An Unified System for Data Analytics and In Situ Query Processing

Alex Watson§, Suvam Kumar Das§, and Suprio Ray
Faculty of Computer Science, University of New Brunswick, Canada. Email: {awatson, suvam.das, sray}@unb.ca

Abstract—In today’s world data is being generated at a high rate due to which it has become inevitable to analyze this data efficiently and produce results quickly. But, data scientists and analysts are required to use different systems, because apart from SQL querying relational databases are not well equipped to perform complex data analyses. Due to this, data science frameworks are in huge demand. This may require significant data movement across multiple systems, which can be expensive. Furthermore, with relational databases, the data must be completely loaded into the database before performing any analysis.

We believe that it has become the need of the hour to come up with a single system which can perform both data analysis tasks and SQL querying. Ideally, this system would offer adequate performance, scalability, built-in functionalities, and usability. We extend the Python’s Dask framework to present DaskDB, a scalable data science system with support for unified data analytics and in situ SQL query processing on heterogeneous data sources. DaskDB supports invoking any Python APIs as User-Defined Functions (UDF). So, it can be easily integrated with most existing Python data science applications. Moreover, we introduce a novel distributed learned index to improve join performance. Our experimental evaluation involve the TPC-H benchmark and a custom UDF benchmark, which we developed, for data analytics. And, we demonstrate that DaskDB significantly outperforms PySpark and Hive/Hivemall.

I. INTRODUCTION

Due to the increasing level of digitalization, large volumes of data are constantly being generated. To make sense of the deluge of data, it must be cleaned, transformed and analyzed. Data science offers tools and techniques to manipulate data in order to extract actionable insights from data. These include support for data wrangling, statistical analysis and machine learning model building. Traditionally, practitioners and researchers make a distinction between query processing and data analysis tasks. Whereas relational database systems (henceforth, databases or DBMSs) are used for SQL-style query processing, a separate category of frameworks are used for data analyses that include statistical and machine learning tasks. Currently, Python has emerged as the most popular language-based framework, for its rich ecosystem of data analysis libraries, such as Pandas, Numpy, scikit-learn. These tools make it possible to perform in situ analysis of data that is stored outside of any database. However, a significant amount of data is still stored in databases. To do analysis on this data, it must be moved from a database into the address space of the data analysis application. Similarly, to do SQL query processing on data that is stored in a raw file, it must be loaded into a database using a loading mechanism, which is known as ETL (extract, transform, load). This movement of data and loading of data are both time consuming operations.

To address the movement of data across databases and data analysis frameworks, recently researchers have proposed several approaches. Among them, a few are in-database solutions, that incorporate data analysis functionalities within an existing database. These include PostgreSQL/Madlib [1], HyPer [2] and AIDA [3]. In these systems, the application developers write SQL code and invoke data analysis functionalities through user-defined functions (UDF). There are several issues with these approaches. First, the vast body of existing data science applications that are written in a popular language (Python or R), need to be converted into SQL. Second, the data analysis features supported by databases are usually through UDF functions, which are not as rich as that of the language-based API ecosystem, such as in Python or R. Third, data stored in raw files needs to be loaded into a database through ETL. Although, some support for executing SQL queries on raw files exist, such as PostgreSQL's support for foreign data wrapper, this can easily break if the file is not well-formatted. In recent years several projects [4], [5], [6] investigated how to support in situ SQL querying on raw data files. However, they primarily focused on supporting database-like query processing, operating on a single machine. These systems lack sophisticated data wrangling and data science features that is available in Python or R. Fourth, most relational databases are not horizontally scalable. Even with parallel databases, the parallel execution of UDFs is either not supported or not efficient. Although “Big Data” systems such as Spark [2] and Hive/Hivemall [8] address some of these issues, they often involve more complex APIs and a steeper learning curve. Also, it is not practical to rewrite the large body of existing data science code with these APIs.

To address the issues with the existing approaches, we introduce a scalable data science system, DaskDB, which seamlessly supports in situ SQL query execution and data analysis using Python. DaskDB extends the scalable data analytics framework Dask [9] that can scale to more than one machine. Dask’s high-level collections APIs mimic many of the popular Python data analytics library APIs based on Pandas and NumPy. So, existing applications written using Pandas collections need not be modified. On the other hand, Dask does not support SQL query processing. In contrast, DaskDB can execute SQL queries in situ without requiring the expensive ETL step and movement of data from raw

---

§Equal contribution
files into a database system. Furthermore, with DaskDB, SQL queries can have UDFs that directly invoke Python APIs. This provides a powerful mechanism of mixing SQL with Python and enables data scientists to take advantage of the rich data science libraries with the convenience of SQL. Thus, DaskDB unifies query processing and analytics in a scalable manner.

A key issue with distributed query processing and data analytics is the movement of data across nodes, which can significantly impact the performance. We propose a distributed learned index, to improve the performance of join that is an important data operation. In DaskDB, a relation (or dataframe) is split into multiple partitions, where each partition consists of numerous tuples of that relation. These partitions are distributed across different nodes. While processing a join, it is possible that not all partitions of a relation contribute to the final result when two relations are joined. The distributed learned index is designed to efficiently consider only those partitions that contain the required data in constant time, by identifying the data pattern in each partition. This minimizes the unnecessary data movement across nodes. DaskDB also incorporates selective data persistence that significantly reduces serialization/de-serialization overhead and data movement.

We conduct extensive experimental evaluation to compare the performance of DaskDB against two horizontally scalable systems: PySpark and Hive/HiveVmall. Our experiments involve workloads from a few queries from TPC-H benchmark, with different data sizes (scale factors). We also created a custom UDF benchmark to evaluate DaskDB and PySpark. Our results show that DaskDB outperforms others in both of these benchmarks. The key contributions of this paper are:

- We propose DaskDB that integrates in situ query processing and data analytics in a scalable manner.
- DaskDB supports SQL queries with UDFs that can directly invoke Python data science APIs.
- We introduce a novel distributed learned index.
- We present extensive experimental results involving TPC-H benchmark and a custom UDF benchmark.

II. BACKGROUND

DaskDB was built by extending the Dask [9], which is an open-source library for parallel computing in Python. The main advantage of Dask is that it provides Python APIs and data structures that are similar to Numpy, Pandas, and Scikit-Learn. Hence, programs written using Python data science APIs can easily be switched to Dask by changing the import statement. Dask comes with an efficient task scheduler, which can run programs on a single node and scale to many nodes.

However, Dask does not support SQL queries. We show that DaskDB, which is built over Dask, can outperform Spark [11].

III. RELATED WORK

In this section, first we discuss about systems to perform data analytics and query processing. Next, we look at works related to learned index, followed by in situ query processing.

A. Data Analytics and Query Processing

1) Dedicated Data Analytics Frameworks: Many open-source data analytic applications traditionally use R. More recently, Python has become very popular because of the Anaconda distribution [12]. It contains many data science and analytics packages, such as Pandas, SciPy, Matplotlib, and scikit-learn. Some popular commercial data analytic systems include Tableau [13] and MATLAB [14].

2) In-Database Analytics: An increasing number of the major DBMSs now include data science and machine learning tools. For instance, PostgreSQL supports SQL-based algorithms for machine learning with the Apache MADlib library [1]. However, interacting with a DBMS to implement analytics can be challenging [15]. Although SQL is a mature technology, it is not rich enough for extensive data analysis. DBMSs typically support analytics functionalities through User Defined Functions (UDF). Since, a UDF may execute any external code written in R, Python, Java or T-SQL, a DBMS treats a UDF as a black box because no optimization can be performed on it. It is also difficult to debug and to incrementally develop [3]. The in-database analytics approaches still have the constraint of ETL (extract, transform, load), which is a time-consuming process and not practical in many cases.

3) Integrating Analytics and Query Processing: There have been several attempts at creating more efficient solutions and they combine two or more of either dedicated data analytic systems, DBMS or big data frameworks. These systems can be classified into 2 categories that we describe next.

Hybrid Solutions. These solutions integrate two or more system types together into one and are primarily DBMS-centric approaches. AIDA [3] integrates a Python client directly to use the DBMS memory space, eliminating the bottleneck of transferring data. In [16] the authors present a prototype system that integrates a columnar relational database (MonetDB) and R together using a same-process zero-copy data sharing mechanism. In [17], the authors proposed an embeddable analytical database DuckDB. The key drawback of these hybrid systems is ETL, since the data needs to be loaded into a database. Moreover, existing data science applications written in Python or R, need to be modified to work in such systems, since their interface is SQL-based.

“Big Data” Analytics Frameworks. The most popular big data frameworks are Hadoop and Spark [2]. Spark supports machine learning with MLlib [18] and SQL like queries. Hive is based on Hadoop that supports SQL-like queries and supports analytics with the machine learning library HiveVmall [8]. Some drawbacks of big data frameworks include more complicated development and steeper learning curve than most other analytics systems and the difficulty in integration with DBMS applications. To run any existing Python or R application within a big data system, it will require rewriting these applications with new APIs. This is not a viable option in most cases.

2
In this section, we present DaskDB. DaskDB, in addition to supporting all Dask features, also enables in situ SQL querying on raw data in a data science friendly environment. Next, we describe DaskDB system architecture and its components.

### A. System Architecture

The system architecture of DaskDB incorporates five main components: the SQLParser, QueryPlanner, DaskPlanner, DaskDB Execution Engine, and HDFS. They are shown in Figure 1. First, the SQLParser gathers metadata information pertaining to the SQL query, such as the names of the tables, columns and functions. This information is then passed along to the QueryPlanner. Next, in the QueryPlanner component, a physical plan is generated from the information sent by SQLParser about the SQL query. The physical plan is then converted into Python code and sent to DaskDB Execution Engine. DaskDB Execution Engine then executes the code and gathers the data from the HDFS, and thus executes the SQL query. Further details are provided in the next sections.

1) **SQLParser**: The SQLParser is the first component of DaskDB that is involved in query processing. The input for the SQLParser is the original SQL query. It first checks for syntax errors and creates a parse tree with all the metadata information about the query. Then, process the parse tree to gather the metadata information needed by the QueryPlanner. This metadata information includes table names, column names and UDFs. Then check if the table(s) exist and if they do, we dynamically generate a schema. The schema contains information about tables and column names and data types used in the SQL query. The schema, UDFs (if any) and the original SQL query are then passed to the QueryPlanner.

2) **QueryPlanner**: The QueryPlanner creates logical and preliminary physical plans. The schema and UDFs produced by SQLParser, along with the SQL query, are passed into the QueryPlanner. The QueryPlanner uses these to first create a logical plan and then an optimized preliminary physical plan. This plan is then sent to the DaskPlanner.

3) **DaskPlanner**: The DaskPlanner is used to transform the preliminary physical query plan from the QueryPlanner into Python code that is ready for execution. The first step in this process is the DaskPlanner to go through the physical plan obtained from QueryPlanner and convert it into a Daskplan. This maps the operators from the physical plan into operators that more closely resemble the Dask APIs, called the Daskplan. The Daskplan is produced from the physical plan, and then converted into Python code, and then sent to DaskDB Execution Engine. The DaskDB Execution Engine then executes the code and gathers the data from the HDFS, and thus executes the SQL query. Further details are provided in the next sections.
Algorithm 1: DaskPlanner: Conversion of Physical Plan to Daskplan

Input: A physical plan (P) is given as input. P contains ordered groups of dependent operators (G). Each G consists of an ordered list of tuples (k, o, d), where k contains the unique key of a operation, o is the operation type and d contains the operation metadata information.

Output: The final result is a Daskplan DP, which consists of an ordered list of operators.

1 DP ← list()
2 for sorted(G ∈ P) do
3   for sorted(k, o, d ∈ G) do
4     dp ← dict() //create Daskplan operator
5     dp[o] ← convertToDaskPlanOperator(o)
6     dp[d] ← getMetadataInfo(d)
7     dp[key] ← k //adds key (used to get data dependencies)
8     DP.add(dp) //adds dp to Daskplan
9 for sorted(dp ∈ DP) do
10    while dp has children (c) do
11       dp[t_i] ← get table information from c_i
12       return DP

throughout the execution of a query. This is because multiple tables and columns may be created, removed or manipulated during execution. For these reasons, the names of the tables, columns, and indexes are dynamically maintained while transforming the Daskplan into Python code to execute it.

4) DaskDB Execution Engine: There are three main components of the DaskDB execution engine: the client, scheduler and workers. The client transforms the Dask Python code into a set of tasks. The scheduler creates a DAG (directed acyclic graph) from the set of tasks, automatically partitions the data into chunks, while taking into account data dependencies. The scheduler sends a task at a time to each of the workers according to several scheduling policies. The scheduling policies for task and workers depend on various factors including data locality. A worker stores a data chunk until it is not needed anymore and is instructed by the scheduler to release it.

5) HDFS: The Hadoop Distributed File System (HDFS) is a storage system used by Hadoop applications. DaskDB uses HDFS to store and share the data files among its nodes.

B. Illustration of SQL query execution

An in situ query is executed within DaskDB by calling query function with the SQL string as argument. The query in Figure 2 is a simplified version of a typical TPC-H query.

The Daskplan, shown in Figure 3, is generated from the physical plan in the DaskPlanner component. The Daskplan operators more closely resemble the Dask API. For example, these include the read_csv and filters methods shown in the tree. This Daskplan is then converted into executable Python code, which is omitted due to space constraint.

C. Support for SQL query with UDFs

DaskDB supports UDFs in SQL as part of in situ querying. A UDF enables a user to create a function using Python code and embed it into the SQL query. Since DaskDB converts the SQL query, including the UDF back into Python code, the UDFs can reference and utilize features from any of the data science packages available in Anaconda Python API ecosystem. Spark introduced UDF’s since version 0.7 but it operated one-row-at-a-time and thus suffered from high serialization and invocation overhead. Later they came up with Pandas UDF which provides low-overhead, high-performance UDFs entirely in Python. Although Pandas UDFs are efficient, but are restrictive to use in queries. Sometimes it also requires to use Spark’s own data types, which would be inconvenient for users who are not experienced in Spark. In contrast, in DaskDB UDFs for SQL queries can easily be written. Any native Python function (either imported from an existing package or custom-made), which accepts Pandas dataframes as parameters can be applied as UDFs to the SQL queries in DaskDB. The return type of the UDFs is not fixed like Spark’s Pandas UDF, and hence allows the user to design UDFs with ease. Like a general Python function, UDFs with code involving machine learning, data visualization and numerous other functionalities can easily be developed and applied on queries in DaskDB.

D. Illustration of SQL query with UDF

We illustrate UDF with SQL in DaskDB with K-Means clustering. Similar to Spark, a UDF needs to be registered to DaskDB system using the register_udf API. As shown in Figure 4, the UDF myKMeans takes as input a single Pandas dataframe having 2 columns; hence the UDF is registered...
as register_udf (myKMeans, [2]). As part of the query, the UDF is invoked as myKMeans(l_discount, l_tax), which means after application of the selection condition (l_orderkey < 50) and the limit (limit 50) to the lineitem relation, both the columns l_discount and l_tax together form a Pandas dataframe and is passed to myKMeans. The output of the code is plotted in Figure 5 where the different clusters are shown by different colours.

```
from daskdb.core import query, register_udf
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans

def myKMeans(df):
    kmeans = KMeans(n_clusters=4).fit(df)
    col1 = list(df.columns)[0]
    col2 = list(df.columns)[1]
    plt.scatter(df[col1], df[col2], c=kmeans.labels_.astype(float), s=50)
    plt.xlabel(col1)
    plt.ylabel(col2)
    plt.show()

register_udf(myKMeans,[2])
sql_kmeans = **select myKMeans(l_discount, l_tax)***
from lineitem where l_orderkey < 50 limit 50; ***
query(sql_kmeans)
```

**Fig. 4: UDF code showing K-Means Clustering**

E. Distributed Learned Index

Join is considered one of the most expensive data operations. We propose a novel distributed learned index, to accelerate distributed execution of join in DaskDB. Our distributed learned index relies on Heaviside step function [24]. Any step function can be represented by a combination of multiple Heaviside step functions, which forms the basis of our learned index structure. A Heaviside step function can be defined as

\[
H(x) = \begin{cases} 
0 & x < 0 \\
1 & x \geq 0 
\end{cases} 
\] (1)

We define a Partition Function, P as

\[
P_{a,b,c}(y) = H((b - y) \ast (y - a)) \ast c 
\] (2)

which returns c whenever \(a \leq y \leq b\), or returns 0 otherwise.

While constructing the distributed learned index it is assumed that one of the relations is sorted by the join attribute. Hence, if an index can maintain the first and last values of the keys for each partition, then given any key, the partition containing the key can be identified by a Partition Function. A sparse index in this case can entail huge storage savings, since all the keys are not required to be stored. We illustrate this using a simplified example with the customer table from TPC-H, where c_custkey is the primary key. If there are 500 tuples in this relation and each table partition can store 100 tuples, then there will be total 5 partitions. The distribution of the keys is shown in Table and also plotted in Figure 6.

It can be seen that the plot is a step function \(f\), where

\[
f(key) = \begin{cases} 
1 & 1 \leq key \leq 200 \\
2 & 250 \leq key \leq 380 \\
3 & 400 \leq key \leq 560 \\
4 & 580 \leq key \leq 700 \\
5 & 701 \leq key \leq 800 
\end{cases} 
\] (3)

which can equivalently be represented by summing several Partition Functions, which constitutes the Learned Index Function \(L_{\text{customer}}\) on the customer table as

\[
L_{\text{customer}}(key) = P_{1,200,1}(key) + P_{250,380,2}(key) + P_{400,560,3}(key) + P_{580,700,4}(key) + P_{701,800,5}(key)
\]

where, \(a, b\) and \(c\) of the Partition Function \(P\) represent the begin and end keys and the corresponding partition id.

Next we explain how our learned index can effectively be used for join queries. Let \(A\) and \(B\) be two relations, which need to be joined on \(col_A\) and \(col_B\) of \(A\) and \(B\) respectively. Without loss of generality, we assume \(col_A\) is sorted and a Learned Index Function \((L_A)\) is generated on this column. Since DaskDB internally uses Dask APIs, before joining the relations, they are converted to Dask dataframes. Each dask dataframe consists of several partitions. For each tuple \(t\) of a partition of \(B\), \(L_A(t[col_B])\) is calculated (which returns the partition number of \(A\) to which \(t[col_B]\) belongs) and is appended to \(t\) as a new ‘Partition’ column. This process is parallely executed for each partition of \(B\). Then for each partition number \(i\) of \(A\), all the tuples \(t\) of \(B\) are selected such that \(t[\text{Partition}] = i\) and are hence joined with the \(i\)th partition of \(A\). The processes of partition identification, partition selection and the partition-wise join are individually executed in parallel. For joining the dataframes, we developed a variant of the merge API of Pandas package.

V. EVALUATION

In this section, we present the experimental setup, TPC-H benchmark results and a custom UDF benchmark results.

A. Experimental Setup

DaskDB was implemented in Python by extending Dask. The SQLParser of DaskDB utilizes the tool sql-metadata [25]. The QueryPlanner of DaskDB extends Raco [26]. We ran experiments on a cluster of 8 machines each having 16 GB memory and 8 Intel(R) Xeon(R) CPUs running at 3.00 GHz and each machine ran Ubuntu 16.04 OS.

We evaluated DaskDB against two systems that support both SQL query execution and data analytics: PySpark and Hive/Hivemall (henceforth referred to as Hive). HDFS was used to store the datasets for each system. The software versions of Python, PySpark and Hive were 3.7.6, 3.0.1 and 2.1.0 respectively. PySpark and Hivemall were allocated maximum resources available (i.e. cores and memory).
TABLE I: Queries with UDF

| Tasks               | Query                                                                 |
|---------------------|----------------------------------------------------------------------|
| LR                  | select myLinearFit(_discount, _tax) from lineitem where _orderkey < 10 limit 50 |
| K-Means             | select myKMeans(_discount, _tax) from lineitem, orders where _orderkey = o_orderkey limit 50 |
| Quantiles           | select myQuantile(_discount) from lineitem, orders where _orderkey = o_orderkey limit 50 |
| CGO                 | select myCGO(_discount, _tax) from lineitem where _orderkey < 10 limit 1 |

Fig. 5: K-Means output

(a) Scale Factor 1 (GB) (b) Scale Factor 5 (GB) (c) Scale Factor 10 (GB) (d) Scale Factor 20 (GB)

Fig. 7: Execution times - TPC-H benchmark queries

(a) UDF on SF 1 (b) UDF on SF 5 (c) UDF on SF 10 (d) UDF on SF 20

Fig. 8: Execution times - SQL queries with UDFs

TABLE II: Sparse index for customer relation

| Begin | End   | Partition |
|-------|-------|-----------|
| 1     | 200   | 1         |
| 250   | 380   | 2         |
| 400   | 560   | 3         |
| 580   | 700   | 4         |
| 701   | 800   | 5         |

Fig. 6: Keys vs Partition plot

B. TPC-H Benchmark Evaluation Results

We evaluated the systems with several queries from TPC-H decision support benchmark [10]. We used 4 scale factors (SF): 1, 5, 10 and 20, where SF 1 indicates roughly 1 GB.

We executed 5 queries from TPC-H benchmark and the results are plotted in Figure 7. As can be seen, DaskDB outperforms PySpark and Hive on all queries for all the scale factors. Hive performs worse than both DaskDB and PySpark in all cases. However, in general higher the SF, larger the performance gap between them. For instance, with Q10, DaskDB is 3.5× faster than PySpark at SF 1 and 4.7× faster than PySpark at SF 20. DaskDB achieves a speedup of 182× with Q5 at SF 20. The superior performance of DaskDB can be credited to its efficient data distribution, join implementation using distributed learned index and selective data persistence.

C. UDF Benchmark Evaluation Results

We developed a custom UDF benchmark, which consists of four machine learning tasks with UDFs: LR (Linear Regression), K-Means (K-Means Clustering), Quantiles (Quantiles Estimation) and CGO (Conjugate Gradient Optimization). They were developed using the available machine learning packages in Python. For each of the machine learning tasks, SQL queries in Table I were executed. The UDFs were written to perform the same task in both the systems by importing the same Python packages. For this evaluation, the performance of DaskDB was compared with that of PySpark, whereas Hive results are skipped due to poor performance.

The results are plotted in Figure 8. Similar to the TPC-H benchmark results, DaskDB outperforms PySpark here as well for all the machine learning tasks for all scale factors. Among all the tasks K-Means performs worst in PySpark. With respect to K-Means, DaskDB performs 28.5× faster than PySpark at SF 1 and 64× faster at SF 10. For SF 20, PySpark took too long to perform K-Means and hence could not be measured, whereas DaskDB took only 41s approximately. For Quantiles, DaskDB was 4× and 16.6× faster than PySpark for SF 1 and
VI. CONCLUSION

We presented DaskDB, a scalable data science system. It brings \textit{in situ} SQL querying to a data science platform in a way that supports high usability, performance, scalability and built-in capabilities. Moreover, DaskDB also has the ability to incorporate any UDF into the input SQL query, where the UDF could invoke any Python library call. Furthermore, we introduce a novel distributed learned index that accelerates join/merge operation. We evaluated DaskDB against two state-of-the-art systems, PySpark and Hive/Hivemall, using TPC-H benchmark and a custom UDF benchmark. We show that DaskDB significantly outperforms these systems.

REFERENCES

[1] J. M. Hellerstein \textit{et al.}, “The MADlib Analytics Library: Or MAD Skills, the SQL,” \textit{PVLDB}, vol. 5, no. 12, pp. 1700–1711, 2012.
[2] A. Kemper and T. Neumann, “Hyper: A hybrid oltp & olap main memory database system based on virtual memory snapshots,” in \textit{ICDE}, 2011, p. 195–206.
[3] J. V. D’alva, F. De Moor, and B. Kemme, “AIDA: Abstraction for Advanced In-database Analytics,” \textit{PVLDB}, vol. 11, no. 11, 2018.
[4] I. Alagiannis, R. Borovica, M. Branco, S. Ideeos, and A. Ailamaki, “NoDB: efficient query execution on raw data files,” in \textit{SIGMOD}, 2012, pp. 241–252.
[5] Y. Cheng and F. Rusu, “Parallel in-situ data processing with speculative loading,” in \textit{SIGMOD}, 2014, p. 1287–1298.
[6] M. Olma \textit{et al.}, “Adaptive partitioning and indexing for in situ query processing,” \textit{VLDB J.}, vol. 29, no. 1, pp. 569–591, 2020.
[7] M. Zaharia \textit{et al.}, “Spark: Cluster computing with working sets,” in \textit{USENIX HotCloud}, 2010, pp. 10–10.
[8] “Hivemall,” https://hivemall.apache.org/.
[9] M. Rocklin, “Dask: Parallel computation with blocked algorithms and task scheduling,” in \textit{Python in Science Conference}, 2015, pp. 130 – 136.
[10] “TPC-H,” http://www.tpc.org/tpch/.
[11] “Apache Spark,” https://spark.apache.org/.
[12] “Anaconda,” https://www.continuum.io/.
[13] “Tableau,” https://www.tableau.com/.
[14] “MATLAB,” https://www.mathworks.com/products/matlab.html.
[15] E. Fouché, A. Eckert, and K. Böhm, “In-database analytics with ibmdbpy,” in \textit{SSDBM}, 2018.
[16] J. Lajus and H. Mühliesen, “Efficient data management and statistics with zero-copy integration,” in \textit{SSDBM}, 2014.
[17] M. Raasveldt and H. Mühliesen, “Data management for data science - towards embedded analytics,” in \textit{CIDR}, 2020.
[18] X. Meng \textit{et al.}, “MLlib: Machine Learning in Apache Spark,” \textit{Journal of Machine Learning Research}, vol. 17, no. 34, pp. 1–7, 2016.
[19] T. Kraska, A. Beutel, E. H. Chi, J. Dean, and N. Polyzotis, “The case for learned index structures,” in \textit{SIGMOD}, 2018, p. 489–504.
[20] A. Galakatos \textit{et al.}, “FITing-Tree: A Data-Aware Index Structure,” in \textit{SIGMOD}, 2019, p. 1189–1206.
[21] P. Ferragina and G. Vinciguerra, “The PGM-index: a fully-dynamic compressed learned index with provable worst-case bounds,” in \textit{PVLDB}, vol. 13, no. 8, 2020, pp. 1162–1175.
[22] “PostgresRAW,” https://github.com/HBPMedical/PostgresRAW.
[23] K. Shivachok, H. Kuang, S. Radia, and R. Chansler, “The hadoop distributed file system,” in \textit{MSST}, 2010, pp. 1–10.
[24] “Heaviside Function,” https://en.wikipedia.org/wiki/Heaviside_step_function.
[25] “sql-metadata,” https://pypi.org/project/sql-metadata/.
[26] J. Wang \textit{et al.}, “The Myria Big Data Management and Analytics System and Cloud Services,” in \textit{CIDR}, 2017.