate physical plans from a logical plan DAG. To begin with, we provide some definitions as follows.

**Definition 5.1 (Pattern Set).** A pattern set \( \text{Pat} : \{\{\text{OP}^l, E^l\} \rightarrow \{\text{OP}^p, E^p\}\} \) is a mapping where a key is a logical sub-DAG and a value is a set of physical sub-plans. The pattern set is ordered by the sizes of keys (i.e., the numbers of nodes in the logical sub-DAGs) to make sure that in the subsequent procedures the larger patterns in a logical plan are matched earlier.

**Definition 5.2 (Candidate Physical Plans).** Candidate physical plans consist of a DAG \( \text{FG} = \{\text{OP}^p, E^p\} \) which contains some virtual nodes, and a map \( \text{PM} : I \rightarrow \{\text{OP}^p, E^p\} \) where a key is a virtual node id and a value is a set of physical sub-plans.

We propose Algorithm 2 to generate the candidate physical plans. Table 4 lists some logical operators and their corresponding physical operators. For some logical operators like LDAOncorpus or some logical sub-DAGs, each corresponds to only one candidate physical operator or sub-plan. In this case, each operator or sub-DAG will be directly replaced by the physical operator or sub-plan.
5.2 Partitioned Data Parallelism

AWESOME exploits data parallelism to take advantage of modern multi-core systems. Table 4 presents some physical operators with their data parallel capabilities. ST means single-threaded operators which can not be executed in a data parallel fashion, PR means data parallelizable operators, and EX means operators provided by external libraries. The execution of EX operators is fully supported by external libraries and can utilize multi-core feature in their native implementation, and thus they are excluded from the subsequent AWESOME optimizations which are based on data parallelism.

For a PR operator with multiple inputs, it is associated with a capOn attribute specifying the input on which it has data parallelism capability. For example, the FilterStopWords operator takes a corpus and also a list of stop-words as input, and it can be executed in parallel by partitioning the corpus input. In this case, capOn will be set as the ID of the corpus variable. Every PR operator will be executed in parallel by partitioning the capOn input data. Figure 8 shows an illustration. The left sub-figure shows the original physical plan DAG and the right sub-figure shows the plan DAG after considering data-parallelism. When an operator with PR capability gets its input: if its capOn input was not partitioned, a Partition step will be added which generates partitioned result; if a non-capOn input was partitioned, then a Merge step will be added to collect data from multi-threads to a single collection; When an operator with ST capability gets data from an operator with PR capability, a Merge step will be added.

5.3 Buffering Mechanism

AWESOME employs a buffering mechanism to avoid storing unnecessary intermediate results in memory. Different from pipeline, buffering mechanism does not utilize multiple cores to execute different operators simultaneously. Some operators can process input in a batch-by-batch manner, and some can generate output in a batch-by-batch manner. We refer data with this manner as stream hereafter. There are four types of buffering capabilities:

(1) SI (Stream-Input): the input can be passed as stream to the operator, but it produces a whole inesperable result at once;
(2) SO (Stream-Output): the operator takes an inseparable input but can produce result progressively as stream;
(3) B (Blocking): both the input and output need to be a whole;
(4) SS (Stream-Stream): both the input and output can be a stream.

Each physical operator is associated with its buffering capability. Table 4 presents it for some physical operators. Similar to data parallelism capability, there is another capOn attribute associated if the operator has more than one input. The physical DAG will be partitioned to a collection of chains. Inside each chain, the intermediate result is not stored in memory; the upstream operator produces stream output to be consumed by the downstream operator. The data across chains has to be stored in memory. The partition rules are presented in technical report [4].
We built a framework that hybridizes pipeline (i.e., task parallelism) and data parallelism due to two properties of AWESOME operators. However, from the experimental results, this framework is not suitable for AWESOME. We briefly introduce this framework and explain why this technique did not boost performance to provide some insights for future researches.

Similar to the buffering mechanism, an AWESOME physical DAG is partitioned into a list of chains based on the partition rules. Then each chain will form a pipeline where operators can be executed simultaneously using multi-cores. Once the upstream operator produces a batch of results, the downstream operator will be executed on that batch immediately and simultaneously. Both pipeline and data parallelism utilizes multi-cores to increase resources utilization, thus we define a scheduling problem to allocate a specific amount of cores (the number of cores in an OS) to operators in each pipeline chain. A simple solution is to allocate cores to match the produce and consume rates of data.

However, from the experimental results, this framework is not more efficient than data parallelism framework even under the best allocation strategy due to two properties of AWESOME operators. In the future, when there are more operators with different properties are added to AWESOME, this framework may have chance to outperform the solely data parallelism framework.

### 5.4 Failed Attempt: Pipeline + Data Parallelism

We built a framework that hybridizes pipeline (i.e., task parallelism) and data parallelism, however, the experimental results reveal that such framework is not suitable for AWESOME. We briefly introduce this framework and explain why this technique did not boost performance to provide some insights for future researches.

Similar to the buffering mechanism, an AWESOME physical DAG is partitioned into a list of chains based on the partition rules. Then each chain will form a pipeline where operators can be executed simultaneously using multi-cores. Once the upstream operator produces a batch of results, the downstream operator will be executed on that batch immediately and simultaneously. Both pipeline and data parallelism utilizes multi-cores to increase resources utilization, thus we define a scheduling problem to allocate a specific amount of cores (the number of cores in an OS) to operators in each pipeline chain. A simple solution is to allocate cores to match the produce and consume rates of data.

However, from the experimental results, this framework is not more efficient than data parallelism framework even under the best allocation strategy due to two properties of AWESOME operators. In the future, when there are more operators with different properties are added to AWESOME, this framework may have chance to outperform the solely data parallelism framework.

### 6 LEARNED COST MODEL

The query planning stage generates multiple candidate physical plans, and in the execution stage, the optimal one will be chosen at run-time based on a learned cost model.

For each virtual node which corresponds to multiple candidate sub-plans, the cost model is applied to each sub-plan to estimate the execution cost and the sub-plan with the lowest cost will be chosen. We use a learned cost model instead of a rule-based model based on two reasons:

- Cost should be decided at sub-plan level instead of operator-level, which makes rule-based optimization hard to design. For a single logical operator with different physical implementations, it is easy to design rules to decide which implementation should be chosen under what circumstance. However, in the pattern set, each logical sub-plan may consist of several logical operators and each of them may be transferred to multiple different physical operators, leading to a large size of rules space.
- The cost of a physical operator may depend on several features and a rule-based model is too simple to represent the complex relationship.

### 6.1 Cost Model

We provide a learned cost model to estimate the execution time for each candidate physical sub-plan denoted as $S$. Suppose that $S$ consists of multiple operators $\{op_1, \ldots, op_n\}$, the overall cost estimation is given as the sum of the estimated cost of all operators since AWESOME does not apply task parallelism, i.e.,

$$
est_S = \text{Cost}(op_1) + \cdots + \text{Cost}(op_n),$$

where $\text{Cost}(\cdot)$ is a trained linear regression model with the polynomial of raw features (degree 2) as variables that predicts the execution cost of a physical operator, i.e.,

$$
\text{Cost}(op) = w_0 + w_1 f_1 + \cdots + w_n f_n + w'_1 f_1^2 + \cdots + w'_n f_n^2 + \cdots + w'_{(n-1)n} f_{n-1} f_n.
$$

---

**Table 4: Summary of AWESOME logical and physical operators.**

| Types          | Logical Operators               | Physical Operators                       | DataParallelCap | BufferingCap |
|----------------|---------------------------------|------------------------------------------|-----------------|--------------|
| Query          | ExecuteCypher                   | ExecuteCypherInNeo4j                     | ST              | SO           |
|                | ExecuteSQL                      | ExecuteSQLInPostgres                    | EX              | SO           |
|                | ExecuteSol                      | ExecuteSQLInSQLite                      | ST              | SO           |
|                |                                 | ExecuteSol                               | ST              | SO           |
| Graph Operations| BuildWordNeighborGraph          | CollectGraphElementsFromDocs             | PR              | SS           |
|                | BuildGraphFromRelation          | CollectGraphElementsFromRelation         | PR              | SS           |
|                | PageRank                        | CreateTinkerpopGraph                    | ST              | SI           |
|                |                                 | CreateNeo4jGraph                        | ST              | SI           |
|                |                                 | PageRank&Tinkerpop                      | EX              | SO           |
| Text Operations | NLPAnnotator                    | CreateDocumentsFromRecords               | PR              | SS           |
|                | LDAOnCorpus                     | CreateDocumentsFromLast                  | PR              | SS           |
|                | TopicModel                      | LDAOnCorpus                              | EX              | SI           |
|                |                                 | SVD                                      | EX              | B            |
where \( f_1, \ldots, f_n \) are the raw features for \( op \). \( \text{Cost}(\cdot) \) is trained based on training data collected from calibration for operator \( op \). For relation-related operators, the raw features include the sizes of tables; for graph-related operators, node count or edge count is selected as a raw feature and for some graph queries, the predicate size can also be a raw feature.

### 6.2 Calibration

To train the individual cost model \( \text{Cost}(\cdot) \), we design a set of synthetic datasets which vary at some parameters, and run each operator on different datasets to collect a set of execution time.

**Operators and features.** We mainly train cost model for operators which are graph-related or relation-related.

For graph operators, we evaluate common operators such as `CreateGraph` and `PageRank`. The graph size serves as a feature for the cost estimation. For `ExecuteCypher`, there are various types of Cypher queries and we evaluate two typical types of queries: **Type I**: Queries with a series of node or edge property predicates. For example, `Match (n)-[l]->(m) where n.value in L and m.value in L where L is a list of strings. The size of L is another raw feature that decides the query cost.**

**Type II**: Full text search queries. In this kind of queries, there is a node/edge property which contains long text and the queries will find out nodes/edges whose text property contains specific strings. For example, `Match (n)-[l]->(m) where n.value contains string1 or n.value contains string2 or .....` The number of the OR predicates is another raw feature of the cost model.

For relation operators, we test the `ExecuteSQL` operator. Based on the locations of the tables in the query, there are different candidate execution sub-plans for this operator. For example, if all tables involved are AWESOME tables generated from the upstream operators, then there are two candidate plans: (a) store all relations in memory SQLite, and execute the query in SQLite; (b) store all relations in PostgreSQL, and execute the query in PostgreSQL. If there are both AWESOME tables and PostgreSQL tables involved in the query, the two candidate plans are illustrated in Figure 9: (a) as the left dashed rectangle shows, we store AWESOME tables to PostgreSQL, then execute the query in PostgreSQL; (b) as the right dashed rectangle shows, we store AWESOME tables to SQLite and select the columns needed from PostgreSQL tables and store them to SQLite, then the query will be executed in SQLite.

**Datasets.** We design a set of graph datasets and relation datasets which are used for graph- and relation-related operators respectively. We present the statistics in Table 5.

For graph datasets, there are two types of graphs: The first type of datasets is used to test operators including `CreateGraph`, `PageRank` and the Type I Cypher queries: We created several property graphs with different edge sizes, and to simplify the model we kept the density of graphs as a constant value 2; each node (or edge) has a value property which is a unigram and we make sure each node’s (or edge’s) property is unique, then we created keywords lists with different sizes from the values set as the predicates. The second dataset is designed for the Type II Cypher queries: We created graphs with different node sizes and each node has a `tweet` property whose value is a tweet text collected from Twitter; All the unigrams are collected from these tweets and after removing the most and the least frequent words, we randomly selected words to create different sizes of keywords lists which will be used to do text search.

**Calibration Results.** We present some calibration results for some operators/patterns in Figure 10 and Figure 11. More results can be found in technical report [4]. Figure 10 shows part of the calibration results for some graph operators. Figure 11 shows the calibration results for the `ExecuteSQL` operator where the query includes a PostgreSQL table and an AWESOME table and the two sub-plans correspond to the sub-plans in Figure 9.

Table 5: Parameters of synthetic datasets for cost model.

| Parameter               | Value         |
|-------------------------|---------------|
| \( \text{graph dataset 1} \) |               |
| \( \text{edge size} \)   | 500, 1k, .. , 800k |
| \( \text{avg. density} \) | 2             |
| \( \text{node property} \) | \( \text{value: String} \) |
| \( \text{keyword size} \) | 50, 100, 500, 1k, 2k |
| \( \text{graph dataset 2} \) |               |
| \( \text{node size} \)   | 5k, 10k, .. , 500k |
| \( \text{node property} \) | \( \text{value: String} \) |
| \( \text{keyword size} \) | 50, 100, 500, 1000 |
| \( \text{relation dataset} \) |               |
| \( \text{PostgreSQL table row count} \) | 100, 1k, 10k, 100k |
| \( \text{Awesome table row count} \) | 100, 1k, 10k, 100k |
6.3 Training and Cost Estimation
The individual cost model for each operator is trained based on the calibration results to minimize the loss function, i.e., mean squared error. At run-time, when the input of a virtual node is returned from the upstream operator, the features are collected and passed to the overall cost model (Equation 1) to compute the cost for each candidate physical sub-plan. The best sub-plan with the lowest cost will be selected.

7 EXPERIMENTS
We empirically validate if AWESOME is able to improve efficiency of analytical workloads. Then we drill into how each component of AWESOME contributes.

7.1 Experimental Setup
We focus on the single-machine multi-cores setting, and the distributed version of AWESOME will be our future work. The machine has 16 Westmere E56xx/L56xx/X56xx cores, 128 GB memory and 100 GB disk space, and it runs Ubuntu 18.04.

Datasets. We collect four real world datasets to run the workloads.
- News: A relation stored in a PostgreSQL database. There are over a million news articles with an average length of about 500 words collected from Chicago Tribune newspaper.
- SenatorHandler: A PostgreSQL relation of about 90 United States senators with their names and twitter user names.
- NewsSolr: A collection of news stored in the Solr database.
- TwitterG: We collect Tweets through the Twitter developer API and then construct several Twitter graphs of different sizes in Neo4j where a node has one of two labels, User or Tweet. A User node has a property userName, and a Tweet node has a property tweet storing tweet content. A User node connects to another User node by a directed edge if the first one mentions the second, and a User node connects to a Tweet node by a directed edge if the user authors the tweet.

Workloads. We evaluate two analytical workloads. PoliSci focuses on the polystore aspect of the system where input data is stored in heterogeneous data stores. NewsAnalysis is a complex text analytical task which focuses on analytical functions including graph algorithm like PageRank [18] and NLP functions like LDA [20]. The illustration and script in ADIL of PoliSci are shown in Figure 1 and Figure 3. This workload queries on the NewsSolr, SenatorHandler and TwitterG dataset. For workload NewsAnalysis, the corresponding ADIL script is given in our technical report [4]. It selects news from News dataset and applies LDA model to detect topics from the corpus. Then it implements the method in [11] to evaluate the quality of topics where a word-topic graph is constructed and the PageRank algorithm is invoked to evaluate the importance for each topic.

Parameter Setting. For the PoliSci workload, we change the size newsS by changing rows = 5000 in the script to different values: newsS ∈ {5K, 10K, 20K). Also, we change the size of tweetG stored in Neo4j: g ∈ {50K, 100K, 500K, 1M}. newsS will have impact on the size of entity and thus will influence the executeSQL execution time, and g will influence on the two executeCypher queries. For the NewsAnalysis workload, we vary two parameters: newsR is the size of news selected from News relation: newsR ∈ {5K, 10K, 50K}; t is the threshold of words weights to be chosen as keywords of topics: t ∈ {0, 0.005, 0.01}. newsR and t control the size of the documents and the size of the text graph for each topic.

Compared Methods. We implement and compare the following methods. Due to the page limit, we put the SQL scripts for Postgres+UDF implementation and ADIL scripts in technical report [4].
- Postgres+UDF: It stores all dataset to a single store, Postgres, and uses pure SQL scripts with user-defined functions written in Python or implemented by MADLIB [13] toolkit.
- SingleThread: It does not use any AWESOME features including data parallel execution and cost model.
- DataParallel: It only applies data parallelism.
- AWESOME: It has full AWESOME features including operators fusion, cost model and data parallelism.

7.2 End-To-End Efficiency
End-To-End execution time is the total execution time from taking a workload as input, parsing, validating, logical planning, physical planning and executing. For Postgres+UDF baseline, to make the comparison fair, in the execution time, we exclude the data movement cost which is the time spent to move data from others stores to Postgres. Figure 12 and Figure 13 present the end-to-end execution costs of the four compared methods. The numbers on top of bars denote the speed-up ratio to the Postgres+UDF baseline. From the results, DataParallel and AWESOME show great efficiency and scalability when varying the parameters. DataParallel dramatically speeds up the execution time, especially when the input sizes are large. For workload PoliSci, when the Solr document size is large (e.g., newsS = 20K), DataParallel speeds up the execution by ∼ 11x. For workload NewsAnalysis, DataParallel can achieve up to ∼ 35x speed-up, and when newsR = 50K, t = {0.0005, 0.01}, Postgres+UDF cannot finish executing in 4 hours, while the DataParallel implementation can finish in minutes. By comparing AWESOME with DataParallel, we found that there is performance gain from AWESOME features especially when some input sizes get larger. We compute the speed up of AWESOME implementation over DataParallel: For workload PoliSci, when news size newsS = 20K and graph size g = 1M, AWESOME saves around 20% time from DataParallel. For workload NewsAnalysis, when t = 0 which means all words in a topic will be selected as keywords of that topic, AWESOME saves around 62% and 69% from DataParallel when newsR = 5k, 10k; when t = 0, newsR = 50k, DataParallel can’t finish in 4 hours while AWESOME is scalable and can finish in around 25 minutes.

Why not single DBMS with UDF? From our experience with implementing the Postgres+UDF, we found that this single DBMS with UDF setting fail to qualify polystore analytical tasks for three reasons: 1) Data movement cost. Users need to write ad-hoc code to move data from various stores to a single store. 2) Programming difficulty. It is not flexible to program with pure SQL. For workload NewsAnalysis, even with MADLIB which implements LDA and PageRank UDFs, hundreds of lines of SQL were written (as shown in the Appendix A of our technical report [4]). 3) Efficiency. The in-DBMS implementation of analytical functions such as LDA and PageRank are much less efficient than using the mature packages.
AWE-SOME achieves a better performance over DataParallel (i.e., the power of AWE-SOME cost model).

We take some snippets from each workload and show the execution time of different candidate sub-plans for these snippets in Figure 14. The bars with stars on top are the best execution plans selected by AWE-SOME cost model.

For workload PoliSci, the first figure presents the execution time for different sub-plans regarding to the ExecuteSQL logical operator where one table (SenatorHandler table) is from PostgreSQL and another (named entity table) is an AWE-SOME table. The two execution plans are illustrated in Figure 9. When the selected documents size increases, the named entity relation’s size will increase and the in-SQLite execution plan will be much more effective than the in-Postgres one by not moving large size of data to PostgreSQL.

For workload NewsAnalysis, the second and third figures show the execution time for two logical sub-plans textit{CreateRelation} → ExecuteSQL and CreateGraph → PageRank respectively. The possible physical sub-plans are shown in the two nodes in Figure 7. The cost model does not look at each single operator, e.g., ExecuteSQL, to decide the best physical operator; instead, it looks at the sub-plan which consists of several logical operators to determine the best physical sub-plan. For the subplan CreateRelation → ExecuteSQL, when LDA weight threshold increases, the size of keywords list in the SQL query will decrease, then Postgres becomes more efficient than SQLite, but when threshold $t = 0.001$, the in-memory SQLite implementation is chosen cause both creation time and execution time are considered. These results on small snippets demonstrate the effectiveness of AWE-SOME’s cost model.

7.3 Drill-Down Analysis

We present some detailed evaluation results to explain how AWE-SOME achieves a better performance over DataParallel (i.e., the power of AWE-SOME cost model).

We take some snippets from each workload and show the execution time of different candidate sub-plans for these snippets in Figure 14. The bars with stars on top are the best execution plans selected by AWE-SOME cost model.

For workload PoliSci, the first figure presents the execution time for different sub-plans regarding to the ExecuteSQL logical operator where one table (SenatorHandler table) is from PostgreSQL and another (named entity table) is an AWE-SOME table. The two execution plans are illustrated in Figure 9. When the selected documents size increases, the named entity relation’s size will increase and the in-SQLite execution plan will be much more effective than the in-Postgres one by not moving large size of data to PostgreSQL.

For workload NewsAnalysis, the second and third figures show the execution time for two logical sub-plans textit{CreateRelation} → ExecuteSQL and CreateGraph → PageRank respectively. The possible physical sub-plans are shown in the two nodes in Figure 7. The cost model does not look at each single operator, e.g., ExecuteSQL, to decide the best physical operator; instead, it looks at the sub-plan which consists of several logical operators to determine the best physical sub-plan. For the subplan CreateRelation → ExecuteSQL,
8 CONCLUSION AND FUTURE WORK

In this paper, we provide a formal description of a dataflow language ADIL and present the architecture of AWESOME polystore system. ADIL is able to express complex real-world applications which involves heterogeneous data models and analytical functions. For AWESOME system, we design end-to-end and drill-down experiments to present its overall scalability and analyze the effectiveness of each component. This paper provides a prototype for polystore system, but there are still some open questions that should be investigated further. For example, we have not exploited the cross model optimization opportunities when data queried from different DBMSs are joined.

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A SQL SCRIPT FOR TWO WORKLOADS

A.1 NewsAnalysis

drop table if exists tokenizednews, graph, topicgraph CASCADE;
drop MATERIALIZED VIEW if exists graphelement;
-- set execution begin time
INSERT INTO timenow(type, starttime, stoptime)
SELECT 'Sk', now(), clock_timestamp();
---- tokenize and build word neighbor graph
CREATE table tokenizednews as (  
    select id as docid, news from usnewspaper  
    where src = 'http://www.chicagotribune.com/'  
    order by id limit 5000);  
ALTER TABLE tokenizednews ADD COLUMN words TEXT[];
UPDATE tokenizednews SET words =  
    regexp_split_to_array(lower(  
    regexp_replace(news, E'[^a-zA-Z0-9]+', 'g')  
    ), e'[^\s\s]+');
---- LDA
DROP TABLE IF EXISTS news_tf, news_tf_vocabulary,lda_model,  
lda_output_data, helper_output_table,
topicgraph, pagerank_out, pagerank_out_summary;
SELECT madlib.lda_term_frequency('  
    tokenizednews', -- input table  
    'docid', -- document id column  
    'words', -- vector of words in document  
    'news_tf', -- output test table with term frequency  
    TRUE); -- TRUE to created vocabulary table
SELECT madlib.lda_train('  
    news_tf', -- test table in the form of term frequency  
    'lda_model', -- model table created by LDA training  
    'lda_output_data', -- readable output data table  
    200000, -- vocabulary size  
    10, -- number of topics  
    1000, -- number of iterations  
    0.01 -- Dirichlet prior for the per-doc topic multinomial  
    0.01 -- Dirichlet prior for the per-topic word multinomial  
    );
SELECT madlib.lda_get_topic_desc('  
    lda_model', -- LDA model generated in training  
    'news_tf_vocabulary', -- vocabulary table that maps wordid to word  
    'helper_output_table', -- output table for per-topic descriptions  
    200000);  
SELECT 'lda', now(), clock_timestamp();
--- create a test network graph  
create table graph as (  
    select wordid, word from graphelement where word1='X' and word2='i'  
    group by wordid, word2  
);  
--- build graph for each one
create table topicgraph as (  
    with topicwords as  
        (select word,wordid from helper_output_table  
         where prob > 0 and topicid = 0  
         order by prob desc limit 10000),
        temp as (  
         select wordid, word2 from graph, topicwords  
         where word1 = word  
         select temp.wordid as word1, topicwords.wordid as word2, 1 as topic  
         from temp, topicwords  
         where temp.word2=word  
        ),
    insert into topicgraph(word1, word2, topic) (  
        with topicwords as  
            (select word,wordid from helper_output_table  
             where prob > 0 and topicid = 1  
             order by prob desc limit 10000),
            temp as (  
             select wordid, word2 from graph, topicwords  
             where word1 = word  
             select temp.wordid as word1, topicwords.wordid as word2, 2 as topic  
             from temp, topicwords  
             where temp.word2=word  
            )
    )

insert into topicgraph(word1, word2, topic) (  
    with topicwords as  
        (select word,wordid from helper_output_table  
         where prob > 0 and topicid = 2  
         order by prob desc limit 10000),
        temp as (  
         select wordid, word2 from graph, topicwords  
         where word1 = word  
         select temp.wordid as word1, topicwords.wordid as word2, 3 as topic  
         from temp, topicwords  
         where temp.word2=word  
        ),
    insert into topicgraph(word1, word2, topic) (  
        with topicwords as  
            (select word,wordid from helper_output_table  
             where prob > 0 and topicid = 3  
             order by prob desc limit 10000),
            temp as (  
             select wordid, word2 from graph, topicwords  
             where word1 = word  
             select temp.wordid as word1, topicwords.wordid as word2, 4 as topic  
             from temp, topicwords  
             where temp.word2=word  
            ),
    insert into topicgraph(word1, word2, topic) (  
        with topicwords as  
            (select word,wordid from helper_output_table  
             where prob > 0 and topicid = 4  
             order by prob desc limit 10000),
            temp as (  
             select wordid, word2 from graph, topicwords  
             where word1 = word  
             select temp.wordid as word1, topicwords.wordid as word2, 5 as topic  
             from temp, topicwords  
             where temp.word2=word  
            ),
    insert into topicgraph(word1, word2, topic) (  
        with topicwords as  
            (select word,wordid from helper_output_table  
             where prob > 0 and topicid = 5  
             order by prob desc limit 10000),
            temp as (  
             select wordid, word2 from graph, topicwords  
             where word1 = word  
             select temp.wordid as word1, topicwords.wordid as word2, 6 as topic  
             from temp, topicwords  
             where temp.word2=word  
            ),
    insert into topicgraph(word1, word2, topic) (  
        with topicwords as  
            (select word,wordid from helper_output_table  
             where prob > 0 and topicid = 6  
             order by prob desc limit 10000),
            temp as (  
             select wordid, word2 from graph, topicwords  
             where word1 = word  
             select temp.wordid as word1, topicwords.wordid as word2, 7 as topic  
             from temp, topicwords  
             where temp.word2=word  
            ),
    insert into topicgraph(word1, word2, topic) (  
        with topicwords as  
            (select word,wordid from helper_output_table  
             where prob > 0 and topicid = 7  
             order by prob desc limit 10000),
            temp as (  
             select wordid, word2 from graph, topicwords  
             where word1 = word  
             select temp.wordid as word1, topicwords.wordid as word2, 8 as topic  
             from temp, topicwords  
             where temp.word2=word  
            ),
    insert into topicgraph(word1, word2, topic) (  
        with topicwords as  
            (select word,wordid from helper_output_table  
             where prob > 0 and topicid = 8  
             order by prob desc limit 10000),
            temp as (  
             select wordid, word2 from graph, topicwords  
             where word1 = word  
             select temp.wordid as word1, topicwords.wordid as word2, 9 as topic  
             from temp, topicwords  
             where temp.word2=word  
            )
    )

Xiuwen Zheng, Subhasis Dasgupta, Arun Kumar, Amarnath Gupta
Processing Analytical Queries in the AWESOME Polystore

```python
subprocess.call([f"temp_file = filename.split('.')\[0\]
                  return temp_file
]
```

```sql
SELECT
  returns character varying
  filename character varying)
colname character varying,
create function callner (tname character varying,
A.2 PoliSci

```python
import subprocess
import os
$$
--- pagerank for each topic
SELECT madlib.pagerank(
  news_tf_vocabulary', -- Vertex table
  'wordid', -- Vertix id column
  'topicgraph', -- Edge table
  'src=wordid, dest=word2', -- Comma delimited string of
  'pagerank_out', -- Output table of PageRank
  NULL, -- Default max iters (100)
  0.00000001, -- Threshold
  'topic');
```

```sql
INSERT INTO timenow( type, starttime, stoptime)
--- record end time
INSERT INTO timenow( type, starttime, stoptime)
SELECT 'all', now(), clock_timestamp();
```

**B ADIL SCRIPT FOR WORKLOAD NEWSANALYSIS**

```sql
/*specify configuration file*/
USE newsDB;
/* main code block */
create analysis NewsAnalysis as (src := "http://www.chicagotribune.com/");
rawNews := executeSQL("News", "select id as newsid, news as newsText from usnewspaper where src = $src limit 1000");
processedNews := preprocess(rawNews.newsText, docid=rawNews.newsid, stopwords="stopwords.txt");
numTop := 10;
DTM, WTM := lda(processedNews, docid=true, topic=numTop);
topicID := [range(0, numberTopic, 1)];
wtmPerTopic := topicID.map(i => WTM where getValue(_,i) > 0.00);
wordsPerTopic := wtmPerTopic.map(i => rowNames(i));
wordsOfInterest := union(wordsPerTopic);
G := buildWordNeighborGraph(processedNews, maxDistance=5, splitter=".", words=wordsOfInterest);
relationPerTopic := wordsPerTopic.map(words =>
  (n =>
    m =>
      r =>
        pageRank(g, src := "http://www.chicagotribune.com/");
aggregatePT := scores.map(i => sum(i.pagerank));
/* store a list to rDBMS as a relation*/
store(aggregatePT t, dbName="News",
columnName=[("id",t.index), ("pagerank",t.value)]);
```

Figure 16: NewsAnalysis workload written in ADIL script.
C PARTITION RULES FOR BUFFERING MECHANISM

For buffering mechanism, a collection of chains is collected from the physical DAG by partitioning it based on the partition rules which are shown below and also illustrated in Fig. 17:

- For an edge $e = (op_{e1}, op_{e2})$, if $op_{e1}$ can’t generate stream result or $op_{e2}$ can’t take stream input, $e$ will be cut. For example, in Fig. 17, the edge between $op_1$ and $op_{21}$ is cut.
- For an edge $e = (op_{e1}, op_{e2})$, if data from $op_{e1}$ to $op_{e2}$ is not the capOn input of $op_{e2}$, $e$ will be cut. In Fig. 17, the edge between $op_{22}$ and $op_{12}$ is cut.
- For an operator $op$, if it has more than one outgoing edges, then all outgoing edges will be cut. In Fig. 17, the outgoing edges from $op_{2}$ are all cut.

D EXPLANATION OF FAILURE ATTEMPT

This section proves that the pipeline + data parallelism framework can’t outperform much to the data parallelism framework because of the properties of AWESOME operators.

For a simple pipeline chain with two operators: $op_1 \rightarrow op_2$, suppose that there are a total of $n$ cores and it costs $t_1$ for $op_1$ to produce a batch of data and $t_2$ for $op_2$ to consume the batch, then there will be $t_1 n / (t_2 + t_1)$ cores assigned to $op_1$ and the rest of cores assigned to $op_2$.

Suppose that $op_1$ will produce $m$ batches in total, then the execution time of applying data parallelism solely $T_1$ and of applying pipeline + data parallelism $T_2$ can be computed as,

$$T_1 = \frac{(t_1 + t_2)m}{n} + agg \times n$$

$$T_2 = \max\{\frac{t_1 m}{n_1}, \frac{t_2 m}{n - n_1}\} + agg \times n_1,$$

where $n_1$ is the number of cores assigned to $op_1$, and $agg \times \#core$ is the sequential aggregation cost of data parallelism. Since for AWESOME aggregation operators such as SUM, the aggregation cost is usually very small and can be negligible comparing to other time-consuming analytical functions, we can prove that $T_1 \approx \frac{(t_1 + t_2)m}{n} \leq \max\{\frac{t_1 m}{n_1}, \frac{t_2 m}{n - n_1}\} \approx T_2$ always holds where the equality is achieved when the above optimal allocation solution is applied. Thus, the pipeline and data parallelism framework can’t outperform data parallelism if all operators in a chain are data parallel-able.

E BENCHMARK RESULTS.

We present more benchmark results for some operators in this section. Fig. 18 and Fig. 19 present the benchmark results for executing Type I and Type II Cypher query respectively with regard to graph size and the number of keywords.
Figure 18: Benchmark results for Type I Cypher query w.r.t. different graph sizes and #keywords.

Figure 19: Benchmark results for Type II Cypher query w.r.t. different graph sizes and #keywords.

Figure 20: Benchmark results for cross-model table join.
## AWESOME LOGICAL AND PHYSICAL OPERATORS.

Table 6: AWESOME logical and physical operators.

| Types          | Logical Operators                  | Physical Operators                  | DataParallelCap | BufferingCap |
|----------------|-------------------------------------|--------------------------------------|-----------------|--------------|
| Query          | ExecuteCypher                       | ExecuteCypherInNeo4j                 | ST              | B            |
|                | ExecuteInMemory                     | ExecuteCypherInMemory                | ST              | B            |
|                | ExecuteSQLite                       | ExecuteSQLInPostgres                 | ST              | B            |
|                | ExecuteSolr                         | ExecuteSQLInSQLite                   | ST              | B            |
|                | FetchDBMSResults                    | FetchBuffer                          | ST              | SO           |
| Graph Operations | CollectGraphElementsFromDocs        | CollectGraphElementsFromRelation     | PR              | SS           |
|                | CreateNeo4jGraph                    | CreateNeo4jGraph                     | ST              | SI           |
|                | CreateInMemoryGraph                 | CreateInMemoryGraph                  | ST              | SI           |
|                | PageRankInNeo4j                     | PageRankInMemory                     | ST              | SO           |
|                | PageRankInMemory                    | PageRankInMemory                     | ST              | SO           |
|                | ComputeNodeDegrees                  | ComputeNodeDegrees                   | PR              | SO           |
|                | ComputeKNeighbors                    | ComputeKNeighbors                     | PR              | SO           |
| Relation Operations | GetColumns               | GetColumns                            | ST              | SS           |
|                | RecordsToList                       | RecordsToList                         | ST              | SS           |
|                | CreatDocumentsFromRecord            | CreatDocumentsFromRecord              | PR              | SS           |
|                | CreatDocumentsFromList              | CreatDocumentsFromList                | PR              | SS           |
|                | FilterStopWords                     | FilterStopWords                       | PR              | SS           |
|                | SplitByPatterns                     | SplitByPatterns                       | PR              | SS           |
|                | CreateTextMatrix                    | CreateTextMatrix                      | ST              | SI           |
|                | PhraseExtraction                    | PhraseExtraction                      | PR              | SS           |
|                | NER                                 | NER                                   | PR              | SS           |
|                | LDA                                 | LDA                                   | ST              | B            |
|                | SVD                                 | SVD                                   | ST              | B            |
|                | TopicModel                          | TopicModel                            | ST              | B            |
|                | GetValue                            | GetValueByIndex                       | ST              | B            |
|                | GetValueByKeys                      | GetValueByKeys                        | ST              | B            |
|                | ColumnKeys                          | ColumnKeys                            | ST              | B            |
|                | RowKeys                             | RowKeys                               | ST              | B            |
| MappedMatrix Operations | LDA                               | LDA                                   | ST              | B            |
|                | SVD                                 | SVD                                   | ST              | B            |
| Text Operations | TopicModel                          | TopicModel                            | ST              | B            |
|                | GetValue                            | GetValueByIndex                       | ST              | B            |
|                | GetValueByKeys                      | GetValueByKeys                        | ST              | B            |
|                | ColumnKeys                          | ColumnKeys                            | ST              | B            |
| Other Functions | Sum                                | SumList                               | PR              | SI           |
|                | Range                               | Range                                 | PR              | SI           |
|                | SumColumn                           | SumColumn                              | PR              | SI           |
|                | SumMatrix                           | SumMatrix                              | PR              | SI           |
|                | SumVector                           | SumVector                              | PR              | SI           |
|                | Range                               | Range                                 | ST              | SO           |
| Data Movement  | ListToPostgres                      | ListToPostgres                        | ST              | SI           |
|                | InMemoryRelationToPostgres          | InMemoryRelationToPostgres            | ST              | B            |
|                | InMemoryGraphToNeo4j                | InMemoryGraphToNeo4j                  | ST              | B            |
|                | RecordsToPostgres                   | RecordsToPostgres                     | ST              | SI           |
|                | GraphElementsToNeo4j                | GraphElementsToNeo4j                  | ST              | SI           |
|                | ListToCSV                           | ListToCSV                              | ST              | SI           |
|                | InMemoryRelationToCSV               | InMemoryRelationToCSV                 | ST              | B            |
|                | RecordsToCSV                        | RecordsToCSV                          | ST              | SI           |