Fine-Tuning Data Structures for Analytical Query Processing

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ABSTRACT
We introduce a framework for automatically choosing data structures to support efficient computation of analytical workloads. Our contributions are twofold. First, we introduce a novel low-level intermediate language that can express the algorithms behind various query processing paradigms such as classical joins, groupjoin, and in-database machine learning engines. This language is designed around the notion of dictionaries, and allows for a more fine-grained choice of its low-level implementation. Second, the cost model for alternative implementations is automatically inferred by combining machine learning and program reasoning. The dictionary cost model is learned using a regression model trained over the profiling dataset of dictionary operations on a given hardware architecture. The program cost model is inferred using static program analysis.

Our experimental results show the effectiveness of the trained cost model on micro benchmarks. Furthermore, we show that the performance of the code generated by our framework either outperforms or is on par with the state-of-the-art analytical query engines and a recent in-database machine learning framework.

1 INTRODUCTION
Query processing engines have undergone a massive progress over the previous decade. Traditionally, the volcano iterator model [33] was considered the de-facto standard for building pipelined query engines. This model streams the data along the query operators, and works well for out-of-core scenarios. For in-memory databases, the runtime overhead caused by this iterator model is mitigated by a mixture of techniques such as query compilation [11, 23, 40, 45, 48, 57, 58, 74, 83] and vectorization [64, 90, 91].

To accommodate specialized query operators in the design of modern query processing engines for in-memory databases, the following considerations are common.

Hash-Based and Sort-Based Query Operators. The efficient evaluation of query operators can benefit from hash-based and sort-based data-structures [13, 32, 67]. The trade-offs between hashing and sorting has been investigated in depth in the literature [10, 14, 43, 52, 56]. Most database systems tend to implement various types of physical query operators using these two approaches (e.g., sort-merge-join and hash-join), and delegate to the optimizer the task of picking the best choice based on the workload features.

Specialized Compound Query Operators. Such operators may be beneficial for OLAP workloads and are implemented in state-of-the-art in-memory database systems [51, 59]. For example, the groupjoin operator [53] merges aggregate and hash-join operators.

Specialized Compound Query Operators. Such operators may be beneficial for OLAP workloads and are implemented in state-of-the-art in-memory database systems [51, 59]. For example, the groupjoin operator [53] merges aggregate and hash-join operators.

The above considerations typically lead to two main challenges for the query optimizer. First, for every specialized query operator, the database developer needs to extend the set of supported query operators. Second, one has to provide a cost model for the new query operator. This can be daunting especially if the difference is only in the low-level implementation details for the data structures. This paper addresses these issues by proposing DBFlex, a query processing engine with two main design decisions. First, DBFlex uses a dictionary-based intermediate language. This language is expressive enough to capture query processing algorithms for, e.g., classical query operators, compound operators, and in-database machine learning engines, and allows a cost-based choice for its dictionary implementation.

Second, DBFlex automatically infers the cost models for alternative implementations of a query and may uncover the right trade-off between hashing and sorting for operators based on the given workload and its underlying hardware architecture. Our design thus frees the database developers from the difficult and error-prone task of defining a cost model for different query operators. Motivating Example. To better understand the differences from previous approaches, consider the following simplified TPCH query Q3, where we removed one join and simplified the group-by clause:

\[
\text{select } \text{L.L, sum(L.P * L.D)} \text{ from L join O on L.K = O.K} \text{ where O.T } < \%DATE\%
\]

\[\text{group by L.K} \]

The join on \(K\) is key/foreign-key. Following TPCH specifications, relation \(O\) cannot be indexed by \(T\). As \(K\) is a part of compound key for relation \(L\), this relation can be ordered on it. Most traditional query engines process the query using two hash-tables. The first hash table is built and probed to construct the intermediate join result. The second hash table is used for the group-by aggregate result. The pseudocode for the corresponding data-centric compiled engine [58] is as follows:

\[
\text{init } \Gamma_{HT}, \Psi_{HT} \text{ as HashTable}
\]

\[
\text{for each tuple } l \text{ in } L
\]

\[
\Psi_{HT}.insert(L.K, 1)
\]

\[
\text{for each tuple } o \text{ in } O
\]

\[
\text{if } o.T \leq %DATE\%
\]

\[
\text{if}(\Psi_{HT}.contains(o.K))
\]

\[
\text{for each tuple } l \text{ in } \Psi_{HT}[o.K]
\]

\[
\Gamma_{HT}[1.K] += L.P \times 1.0
\]

\[
\text{return } \Gamma_{HT}
\]

This evaluation strategy can be improved as follows:

1) Compound Groupjoin. In this query, the join key and the group-by attribute are the same. Thus, the intermediate hash tables \(\Gamma_{HT}\) and \(\Psi_{HT}\) can be merged. The resulting compound operator is referred to as groupjoin [53]. As a result, the previous query can be rewritten as follows:

\[
\text{init } \Psi_{HT} \text{ as HashTable}
\]

\[
\text{for each tuple } o \text{ in } O
\]

\[
\text{if } o.T \leq %DATE\%
\]

\[
\Psi_{HT}[o.K] = 0
\]
2) Specialized Hash-Tables. The intermediate hash table for join, group-by aggregate, and groupjoin can be implemented in various ways. As an example, to resolve hash collisions there are different approaches such as Hopscotch [35] and Robin hood [20] hashing. Each implementation can be beneficial for different selectivities (cf. Figure 1).

3) Sort-Based Dictionaries. Apart from using hash tables, one can use sort-based dictionaries in order to maintain the intermediate joins and aggregates. Examples are tree-based dictionaries (e.g., B*-trees, Red-Black trees, etc.) and sorted arrays. These dictionaries can be especially useful when one of the input relations is already ordered based on the join/group-by key, which is the case for relation $L$ in our running example. Similarly, one can also have a sort-based variant of groupjoin operator, which is used in engines such as LMFAO [70] and FDB [60].

In order to support these specialized operators we need to overcome the following challenges. First, the database developer needs to extend the set of query operators with hash-based and sort-based groupjoin, each variant with possibly different specialized implementations. Second, designing the cost model for each variant is very tedious and is not easily portable to different hardware architectures.

DBFlex solves these issues by introducing an intermediate language around dictionaries. First, the program in this language does not specify the data structure for dictionary $\mathcal{D}_{\text{Dict}}$. Nevertheless, it encodes the join order as well as the basic algorithm behind groupjoin. Hence, there is no need to extend the set of query operators. More specifically, the query is expressed as follows:

```java
for each tuple $l$ in $L$
    if ($\sigma_{LT}.contains(1.K)$)
        $\mathcal{D}_{LT}[1.K] += l.P \times 1.0$
    return $\mathcal{D}_{LT}$
```

Figure 1 shows that the best dictionary implementation depends on the selectivity: 1) this is hopscotch hashing for selectivities under 0.1%, 2) it is robin hood hashing for selectivities between 0.1% and 5%, and 3) becomes sorted table for selectivities larger than 5%, as its amortized lookup cost starts paying off. DBFlex uses dictionary size and number of access tuples, which define the selectivity.

The contributions of this paper are as follows:

- We propose a new architecture for building database systems using our proposed intermediate language (Section 2). The high-level view of the architecture of DBFlex is shown in Figure 2. DBFlex allows for defining specialized dictionary implementations, the cost models of which can be automatically learned.
- We introduce a novel low-level intermediate language, called LLQL. Our intermediate language is designed around the notion of nested dictionaries [73] that generalize flat relations, nested relations [69], tree-based indices, and trie-based representations [60] (Section 3). LLQL can express various basic query operators (selection, projection, aggregation, and nested loop join). Furthermore, it can express physical operators (hash-based and sort-based groupby, hash join, sort-merge join, and index-merged loop join), compound operators (hash-based and sort-based groupjoin), and efficient in-DB machine learning engines.
- LLQL is designed with two goals in mind. First, it has to be low-level enough to capture the underlying hardware architecture behavior (e.g., execution time of dictionary operations). Second, it should be high-level enough to allow for statically reasoning about the programs (e.g., run-time execution cost of programs). We show how the low-level nature of LLQL allows us to use regression models learned over dictionary-related features such as dictionary size, number of operator invocations, and orderedness of data to capture the dictionary cost model (Section 4.1).
Furthermore, thanks to the domain-specific nature of LLQL, we show how we use reasoning to infer the cost of LLQL expressions by using the dictionary cost model and a cardinality model (Section 4.2).

- The derived cost model (Section 4) allows DBFlex to automatically synthesize the LLQL program with the best cost. We present a greedy algorithm for choosing the dictionary implementations that lead to the LLQL with the lowest cost estimate (Section 5).
- Finally, we show experimentally the effectiveness of the learned dictionary cost model and the inferred LLQL cost model. Also, we show the advantage of using several dictionary implementations for a query over using a single dictionary. Overall, our engine outperforms the state-of-the-art engines Typer and Tectorwise by 1.5x and respectively 2x in average, while also recovering the runtime performance of the LMFAO in-database machine learning engine, which is tuned for specific workloads (Section 6).

2 ARCHITECTURE AND SYSTEM DESIGN

In this section, we present the architecture of DBFlex. First, we describe the high-level architecture of our system (Section 2.1). Then, we describe the workflow of our cost-based program synthesis (Section 2.2). Finally, we show how database developers can extend DBFlex with alternative dictionary implementations (Section 2.3).

2.1 Overall System Architecture

The architecture of DBFlex is presented in Figure 2. The input program can be in a variety of languages including SQL, linear algebra, and functional collection programming languages. This means that DBFlex can serve as the backend engine of existing DBMSes by getting their produced query plan and generating the optimized C++ code for it. Furthermore, DBFlex can not only run a wide range of analytical workloads, but also hybrid workloads such as in-database machine learning.

As opposed to optimizing queries at the level of physical query plan, DBFlex goes deeper [24]. Given a dataflow of query operators (i.e., the join order is specified using state-of-the-art techniques [81, 88]), DBFlex synthesizes a LLQL program with the dictionary implementations that lead to lowest cost estimates.

Similar to query optimization, there are two main components for the synthesis:

- **Cost Model**: DBFlex defines cost model at the level of dictionary operations and LLQL program. The dictionary cost model is learned using a regression model over the profiling data (Section 4.1). The LLQL cost model is statically inferred using inference rules over LLQL constructs (Section 4.2).

- **Search**: LLQL synthesis can be implemented using the same search techniques employed in query optimizers such as dynamic-programming, randomized algorithms, or other optimization techniques such as integer linear programming [81, 88]). Section 5 gives a greedy algorithm for this component.

2.2 Workflow

Figure 3 shows the workflow of DBFlex in three stages.1

1) **Installation Stage**: At this stage, the database system is being deployed to a particular machine. By generating a synthetic profiling data and running the operations of various dictionary implementations we generate a training set. Then, we can train a regression model to capture the dictionary cost model.

2) **Query Optimization**: The input query is provided at this stage, and is translated to a logical execution plan with the choice for join orders (e.g., by PostgreSQL or Apache Calcite). The logical plan is translated into LLQL without the implementation choice for dictionaries. The program synthesis generates the search space of alternative LLQL programs with different dictionary implementations. By using the trained regression models and inferring the execution cost of alternative LLQL programs (Section 4.2), the LLQL with the best dictionary implementations is chosen. The best LLQL program is translated to low-level specialized engine code in C++.

3) **Query Execution**: Finally, the input data is passed to the generated specialized engine and output result is produced.

2.3 Extensions

DB developers can extend DBFlex in three dimensions:

- **Dictionary Implementation**: The runtime of DBFlex includes a dictionary interface serving as an extension point (cf. Figure 3). DBFlex exposes the API shown in Figure 4, inspired by the API of standard library of C++ for dictionaries. After providing an appropriate hash-based or sort-based dictionary implementation, the developer needs to register the dictionary to be used during the installation.

- **Regression for Dictionary Cost Model**: DBFlex uses out-of-the-box regression models provided by machine learning frameworks (e.g., sklearn and TensorFlow). The developers can provide additional regression models.

- **Cardinality Model**: Cardinality and selectivity estimates are essential components for cost-based optimizers. DBFlex relies on state-of-the-art cardinality estimation models [31, 54, 89], as studying the impact of different cardinality estimation models is beyond the scope of this paper. However, the developer can use alternative cardinality models.

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1In practice, the query optimization and query execution are the same stages. We make this distinction for the sake of presentation.
3 LLQL

LLQL is a domain-specific language inspired by bag-based and dictionary-based query languages (e.g., AGCA [45] and FAQ [8]). There are two major design decisions behind this language. First, LLQL is not a purely functional language; in order to have full control on performance, the dictionary data-structure is not immutable. This means that one can destructively update the value associated with a key without the need to recreate another dictionary. Second, LLQL can be data-structure-aware and encode the implementation choice for the underlying dictionaries. More specifically, the dictionary accesses in this language are either based on hash tables or sorted data-structures. LLQL can express physical operators (hash-based and sort-based groupby, hash join, sort-merge join, and index-nested loop join), compound operators (hash-based and sort-based groupjoin), and efficient in-DB ML engines.

3.1 Syntax

Figure 5 shows the grammar of LLQL for both expressions (e) and types (T). The core data type supported by LLQL is a dictionary, represented as ({{ T -> T }}). LLQL represents input relations as pairs of tuples to their multiplicity, because of their bag semantics in database systems, as opposed to the set semantics in relational algebra.

The expression for (r <- R) e specifies iteration over the elements of dictionary R, and performing e at each iteration. Records can be constructed using { a_1 = e_1, ..., a_n = e_n } and the field a_i of record rec can be accessed using rec.a_i.

3.2 Dictionaries

The ( { k -> v } ) constructs a singleton dictionary that has k and v as its key and value, respectively. The dict (k) operator performs a lookup for key k in the dictionary dict. The elements of a dictionary are key-value pairs, which can be seen as records with field names key and val. Thus, in the body of the loop for (r <- R), one has to use r.key and r.val to access the key and value of r, respectively. The addition for dictionaries is defined in terms of element-wise addition; the values with the same key are added.

The choice of data structure is specified using @ds, which is used for constructing a dictionary: @ds ({{ e -> e }}). We can use every specialized dictionary data structure instead of @ds. However, for the sake of brevity, we only use these two annotations: 1) @ht for hash-based dictionaries, and 2) @st for sort-based dictionaries. Next, we present these two types of dictionaries.

3.2.1 Hash-based Dictionaries. One of the most obvious ways of implementing a dictionary is by using a hash-table data-structure. The keys are first mapped through a hash function to a particular bucket and the associated values can be accessed, inserted, or removed with a constant-time complexity.

One of the key challenges for hash-based dictionaries is handling collisions. Database systems have developed different approaches such as robin hood hashing and chained hashing [68]. LLQL can make such choices explicit by using an appropriate hash table implementation.

The operators provided for a hash-based dictionary are: 1) iterating over a dictionary dict is specified using for (x <- dict), 2) inserting or updating the value v associated with the key k in a dictionary dict is specified using dict += k -> v, and 3) looking up the value associated with key k in a dictionary dict is specified using dict(k).2

3.2.2 Sort-Based Dictionaries. In databases, there has always been a dual approach to hashing, which is based on sorted data structures [67]. Such data structures can be either implemented using sorted collections, or through tree-based data structures such as B-Trees, B*-Trees, Red-Black Trees, etc.

\[^{2}\text{LLQL can be extended to support deletions as well. This makes it appropriate for transactional workloads, which we leave for the future.}\]
Dictionaries that are implemented using such sort-based data structures can achieve logarithmic time for access, insertion, and updates. Similar to hash-based dictionaries, the sort-based dictionaries have the following three operations: 1) iteration using \( \text{dict}(k) \), 2) insertion or update using \( \text{dict} += k \rightarrow v \), and 3) the iterator \( \text{dict}_\text{iter} \).

Dictionaries can be used to store partial aggregates, which can be useful in analytical query processing. Figure 6 shows LLQL expressions for different query operators: (a) Hash join of R and S, join key given by \( \text{part}(r) \), (b) Sort-merge join of R and S, join key given by \( \text{part}(r) \), (c) Hash-based groupjoin on \( A \) with partial aggregates \( f \) and \( g \), and (d) Sort-based groupjoin on \( A \) with partial aggregates \( f \) and \( g \).

### Figure 6: Different query operators as LLQL expressions.

3.2.3 Mapping to Runtime. The iteration over a dictionary corresponds to the `begin()` and `end()` functions of the Runtime API in Figure 4. The lookup corresponds to the `find()` function. The update construct is implemented by first invoking `find()`. In the case that a match is found, the corresponding value is incremented by the input value. Otherwise, the corresponding key-value pair is inserted by using the `emplace()` function. Finally, the hinted versions correspond similarly to `find_hint()` and `emplace_hint()`.

Next, we show how both these two data structures can be used for implementing various physical query operators.

3.3 Basic Query Operators

3.3.1 Selection. Consider a relation \( R \), for which we are interested in selecting the elements that satisfy a predicate \( p \). For each element \( r \) of this relation, if the predicate is satisfied, we increment the multiplicity of the associated value with the key \( r.\text{key} \) (which specifies the row of the relation) by \( r.\text{val} \) (which specifies the multiplicity of that row). Otherwise, we do nothing.

```cpp
let sel = (()) in
for(r <- R) {
    if(p(r.\text{key})) then sel(r.\text{key}) += r.\text{val}
    else ()
}
```
3.3.2 Projection. Similar to selection, we iterate over the elements of the relation \( R \). This time, we update the element of the dictionary specified the application of the projection function \( f \) on each row of relation \((r \cdot \text{key})\) as its key and unchanged value \((r \cdot \text{val})\).

```
let proj = (\{}) in
for (r <- R) {
  proj(f(r.key)) += r.val
}
```

3.3.3 Nested-Loop Join. For this operation, we have to use nested loops iterating over the elements \( r \) and \( s \) of relations \( R \) and \( S \), respectively. For each combination of tuples, we check if \( \text{joinCond} \) is satisfied. If this is the case, we update the dictionary with an element that has the combination of the tuples of these two relations using function concat as its key, and \( r.val * s.val \) as its value.

```
let join = (\{}) in
for (r <- R) {
  for (s <- S) {
    if (joinCond(r.key, s.key)) then
      join(concat(r.key, s.key)) += r.val * s.val
    else
      ()
  }
}
```

This expression is inefficient because one has to consider all combinations of \( r \) and \( s \). This situation can be improved by leveraging data locality as will be shown in Section 3.4.

3.3.4 Scalar Aggregation. These operators can be implemented by iterating over the elements of the relation and computing the appropriate aggregate function \( \text{aggFun} \). For example, in the case of summing the attributes \( A \), \( \text{aggFun}(r.key) \) is replaced by \( r.key \cdot A \), and in the case of counting, is replaced by \( 1 \). As there could be duplicates of an element in the input relation (the multiplicity of which is shown by \( r.val \)), the aggregate result for each element needs to be multiplied by \( r.val \).

```
let agg = ref(double) in
for (r <- R) {
  agg += aggFun(r.key) * r.val
}
```

3.3.5 Group-by Aggregate. The key difference between this operator and its non-grouped variant is that at each iteration, a group-by aggregate returns a single dictionary with the key specified by the grouping function \( \text{grp} \), and the value specified using the aggregate function \( \text{aggFun} \):

```
let Agg = (\{}) in
for (r <- R) {
  Agg(grp(r.key)) -> aggFun(r.key) * r.val })
```

Both scalar and group-by aggregate operators can be generalized to compute other forms of aggregates such as minimum and maximum by supplying appropriate addition and multiplication operators. For example, in the case of maximum, the maximum and numerical addition need to be supplied as the addition and multiplication operators, respectively [55]. To compute aggregates such as average, one has to compute both summation and count.

3.4 Partitioned Joins

In the case of equality joins, one can partition the elements of the relations based on their join key, and then only combining the elements of the two relations that fall into the same partition.

3.4.1 Hash Join. Using a hash-table data-structure for a partitioned join results in a hash-join operator. For example, the partitioned join between relations \( R \) and \( S \) is lowered to hash join in Figure 6a.

3.4.2 Sort-Merge Join. In a partitioned join, if one uses a sort-based dictionary rather than a hash table. In this case, if one of the relations is ordered on the join key, one can avoid searching the entire range from scratch for the next matching partition, by using the hinted lookup operator.

As shown in Figure 6b, the iterator \( it \) is first set to the beginning of the dictionary \( Ss \). At the first iteration over relation \( R \), the hinted lookup \( Ss < it > (r.key) \) searches the entire range to find the next matching element. After returning the matching element (or an empty dictionary if it does not find any match), the iterator \( it \) is updated to the least upper bound position. This limits the next lookups to the ranges that have been explored before. Thus, these hinted lookups have an amortized constant time.

This algorithm has the same behavior as a sort-merge join operator. More generally, in the case where the relation \( R \) is not ordered based on the join key, one needs to use the partitioned join operator that partitions (by sorting) relation \( R \) based on the join key.

Furthermore, when relation \( S \) is already sorted based on the join key, one can use a hinted insert operator. This brings the computational complexity of the build phase from \( O(n \cdot \log n) \) to \( O(n) \). This algorithm is essentially the same as merge join, when the input relations are already sorted:

```
let Ss = @st (\{}) in
let it! = Ss.iter in
for (s <- S) {
  Ss<it>(part(s.key)) += (@ht (\{(s.key -> s.val\})))
} ;
... // same as Figure 6b
```

3.4.3 Tree-Based Join. If rather than using a sorted dictionary, one uses a tree-based dictionary (e.g., a dictionary implemented using B*-Tree), DBFlex synthesizes a tree-based join algorithm. The tree-based data structures have a significantly better insertion time in the case where the input data is not already ordered.

3.5 Index-Nested Loop Join

Index-Nested Loop Join can be thought of as a specific case of partitioned join; when one of the relations is already partitioned (i.e., indexed) on the join key, there is no need to perform the partitioning in the query processing time. In this case, the partitioned join operator can be seen as an index-nested loop join operator.

As an example, consider the case where there is a hash-based index, named as \( S \) and, for relation \( S \) using the function \( \text{part}(s.key) \). The index-nested loop join for \( S \) and \( R \) is expressed as follows:

```
let RS = @ht (\{}) in
for (r <- R) {
  for (s <- S.ind(part(r.key))) {
    RS( join(r.key, s.key) ) += r.val * s.val
  }
}
```
The dictionaries used for computing group-by aggregates can also be hash-based or sort-based. For each element \( r \) of relation \( R \), we update the value associated with key \( r \). In our previous group-by aggregate example, the final result is stored in the variable \( Ragg \). As a result, the group-by aggregate can be computed in linear time rather than \( O(n \log n) \). Furthermore, in the case where a sorted result is more preferable (e.g., the presence of \texttt{ORDER BY} or if the next operator can benefit from sorted input), using sort-based aggregates can be more beneficial over their hash-based counterparts.

### 3.6 Group-By Aggregation

The dictionaries used for computing group-by aggregates can also be hash-based or sort-based.

#### 3.6.1 Hash-Based Aggregation

Using a hash table as the underlying data structure for dictionaries, results in a hash-based group aggregate. In our previous group-by aggregate example, the final result is stored in the variable \( Ragg \), which is instantiated with an empty hash-based dictionary. For each element \( r \) of relation \( R \), we update the value associated with key \( r \) with the new value \( g(r, key) + r, val \) (cf. Figure 6c).

#### 3.6.2 Sort-Based Aggregation

We can use a sort-based dictionary for group-by aggregates as well. Furthermore, if the elements of relation \( R \) are already sorted based on their group-by key, one can use hinted inserts, as shown in Figure 6d.

As a result, the group-by aggregate can be computed in linear time rather than \( O(n \log n) \). Furthermore, in the case where a sorted result is more preferable (e.g., the presence of \texttt{ORDER BY} or if the next operator can benefit from sorted input), using sort-based aggregates can be more beneficial over their hash-based counterparts.

### 3.7 Groupjoin Operators

Consider an aggregation over the result of join between two relations. The aggregate can be interleaved by the join computation. This is achieved by decomposing the aggregate function into functions that are only dependent on one of the relations. Then, one can push the decomposed functions into their corresponding relations. Finally, the result of these partial aggregates are joined together.

#### 3.7.1 Hash-Based Groupjoin

In essence, this optimization has the effect of fusing a partitioned join operator with an aggregate operator. In fact, in the specific case of using a hash-table data-structure for dictionaries, this optimization produces a groupjoin operator [53].

#### 3.7.2 Sort-Based Groupjoin

In the case of using a sort-based dictionary, LLQL synthesizes the dual form of groupjoin operator. In the previous example, if the elements of \( R \) are sorted based on \( A \), then one can make the aggregation even faster by having an amortized constant time access for the elements of \( Ss \) (cf. Figure 6f).

![Figure 7: Different LLQL expressions representing covariance matrix computation over join of two relations.](image)

| (a) Initial unoptimized LLQL expression. | (b) After interleaving join and aggregations. |
|---|---|
| \[
\text{let Rp = \{()}\;\text{in}
\text{for}(r < - R) \{ 
\text{Rp(r. key.s) += ((r.key -> r.val))}
\};
\text{let Q = \{()}\;\text{in}
\text{for}(s < - S) \{ 
\text{for}(r < - Rp(s.key.s)) \{ 
\text{Q(i=s.key.i, c=r.key.c) += r.val * s.val}
\}\}
\;}\]

| (c) After introducing trie indices. | (d) After factorization and loop-invariant code motion. |
|---|---|
| \[
\text{let Ragg = \{()}\;\text{in}
\text{for}(r < - R) \{ 
\text{Ragg(r.key.s) += ((m = r.val, c = r.key.c * r.val, c_c = r.key.c * r.key.c * r.val)}
\}\}
\]}\]

| \[
\text{let Covar = ref((i_i:double, i_c:double, c_c:double)) in}
\text{for}(x < - Q) \{ 
\text{Covar += \{ i_i=x.key.i*x.key.i*x.val, i_c=x.key.i*x.val, c_c=x.key.c*x.key.c*x.val \}}
\}\]

| \[
\text{let Ragg = \{()}\;\text{in}
\text{for}(r < - R) \{ 
\text{Ragg(r.key.s) += ((m = r.val, c = r.key.c * r.val, c_c = r.key.c * r.key.c * r.val)}
\}\}
\};
\text{let Covar = ref((i_i:double, i_c:double, c_c:double)) in}
\text{for}(s < - S) \{ 
\text{let r = Ragg(s.key.s) in}
\text{ Covar += \{ i_i=s.key.i*s.key.i*s.val*r.m, i_c=s.key.i*s.val*r.c, c_c=s.val*r.c_c \}}
\}\]

| \[
\text{let Rp = \{()}\;\text{in}
\text{for}(r < - R) \{ 
\text{Rp(r. key.s) += ((r.key -> r.val))}
\};
\text{let Q = \{()}\;\text{in}
\text{for}(s < - S) \{ 
\text{for}(r < - Rp(s.key.s)) \{ 
\text{Q(i=s.key.i, c=r.key.c) += r.val * s.val}
\}\}
\;}\]

| \[
\text{let Covar = ref((i_i:double, i_c:double, c_c:double)) in}
\text{for}(x < - Q) \{ 
\text{Covar += \{ i_i=x.key.i*x.key.i*x.val, i_c=x.key.i*x.val, c_c=x.key.c*x.key.c*x.val \}}
\}\]

| \[
\text{let Ragg = \{()}\;\text{in}
\text{for}(r < - R) \{ 
\text{Ragg(r.key.s) += ((m = r.val, c = r.key.c * r.val, c_c = r.key.c * r.key.c * r.val)}
\}\}
\];
\text{let Covar = ref((i_i:double, i_c:double, c_c:double)) in}
\text{for}(s < - S) \{ 
\text{let r = Ragg(s.key.s) in}
\text{ Covar += \{ i_i=s.key.i*s.key.i*s.val*r.m, i_c=s.key.i*s.val*r.c, c_c=s.val*r.c_c \}}
\}\]
3.8 In-DB Learning Engines

Recently, there has been an increasing interest in performing machine learning tasks inside a database system. One of the main techniques for in-DB machine learning is to express the machine learning task as an aggregation query. This way, one can globally optimize both the feature extraction part of the ML task and its training, achieving orders of magnitude performance improvement [70].

As an example, let us consider a database with two relations: \( S(i, u) \) and \( R(s, c) \). The goal is to train a linear regression model that predicts \( u \) given features \( F = \{i, c\} \), where the training dataset is the join of two relations \( Q = S \bowtie R \).

Covariance matrix computation is an essential technique for efficiently training machine learning models such as linear regression [7]. In our example, we consider the part of covariance matrix that considers the interactions of \( i \) and \( c \), which is defined by \( \Sigma_{xQxT} \), where \( \ell, j \in F \). The naive approach for computing the covariance matrix consists of two stages: 1) computing the join of the input relations using a feature extraction query, followed by 2) aggregations computing the elements of this matrix. Thus, this computation can be seen as a multi-aggregate query, the code of which is shown in Figure 7a.

By interleaving the aggregate and join computations [4, 70], there is no more need to compute the intermediate query \( Q \), as can be seen in Figure 7b. Instead the partial aggregates that are dependent only on relation \( R \), bound to variable \( \text{Ragg} \), are computed while scanning this relation.

Next, we introduce a trie index for relation \( S \), represented as the nested dictionary \( \text{Strie} \). Instead of an iteration over the relation \( S \), this program performs a nested iteration over the trie \( \text{Strie} \) (cf. Figure 7c); the outer iteration is over the first level of trie \( \text{Strie} \), and the second iteration is over the second level \( \text{st.val} \).

Finally, we further improve the performance by factorizing the independent factors from the inner loop and performing loop-invariant code motion to hoist them outside. The expression \( \text{sagg} \) computes the partial aggregates dependent only on relation \( S \). The last expression computes the final aggregate by multiplying the corresponding factors from the two partial aggregates of relations \( R \) and \( S \) (cf. Figure 7d).

4 COST ENGINE

In this section, we present how DBFlex automatically infers the execution cost of LLQL programs by combining machine learning and program reasoning. First, we present the dictionary cost model trained by regression models in Section 4.1. Then, we show the cost inference rules required for estimating the run-time cost of LLQL programs using the dictionary cost model and cardinality model in Section 4.2.

4.1 Dictionary Cost Model: Regression Learning

The training set is generated by profiling the run time of the insert and lookup operations for different dictionary implementations. For insert, the profiling is generated for different dictionary sizes. For lookup, the profiling is generated for different dictionary sizes and number of accessed tuples. Note that the lookup operator shows a different runtime behavior depending on whether the lookup is successful or not. Hence, the training set contains profiling for both successful and unsuccessful lookups.

Another important feature is the orderedness of the input data. As observed in Section 3, the sort-based dictionaries can use hinted lookups and inserts when the input keys is ordered. We profile the situations where the sequence of key-value pairs to insert or to look up are ordered or unordered. Note that the performance of hash tables is independent of orderedness of keys.

In summary, our training dataset has the following features: dictionary size, number of accessed tuples, and orderedness of data. We also enhanced the features by adding the logarithm of dictionary size and number of accessed tuples as explained in Section 6.2. The labels are the run time performance for various operations in milliseconds. As future work, one can investigate further features, such as data distribution parameters, tuple arity, and data type.

The next step involves training a regression model over the profiling training set to predict the run time cost of dictionary operations. This defines our dictionary cost model. We have used a wide range of regression models, the behavior of which can be observed in Section 6.2.

Next, we use program reasoning to derive the cost of LLQL programs.

4.2 LLQL Cost Model: Program Reasoning

The trained regression models give a cost estimate for individual dictionary operations. However, the program synthesizer requires the cost estimate for LLQL expressions. Figure 8 shows how the dictionary cost model (\( \Delta \equiv \) ) and cardinality model (\( \Sigma \equiv \) ) are combined with the runtime context of LLQL expressions to derive their execution cost.

In Figure 8, the top and bottom parts of the inference rules specify the premises and the conclusions, respectively. As an example, the premises for the second inference rule specifies that for the expression \( \text{for } x <- e1 \ e2 \), the runtime context of \( e2 \) (\( \Gamma' \)) should extend the runtime context of \( e1 \) (\( \Gamma \)) by recording that the number of invocations is multiplied by the cardinality of \( e1 \) (\( \Sigma_{\text{card}}(e1) \)). The conclusion of this rule specifies that the execution cost of the mentioned expression is \( c1 + c2 \) given that the execution cost of \( e1 \) and \( e2 \) is \( c1 \) and \( c2 \), respectively.

Example for Cost Inference. To give a more concrete example, consider the hash-based group-by aggregate from Figure 6c. The initial runtime context is set as \( \Gamma = (\Gamma_{\text{calls}} = 1, \Gamma_{\text{cond}} = 1) \), specifying that the number of invocations and the probability of taking the execution path are both 1. The runtime context of the update statement, which is the body of the loop, is modified with \( \Gamma'_{\text{calls}} = \Sigma_{\text{card}}(R) \). In the case of having a filter, \( \Gamma'_{\text{cond}} \) is modified according to the inference rule of \( \text{if} \) statements.

The execution cost of the update statement is computed following the corresponding inference rule. First, assume that the cost for the group-by key (\( \text{grp}(r \ . \ \text{key}) \)) and value (\( \text{agg}(r \ . \ \text{key}) \ast r \ . \ \text{val} \)) are \( c_k \) and \( c_v \), respectively. Second, the number of invocations of the update statement and the size of dictionary are computed as \( C = \Gamma'_{\text{calls}} \ast \Gamma'_{\text{cond}} = \Sigma_{\text{card}}(R) \) and \( N = \Sigma_{\text{card}}(\text{Ragg}) \). Then, the number of lookup hits is computed as \( H = C + N = \Sigma_{\text{card}}(R) - \Sigma_{\text{card}}(\text{Ragg}) \). Finally, total execution time is computed as \( c_k \ast c_v \mid \Delta_{\text{lus}}(H, N) + \Delta_{\text{uf}}(N, N) + \Delta_{\text{ins}}(N) \), where \( \Delta_{\text{lus}}(H, N) \) is...
Accumulative probability
Selectivity of condition
Number of distinct elements
Cost of insertion

with the minimum total run-time cost estimate (Line 6). The func-
Accordingly we update the runtime context with best dictionary
This section presents fine-tuning of the dictionary implementations
In such cases, the greedy algorithm finds the optimal program (assuming that the
the estimation cost returned by the regression model for successful
Then, the search space for using different combinations of
diction implementations is generated. By using the cost infer-
dictionaries are introduced with the corresponding dic-
them in dependency order (Line 3).
dictionary implementations that lead to the lowest execution time.
Algorithm 1 shows a greedy algorithm for the data-structure
exp: Input expression
Σ: Cardinality model
Δ: Dictionary cost model
DS: Dictionary implementations

5 PROGRAM SYNTHESIS
This section presents fine-tuning of the dictionary implementations
by using program synthesis. The input to the program synthesis
is an LLQL expression for which the join order is already speci-
fied. Then, the search space for using different combinations of
dictionary implementations is created. By using the cost infer-
ence graph shown in the previous section, we find the LLQL with
dictionary implementations that lead to the lowest execution time.
Algorithm 1 shows a greedy algorithm for the data-structure
selection process. First, the distinct dictionaries that exist in
the input LLQL expression are extracted (Line 2). Then, a dependency
graph [28] among these dictionaries is created, so that we traverse
them in dependency order (Line 3).
For each dictionary symbol (sym), we select the data structure
with the minimum total run-time cost estimate (Line 6). The function
Cost uses the inference rules presented in Figure 8, and its
runtime context is updated to use ds for the dictionary symbol sym.
Accordingly we update the runtime context with best dictionary
implementation for sym (Line 7).
Finally, we replace the dictionary symbols in exp by the imple-
mentations choices collected in the runtime context (Line 9). This is
achieved by changing the annotations @ds in the statements where
the dictionary symbols are introduced with the corresponding
dictionary implementation.
We observe that for many analytical queries, where one uses pipelining or the intermediate results only used for probing, there
is no dependency between dictionary symbols. In such cases, the greedy algorithm finds the optimal program (assuming that the
Inputs:
exp: Input expression
Σ: Cardinality model
Δ: Dictionary cost model
DS: Dictionary implementations

1. function ProgramSynthesis(exp, Σ, Δ, DS)
2. Dict ← ExtractDictSymbols(exp)
3. DAG ← DependencyGraph(Dict)
4. Γ ← (Γcalls = 1, Γcond = 1)
5. for sym ← DAG do
6. dSBest ← argmin Cost(exp, Σ, Δ, Γ[Γdict(sym) = ds])
7. Γ ← Γ[Γdict(sym) = dSBest]
8. end for
9. final ← ChooseDictDS(exp, Γdict)
10. return final

Algorithm 1: A greedy algorithm for program synthesis.
cost/cardinality models are precise). However, in cases where one
needs to iterate over the intermediate dictionaries (e.g., in-DB ML
and TPCH query 18), the greedy algorithm can fall into local opti-
mum. We leave the usage of further search algorithms [38, 81, 88]
for future work.

6 EXPERIMENTAL RESULTS
In this section, we investigate the experimental results of DBFlex.
Our findings are summarized as follows:
• The predicted cost by the dictionary cost model is proportional to
the actual time spent for each operation using different dictionary
implementations (Section 6.2.1).
• Utilizing the LLQL cost model to find the best query operator
can prevent a slowdown compared to the best plan in most cases
(Section 6.2.2).
• If we resort to a single dictionary implementation for the entire query, we observe our engine performs on par with state-of-the-art analytical engines (Section 6.3).
• By using several dictionary implementations for one query, we observe an average of 70% performance improvement over the version that uses a single dictionary implementation. This is in particular the case for queries that can benefit from sort-based group-by and join (Section 6.3).
• Overall, DBFlex outperforms the state-of-the-art query engines Typer and Tectorwise by 1.5x and respectively 2x on average (Section 6.3), while also recovering the runtime performance of the LMFAO specialized in in-DB machine learning (Section 6.4).

6.1 Experimental Setup

All experiments are performed on two machines:
• **Machine 1** is an iMac equipped with an Intel Core i5 CPU running at 2.7GHz, 32GB of DDR3 RAM with OS X 10.13.6. We use CLang 900.0.39.2 for compiling the generated C++ code using the O3 optimization flag.
• **Machine 2** is equipped with Intel(R) Core(TM) i7-4770 at 3.40GHz, 32GB of DDR3 RAM, running Ubuntu 18.04. We use g++ 6.4.0 for compiling the generated C++ code using the O3 flag.

We use the following dictionary implementations:
• unordered_map: C++ STL hashing.
• robinhood_dict: robin-hood hashing [3].
• tsl_dict: hopscotch hashing [2].
• boost_unordered_map: Boost hashing [5].
• map: C++ STL Red-Black tree dictionary.
• boost_flat_map: Boost sorted flat array [5].
• tlx_dict: TLX B*-tree dictionary [6].
• absl_dict: Abseil B-tree dictionary [1].

**Competitors.** We benchmark our engine against the following in-memory engines¹: (1) Typer and (2) Tectorwise [23], the open source implementation⁴ of HyPer [58] and Vectorwise [91], and (3) the in-DB ML engine LMFAO [70].⁵ Typer and LMFAO use query compilation and Tectorwise uses vectorization. The code for queries in all systems is in C++.⁶

For all the experiments, we compute the average of ten subsequent runs. We perform all experiments using a single core. We leave the experimentation for multi-core environments for the future since it requires dealing with parallelization concerns (e.g., lock-based vs. lock-free data structures). The loading time of the database into main memory is not considered. For in-DB machine learning experiments, all relations are sorted by their join attributes for both DBFlex and LMFAO.

6.2 Cost Engine Performance

6.2.1 Dictionary Cost Model. In this section, we report the performance of our dictionary cost model using various regression models for prediction. Several regression models were trained over

The profiling training set to predict the run time cost of dictionary operations using three different methods:
• All in One Model: A single regression model is used for cost prediction. The model uses the dictionary size, number of accessed tuples, orderedness of data, dictionary type, and the operation as features. The last two mentioned features are passed to the model in the one-hot encoded format.
• Individual Models Without Feature Engineering: 32 different regression models are constructed based on the combinations of data order, dictionary implementation, and operations. Each model takes the dictionary size and the number of accessed tuples as features.
• Individual Models With Feature Engineering: It is constructed in the same way to the previous method. However, its features are enriched with the logarithm values of the dictionary size and the number of accessed tuples.

Figure 9 shows a comparison between our cost model with the actual run-time spent on basic operations (lookup and insert). We observe that in most cases, our cost model is proportional to the actual time on a logarithmic scale. Since the logarithm of dictionary size accurately captures the relationship between dictionary size and actual operation cost, the models that have been trained with feature engineering outperform other methods. Overall, KNN with K = 4 and trained with logarithmic features performs the best among all these models.

6.2.2 LLQL Cost Model. To evaluate the LLQL cost model, we benchmark the LLQL program for the group-by operation by varying the selectivity of the input relation. Overall, we generate 70

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1 Comparing against disk-based engines requires our cost model to consider hardware characteristics of HDDs and SDDs (e.g., erase time), which we leave for future.
2 https://github.com/TimoKersten/db-engine-paradigms
3 https://github.com/fdbresearch/LMFAO
4 Generating LLVM or machine code can improve query compilation time [46]. However, improving compilation time is beyond the scope of this paper; instead we only focus on query execution time.
5 Comparing against disk-based engines requires our cost model to consider hardware characteristics of HDDs and SDDs (e.g., erase time), which we leave for future.
**6.3 Analytical Query Engines**

In this section, we investigate the performance of DBFlex for OLAP workloads. For this purpose, we use a representative subset of TPCH queries involving joins and aggregations with a wide range of intermediate cardinals [16, 41]. We compare the performance of generated optimized code for two best hash-based dictionaries, the best sort-based dictionary, the fine-tuned versions (M1 Tuned and M2 Tuned), Typer, and Tectorwise.

As Figure 11 shows, we observe that overall the fine-tuned optimized queries perform better or the same as the Typer and Tectorwise engines. Furthermore, we observe that in most cases, the tuned versions for the two machines produce identical query plans. In Q1, the only involved dictionary favors a robinhood_dict dictionary in machine 1, instead of tsl_dct in machine 2.

Q3, Q5, and Q9 all involve multiple joins, and for all of them the hash-based robinhood_dict dictionaries show promising performance. However, the fine-tuned optimized query for all of them involves a mixture of boostFlatMap and robinhood_dict. Furthermore, all these queries show good performance for vectorized engines such as Tectorwise. Especially, Q9 involves a large intermediate dictionary, for which a vectorized engine is better at hiding memory stalls for a large intermediate hash join [41].

Finally, Q18 involves a high-cardinality aggregation operator. For this query, we observe that sort-based dictionaries such as boostFlatMap outperform hash-based ones. A particular interesting characteristic of this query is that two instances of the sort-based dictionaries cannot use the hinted version of lookup. Nevertheless, due to the low cardinality of the corresponding intermediate dictionaries, makes the overall non-hinted and logarithmic lookup computation time of sort-based dictionaries is comparable to the constant lookup time of hash-based ones. Thus, the overall performance of sort-based dictionaries is better than hash tables.

**6.4 In-DB Machine Learning**

As the final set of experiments, we show the performance of DBFlex for in-DB ML workloads. We use two real-world datasets: 1) Favorita [25], which is a publicly available Kaggle dataset, and 2) Retailer is a dataset from a US retailer [71]. Both datasets are used in retail forecasting scenarios and have a snowflake schema with 4 dimension tables for both and with fact tables of 87 million and 125 million tuples, respectively. We only use the continuous attributes of these datasets, which are 6 and 35 attributes, respectively.

Figure 12 shows the run-time comparison of different configurations of DBFlex for computing the covariance matrix on these two datasets. As the input relations are already indexed as ordered tries, sort-based dictionaries show better performance. Thus, we compare the generated code using two best sort-based dictionaries and the best hash table.

For the Favorita dataset, we observe that boostFlatMap outperforms robinhood_dict and tlx_dct. The sort-based dictionaries use hinted lookups and inserts in all cases by default thanks the ordered nature of their input data. However, the fine-tuned version for both machines prefer a non-hinted lookup in the case where the size of the intermediate dictionary is too small and there are too many failed lookups in deeply nested loops. This kind of knowledge is not possible to be captured by the competitor systems such as LMFAO.
7 RELATED WORK

**Query Languages.** Nested relational model [69], monad calculus, and monoid comprehension [17–19, 26, 34, 80, 84, 87] are query languages for nested collections, whereas AGCA [45], FAQ [8], and HoITSQL [22] represent relations as bags. The dictionary-oriented nature of LLQL combines these two lines of work; both relations and group-by aggregates are represented as dictionaries. Furthermore, LLQL allows hash-based and sort-based data structures to be used for dictionaries, with the capability of encoding hinted lookup and insertions for sort-based ones.

**Query Compilation.** Just-in-time compilation of queries allows for generating specialized engines and has been heavily used for analytical query processing [11, 23, 40, 45, 48, 57, 58, 61, 74, 75, 83]. In parallel, the compilers of functional languages heavily investigated the specialized low-level code generation with focus on fusion of intermediate collections [44, 50, 72]. Recently, there has been several efforts on low-level query plan languages, mainly inspired by functional collections [15, 27, 47, 63]. None of these systems have focused on fine-tuning data structures and do not support automatic inference of cost models.

Data-structure specialization in LegoBase [74] and LB2 [79] focuses on more aggressive partial evaluation for the provided hashable implementations, without tuning based on cardinalities or using sort-based dictionaries.

Chestnut [88] uses integer linear programming to specify data layouts used for database-backed applications, using manually specified cost models. Micro adaptivity [66] is a technique for choosing the best function implementation in runtime for Vectorwise. Similar to DBFlex, it frees database developers from manually writing cost models. DBFlex generalizes this idea to higher-level decisions such as the choice of data structures, while combining it with query compilation.

**In-DB Machine Learning.** Training ML models inside the database system by avoiding the materialization of join has recently gained great interest in the community. The current solutions are currently divided into two categories. First, systems such as Morpheus [21, 49] cast the in-DB ML task as a linear algebra problem. For example, such tasks are expressed on top of linear algebra libraries of R [21] and NumPy [49]. The second category casts the in-DB ML task as a multi-aggregate analytical query. Systems such as F [60, 71], AC/DC [42], LMFAO [70], IFAQ [76, 77], SDQL [73], as well as DBFlex fall into this category. None of the mentioned systems support fine-tuning hash-based and sort-based data structures as well as automatic inferring of cost models.

**Cost Inference.** The run-time cost estimation of programs has been heavily investigated for databases [67] and programming languages [9, 36, 39, 85]. In addition to improving the performance, cost estimation can be used for verification purposes (e.g., ensuring resource usage is bounded for embedded devices) [37]. The cost model used in DBFlex estimates the run-time cost by relying on the trained models over actual profile data, as opposed to the alternative approaches which mostly rely on asymptotic reasoning [85].

**Auto-Tuning.** Automatic tuning of performance-critical kernels is a well-investigated topic in the high-performance computing and compilers communities [12]. Examples include FFTW [30] and Spiral [65] for Fourier transforms, and LGen [78] and ATLAS [86] for linear algebra. None of the mentioned systems support query processing workloads, and do not fine-tune data structures.

8 CONCLUSION

In this paper, we present DBFlex, a framework that automatically synthesizes analytical engines with fine-tuned data structures. This is facilitated by LLQL, a low-level intermediate language based on dictionaries. The execution cost of LLQL is automatically inferred by 1) training regression models for the cost model of dictionary implementations, and 2) using cost inference rules on LLQL statements for the cost model of the entire LLQL program. Our experimental results show the effectiveness of our cost model and its performance in comparison with state-of-the-art in-memory engines for query processing and in-database machine learning. We plan to explore including more features for the dictionary cost model. Another promising future direction is multi-core and parallel architectures that can impose further challenges.

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A MICRO BENCHMARKS

We next report on micro-benchmarks for the eight dictionary implementations in the following disciplines: (1) inserts of a varying number of data points into a dictionary; (2) successful and (3) unsuccessful lookups for a varying number of keys into dictionaries of varying size. The key-value pairs to be inserted, or the keys to be looked up are integer values generated following a uniform distribution. The keys can be either ordered or unordered.

Figure 13 shows the results for the case of insertion. For the case of unordered keys, we observe the superiority of hash-based dictionaries over sort-based ones. However, for ordered keys, the sort-based dictionaries perform better than most hash-based ones. An interesting case is boost_flat_map, which behaves poorly for the case of unordered keys, due to the linear insertion needed for bigger keys. Nevertheless, this data structure outperforms others for ordered keys.

![Figure 13: Micro benchmark results for insert in different dictionary data structures.](image)

As previously mentioned in Section 5, the performance of lookup operation is different in the case of a successful lookup and unsuccessful one. Figure 15 shows the performance of successful lookup operations. Apart from unordered and ordered data, to better demonstrate the behavior of different dictionaries, we vary both the dictionary size and the number of lookup invocations. Similarly to the insert operation, for unordered data one observes the superiority of the hash-based dictionaries. For ordered data, the sort-based dictionaries outperform the hash-based ones, and the performance gap widens as the number of lookup invocations increases. One exception is map, for which the inefficient tree traversal leads to worse performance. Furthermore, for a fixed dictionary size, decreasing the number of lookup invocations may make the amortized hinted lookup cost more than the non-hinted lookup. We later observe in Section 6.4 the cases where using non-hinted lookups is preferred over hinted ones.

Figure 14 shows the results for unsuccessful lookups. Although for insertion and successful lookup operations both tsl_dict and robinhood_dict behave similarly, for unsuccessful lookups the latter dictionary clearly shows a better behavior. For ordered keys, the performance are similar to successful lookups, thus, omitted from the experiments.

![Figure 14: Micro benchmark results for unsuccessful lookups in different dictionary data structures.](image)

Note that all figures use a logarithmic scale for both axes. For both insertion and lookup we observe up to three orders of magnitude performance difference among the different dictionary implementations. This is interesting because all the implementations are stable and used massively in software artifacts written using C++.

Finally, we observe that for all operations, the micro-architecture of the underlying hardware has an impact on the relative performance of different dictionary implementations. Here we give three important examples. First, boost_flat_map performs better than hash-based dictionaries on insertions for dictionary size of smaller than 100 elements in machine 2, but not in machine 1. Second, the successful lookup operator of map for ordered data is faster than all other dictionaries for dictionary size of smaller than 8000 elements in machine 2, but not in machine 1. Third, the unsuccessful lookup operator of robinhood_dict is consistently better than other dictionaries for every dictionary size in machine 1, but not in machine 2.

B REGRESSION MODELS

In this section, we investigate the space of possible regression models trained using scikit-learn. All of the models are trained based on all three methods explained in section 6.2: (1) Linear: linear regression. (2) Polynomial: degree-2 polynomial regression. (3) SVM: linear support-vector machine. (4) KNN: K-nearest neighbor (K = 4). (5) Decision Tree: regression decision tree of depth 5. (6) AdaBoost: AdaBoost [29] with 200 estimators. (7) Gradient Boost: gradient boosting with 200 estimators. (8) Random Forest: random forest with 200 estimators.

Figure 16 shows the relation between the predicted and actual running times for operations such as lookup and insert. Utilizing 32 models (with and without feature engineering) outperforms the All in One Model training method. Splitting the cost prediction task among several models and providing them simpler integral feature values (not one-hot encoded) makes the estimation easier. Therefore, such performance is expected.
Figure 15: Micro benchmark results for successful lookups in different dictionary data structures.

Figure 16: Comparison of the prediction of 8 different regression models trained under various methods with operation running times.

The KNN model training with logarithmic features performs the best among all these models. It uses as feature the logarithm of dictionary size which captures accurately the relationship between dictionary size and actual operation cost. For the same reason, POLYNOMIAL model which trained with similar method behaves better than LINEAR and POLYNOMIAL models W/o feature engineering. This may be unsurprising, as the expected cost is logarithmic in dictionary size for sort-based dictionaries. Yet the constant factors in the complexity are now captured more accurately by the model. Among the tree-based models, GRADIENT BOOST outperforms others and trained them using scikit-learn [62]