An Index Bucketing Framework to Support Data Manipulation and Extraction of Nested Data Structures

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Keywords: Nested Data Structures, Irregular Schema, Skewed Distribution, Information Loss, Duplication Explosion.

Abstract: Handling nested data collections in large-scale distributed data structures poses considerable challenges in query processing, often resulting in substantial costs and error susceptibility. These challenges are exacerbated in scenarios involving skewed, nested data with irregular inner data collections. Processing such data demands costly operations, leading to extensive data duplication and imposing challenges in ensuring balanced distribution across partitions—consequently impeding performance and scalability. This work introduces an index bucketing framework that amalgamates upfront computations with data manipulation techniques, specifically focusing on flattening procedures. The framework resembles principles from the bucket spreading strategy, a parallel hash join method that aims to mitigate adverse implications of data duplication and information loss, while effectively addressing both skewed and irregularly nested structures. The efficacy of the proposed framework is assessed through evaluations conducted on prominent question-answering datasets such as QuAC and NewsQA, comparing its performance against the Pandas Python API and recursive, iterative flattening implementations.

1 INTRODUCTION

The widespread rise in big data analytics has spurred interest in query processing systems that allow for performing complex analytical tasks over distributed data structures of arbitrary data types—including nested data collections. Implementations of languages integrated with query systems are evidenced in large-scale distributed data processing platforms (*Apache Flink. http://flink.apache.org/*; *Apache Spark, http://spark.apache.org/*; *Pandas Python, https://pandas.pydata.org/*). Despite their vaunted support of nested data, these systems provide no direct processing for nested data manipulation over different distributed collections, whose values may themselves be collections.

To stave off this penalty, declarative querying APIs have been employed for integrating data query languages with host programming languages' data processing features using higher-order operations—i.e., Google's F1 query (Samwel et al., 2018).

Apart from their intricate and computational challenges, unnesting and manipulating data collections inherently entail the generation of large amounts of duplicated data and redundant computations that significantly degrade the run-time performance of these techniques. These challenges are exacerbated for skewed nested data with irregular inner data collections – where loading unnecessarily large amounts of data to enforce balancing across partitions can lead to performance deficiency and error susceptibility (Diestelkämper et al., 2021; Smith, 2021).

To illustrate these challenges, consider the reading comprehension question-answering dataset. The dataset consists of questions where the answer to every question is a segment of text, or span, from the corresponding reading passage, or the question might be unanswerable with an indeterminant plausible answer (Fig. 1).

The dataset articulates a schema that can be structured within the following relational database tables: Sources (src), Questions (qst), Answers (ans), and Plausible Answers (pls). For the sake of clarity and brevity, the number of records within a table is denoted as *n*. Table 1 comprises source records featuring *id* and *context* fields. The *id* field encompasses incremental integers (INC), $i = 1, \ldots, n,$ while *context* (ctx) stores textual excerpts (STR), extracted from source document paragraphs. Table 2 incorporates *id*, *text* (txt), and *i* fields. The *id* field embodies incremental integers (INC), $j = 1, \ldots, n,$

Myers II, J. and Mowafi, Y.
An Index Bucketing Framework to Support Data Manipulation and Extraction of Nested Data Structures.
DOI: 10.5220/0012828800003838
Paper published under CC license (CC BY-NC-ND 4.0)
In *Proceedings of the 16th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2024) - Volume 1: KDIR*, pages 191-199
ISBN: 978-989-758-716-0; ISSN: 2184-3228
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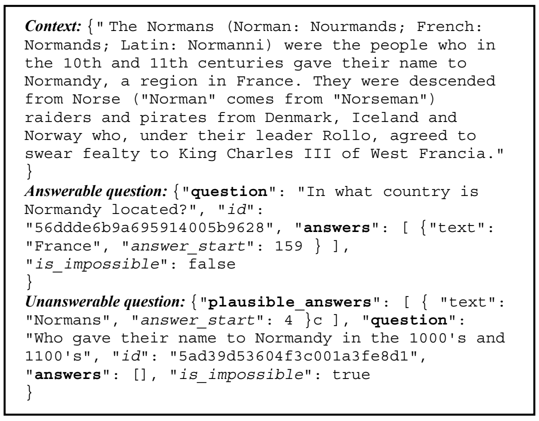

Context: {" The Normans (Norman: Nourmands; French: Normands; Latin: Normanni) were the people who in the 10th and 11th centuries gave their name to Normandy, a region in France. They were descended from Norse ("Norman" comes from "Norseman") raiders and pirates from Denmark, Iceland and Norway who, under their leader Rollo, agreed to swear fealty to King Charles III of West Francia."
}
Answerable question: {"**question**": "In what country is Normandy located?", "*id*": "56ddde6b9a695914005b9628", "**answers**": [{"text": "France", "*answer_start*": 159 }], "*is_impossible*": false
}
Unanswerable question: {"**plausible_answers**": [{ "text": "Normans", "*answer_start*": 4 }c], "**question**": "Who gave their name to Normandy in the 1000's and 1100's", "*id*": "5ad39d53604f3c001a3fe8d1", "**answers**": [], "*is_impossible*": true
}

Figure 1: Question-answering dataset structure of answerable and unanswerable plausible answers.

housing textual representations (STR) of questions. The *i* field functions as a foreign key (FK) referencing records in Table 1. Table 3 encompasses the *id*, answer *start* (srt), answer *end,* and *j* fields. The *id* field spans incremental integers (INC), *k = 1, …, n*, while *start* (srt) and *end* signify the index positions of answers within the context of the related resource dataset. The *j* field acts as a foreign key (FK) referring to records in Table 2. Table 4 accommodates plausible yet indeterminate answers to questions, acknowledging instances, where a definitive answer might be unattainable. Table 4 augments the dataset by mirroring fields akin to those in Table 3, with incremental integers (INC), *l = 1, …, n,* representing its incremental *id*. The *j* field acts as a foreign key (FK) referring to records in Table 2.

Table 1: Sources (src).

id (i)	Context (ctx)
INC	STR

Table 2: Questions (qst).

id (j)	text (txt)	i
INC	STR	FK

Table 3: Answers (ans).

id (k)	start (srt)	end	j
INC	INT	INT	FK

Table 4: Plausible Answers (pls).

id (l)	Start (srt)	end	j
INC	INT	INT	FK

These interconnected tables establish a nested relationship structure, delineating diverse data distribution patterns, while exemplifying irregular schema through the inclusion of Table 4. To further visualize the nested data structure portrayed by the relational Tables 1, 2, 3, and 4, consider the tree representations in Fig. 2 of an *irregular* nested structure with a given source (src), *i* of a *context* (ctx), and *j* questions (qst). A given question (qst), *j* of a *text* (txt) may have *k* answers (ans) or *l* plausible answers (pls) or both, where each answer (ans), *k* or plausible answer (pls), *l* has a *start* (srt) and *end*.

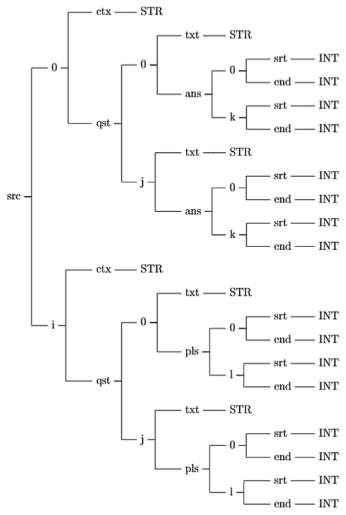

Figure 2: Irregular question answering nested structure.

With the tree-based representations, it becomes evident that sources might lack associated questions, and questions might encompass answers, plausible answers, both, or neither. This variability extends to the varying counts of answers and plausible answers within each question, along with fluctuations in the number of questions within each source. Such variability typifies an irregular nested structure marked by skewed data distribution. Next, we present the challenges associated with manipulating and information extraction of these nested data structures.

2 CHALLENGES

2.1 Duplication Explosion

Duplication explosion is a phenomenon characterized by an overwhelming proliferation of duplicated data during the flattening process. As the term implies, this explosion also known as a data avalanche or data storm results in an excessive replication of data, aka N + 1 query problems or avalanches (Grust et al., 2010). This often leads to severe memory utilization issues and potential system failures, especially when handling extensive datasets. Current flattening solutions, primarily relying on recursion, fail to mitigate the adverse effects of this rampant data duplication.

2.2 Skewed Distribution

Another hurdle to overcome in nested data collections is unbalanced distributions of information. When flattening such data, ensuring that each flattened instance contains all requisite keys introduces a problem akin to duplication explosion. However, in this case, missing keys necessitate filling with null values, requiring comprehensive parsing of the dataset to gather all keys. The challenge lies in distributing these missing keys throughout the flattened data. Strategies may involve parsing before flattening, allowing simultaneous filling, or conducting a secondary traversal after flattening, although the former, while superior, present implementation complexities (Smith et al., 2020).

2.3 Irregular Schema

Here, disparate data collections within the dataset may contain entirely different keys at the same nesting level, significantly complicating parsing and filling algorithms. Akin to skewed distribution, solving irregular schema involves filling in missing keys throughout the dataset. However, it presents an even more intricate challenge, where the endeavor to enforce balance across partitions escalates runtime inefficiencies and scalability limitations, exacerbating disk spillage and load imbalance issues (Smith et al., 2021).

2.4 Information Loss

The final challenge, information loss, poses some concern, describing the repercussions of processing nested data structures. The flattened data loses crucial information required for reconstructing the original nested form. Without incorporating metadata into the flattened dataset, reconstructing the initial hierarchical structure becomes unfeasible (Diestelkämper, 2021). Reverting to the original data necessitates reloading the data file or maintaining a copy of the original data, which could be time-consuming and can proliferate memory utilization problems, especially with large datasets.

To address these challenges, we propose a novel framework, which we refer to as index bucketing. The basis of our framework resembles principles from the bucket spreading strategy, a parallel hash join method that allows for handling irregular data distribution for relational database systems by utilizing bucketing mechanisms. The strategy aims to evenly distribute the load among processes, always fully exploiting (Kitsuregawa & Ogawa, 1990). Index bucketing draws on applying these principles to a tree-based nesting by mapping the data indexes corresponding to their respective hierarchical structure within the original data.

3 FRAMEWORK

This section delineates a concise implementation of the index bucketing framework provided by the following algorithmic classes (Algorithms 1, 2, 3, 4, 5, 6). The framework is designed to address the aforementioned challenges, accentuating the framework's prowess in surmounting the diverse challenges encountered in nested data structure manipulation.

3.1 Base Node – Algorithm 1

As a foundational base class, the NODE class serves as the common blueprint inherited by the LEAF, BRANCH, and ROOT classes within the index bucketing framework. The NODE class lays out the essential structural elements shared across all inheriting classes:

- NODE – This is the shared base constructor for all inheriting node classes and is responsible for setting the shared node attributes – *kdx*, *value*, *level*, and *parent*. The *kdx* attribute is a key or index value used for gathering index and key paths. The *value* attribute contains a collection of child NODE types or serves as a BASE value type for leaves. The *level* attribute is used to determine the depth of the node within the tree. The *parent* attribute is used to establish a link to the node's parent node.
- IBUCKET – By collecting a set of index paths, each aligning with the maximum *depth* of the nested data tree, this method is responsible for gathering the index bucket.

Algorithm 1: Node Class.

```
class NODE
    function NODE(kdx, value, level, parent)
        this.kdx ← kdx
        this.value ← value
        this.level ← level
        this.parent ← parent
    function IPATH
        return this.parent.IPATH()
    function KPATH
        return this.parent.KPATH()
    function IBUCKET(depth)
        ibucket ← SET[IPATH]()
        for all child ∈ this.value do
            ibucket.UPDATE(child.IBUCKET(depth))
        return ARR(ibucket).SORT()
    function FLATTEN(ipath)
```

This standardized class structure established by the NODE class ensures coherence and consistency in defining and organizing nodes across the index bucketing framework.

3.2 Leaf Node – Algorithm 2

Within the framework, the LEAF class, along with its inheriting classes – INDEXEDLEAF and KEYEDLEAF –

fulfill the role of nodes encapsulating the terminus of nested data structures. These classes define essential functionalities pivotal to handling leaf nodes within the index bucketing framework:

- LEAF – Rather than directly receiving the level parameter argument, the LEAF constructor derives its level value from the parent node, ensuring hierarchical consistency within the tree structure.
- IBUCKET – This method accepts the maximum depth value of the tree as a parameter argument. It validates whether the depth value matches its level, subsequently returning its index path enclosed in an index bucket set object if true; otherwise, an empty index bucket set object is returned. Employing a bottom-to-top algorithm, this method is invoked by non-leaf nodes to update and collate their child leaf node value fields into a set collection.
- FLATTEN – Disregarding the index path parameter argument, *ipath*, when invoked by the leaf nodes corresponding parent, this method returns a new mapping of the leaf node's key path and *value*, adhering to a top-to-bottom calling sequence and resulting in a bottom-to-top return sequence.
- IPATH & KPATH – Defined in the INDEXEDLEAF and KEYEDLEAF classes which serve to differentiate leaves based on their indexing nature: indexed with integers or keyed with strings during tree initialization, these class methods manage bottom-to-top index paths or key paths by integrating the leaf node's *kdx* field along with its parent's index or key path, respectively. In cases where index paths are gathered, the leaf node converts arrays of index values into tuples of the same size.

Algorithm 2: Leaf Classes.

```
class LEAF inherits Node
    function LEAF(kdx, value, parent)
        SUPER(kdx, value, parent.level, parent)
    function IBUCKET(depth)
        ibucket ← SET[IPATH]()
        if this.level = depth then
            return ibucket.ADD(this.IPATH())
        else return ibucket
    function FLATTEN(ipath)
        return MAP(this.KPATH(), this.value)
class INDEXEDLEAF inherits Leaf
    function IPATH
        ipath ← this.parent.IPATH()
        return TUP[INT](ipath.APPEND(this.kdx))
    function KPATH
        return STR(".").JOIN(this.parent.KPATH())
class KEYEDLEAF inherits Leaf
    function IPATH
        return TUP[INT](this.parent.IPATH())
    function KPATH
        kpath ← this.parent.KPATH()
        return STR(".").JOIN(kpath.APPEND(this.kdx))
```

By segregating leaves between indexed and keyed types during tree initialization, the classes circumvent the need for conditional evaluations. This strategic segregation bolsters performance and scalability, especially in managing larger datasets.

3.3 Branch Node – Algorithm 3

The BRANCH class integrates into various specialized nodes, including I2B, KIB, IKB, and K2B which are defined by inheriting combinations of INDEXED and KEYED classes with INDEXINGBRANCH and KEYINGBRANCH classes.

- INDEXED – The INDEXED class encapsulates nodes indexed with integers, defining the IPATH method to append the current node's index value to the parent's index path.
- KEYED – The KEYED class represents nodes keyed with strings, providing the KPATH method to append the node's key value to the parent's key path.
- INDEXINGBRANCH – The INDEXINGBRANCH class inherits from BRANCH, designed for indexed branches. Its constructor sets attributes based on the provided values and parent node, and the FLATTEN method retrieves the corresponding child node based on the index path.
- KEYINGBRANCH – The KEYINGBRANCH class, also extending BRANCH, targets keyed branches. Its constructor initializes attributes, and the FLATTEN method iterates through child nodes, updating a map with their flattened results.
- I2B – The I2B class combines INDEXED and INDEXINGBRANCH functionalities.
- KIB – The KIB class combines KEYED and INDEXINGBRANCH functionalities.
- IKB – The IKB class combines INDEXED and KEYINGBRANCH functionalities.
- K2B – The K2B class combines KEYED and KEYINGBRANCH functionalities.

Algorithm 3: Branch Classes.

```
class INDEXED
    function IPATH
        return this.parent.IPATH().APPEND(this.kdx)
class KEYED
    function KPATH
        return this.parent.KPATH().APPEND(this.kdx)
class BRANCH inherits Node
class INDEXINGBRANCH inherits Branch
    function INDEXINGBRANCH(kdx, value, parent)
        SUPER(kdx, value, parent.level + 1, parent)
    function FLATTEN(ipath)
        idx ← ipath.AT(this.level)
        if idx ∈ this.value.KEYS() then
            child ← this.value.GET(idx)
            return child.FLATTEN(ipath)
        else return MAP()
class KEYINGBRANCH inherits Branch
    function KEYINGBRANCH(kdx, value, parent)
        SUPER(kdx, value, parent.level, parent)
    function FLATTEN(ipath)
        flat ← MAP()
        for all child ∈ this.value do
            flat.UPDATE(child.FLATTEN(ipath))
        return flat
class I2B inherits Indexed, IndexingBranch
class KIB inherits Keyed, IndexingBranch
class IKB inherits Indexed, KeyingBranch
class K2B inherits Keyed, KeyingBranch
```

These specialized branch classes cater to different scenarios, providing distinct methods for handling various types of nested data collections. Each class offers unique functionalities for efficient execution, minimizing conditional evaluations during execution.

3.4 Root Node – Algorithm 4

The Root class, and its inheriting classes, mark the starting point of top-to-bottom processes and the conclusion of bottom-to-top processes within the index bucketing framework.

- ROOT – Inheriting from the Node class, the base Root class undergoes constructor modification, accepting solely *value* and *level* parameters. Root nodes lack *kdx* or *parent* attributes. Consequently, both the IPATH and KPATH methods return new empty arrays. Notably, the FLATTEN method's signature undergoes modification, now accepting the index bucket, *ibucket*, and flat *template* as parameters, and returning an array of flat mappings rather than a single mapping as seen in prior class definitions.
- INDEXINGROOT – This class inherits the base ROOT class, but its constructor configures the root node's level to 0 during instantiation, aligning its child node calling behavior with that of INDEXINGBRANCH nodes. Its FLATTEN method iterates over the index bucket, IBUCKET, dispatching each index path to the appropriate child nodes for further processing. An array of flat mappings, each of which is applied to a copy of the flat template, is gathered from the child nodes and is returned.
- KEYINGROOT – Also inheriting from the base ROOT class, the KEYINGROOT class sets its level to -1 within the constructor since its child-calling behavior does not utilize the indexes from the index bucket. Its FLATTEN method operates by passing index paths, IPATH, from the index bucket, IBUCKET, to its child nodes for further processing. Likewise, an array of flat mappings, each of which is applied to a copy of the flat *template*, is gathered from the child nodes and is returned.

By distinguishing between KEYINGROOT and INDEXINGROOT nodes, the tree's root node ensures that subsequent *level* attributes are set appropriately during initialization and the index bucket is distributed accordingly during execution.

Algorithm 4: Root Classes.

```
class ROOT inherits Node
    function ROOT(value, level)
        SUPER(null, value, level, null)
    function IPATH
        return ARR()
    function KPATH
        return ARR()
    function FLATTEN(ibucket, template)
class INDEXINGROOT inherits Root
    function INDEXINGROOT(value)
        SUPER(value, 0)
    function FLATTEN(ibucket, template)
        flats ← ARR[MAP]()
        for all ipath ∈ ibucket do
            flat ← template.COPY()
            idx ← ipath.AT(this.level)
            child ← this.value.GET(idx)
            flat.UPDATE(child.FLATTEN(ipath))
            flats.APPEND(flat)
        return flats
class KEYINGROOT inherits Root
    function KEYINGROOT(value)
        SUPER(value, -1)
    function FLATTEN(ibucket, template)
        flats ← ARR[MAP]()
        for all ipath ∈ ibucket do
            flat ← template.COPY()
            for all child ∈ this.value do
                flat.UPDATE(child.FLATTEN(ipath))
            flats.APPEND(flat)
        return flats
```

3.5 Tree Structure – Algorithm 5

The Tree class serves as the foundational structure to organize the nested dataset for the execution of the index bucketing algorithm. In the constructor, the initialization commences by setting the depth field to 0 and creating an empty set object for the key bucket, kbucket. These fields are then used to analyze the data parameter's nested structure while the tree itself is constructed and stored within the tree field which acts as a reference to the root node. Next, the algorithm gathers the index bucket, ibucket. Additionally, it constructs the template by iterating through the key bucket, compiling all key paths into a mapping with initial null values for each key path. This flat template formation streamlines the subsequent data organization process.

- FLATTEN – To facilitate the flattening process, the Tree class defines its own FLATTEN method. This method initiates the root node's FLATTEN method, passing along the index bucket and flat template.
- LEAF – The LEAF method initializes and returns the relevant LEAF class node. Additionally, the LEAF method identifies the maximum depth of the tree and aggregates key paths into the key bucket.
- BRANCH – The BRANCH method initializes and returns the relevant BRANCH class node. If the collection passed as *data* is empty, then the BRANCH method delegates the parameter arguments to the LEAF method with null passed for the *data* parameter's argument. Otherwise, respective to the nested data types, the BRANCH method directs nested information to either another BRANCH method call or a LEAF method call.

- ROOT – The ROOT method initializes and returns the relevant ROOT class node. The ROOT method returns null when the *data* parameter is an empty collection, indicating that no data is present. Otherwise, respective to the nested data types, the ROOT method directs nested information to either BRANCH method call or a LEAF method call.

Algorithm 5: Tree Class.

```
class TREE
    function TREE(data)
        this.depth ← 0
        this.kbucket ← SET()
        this.tree ← this.ROOT(data)
        this.ibucket ← this.tree.IBUCKET(this.depth)
        this.template ← MAP()
        for all kpath ∈ this.kbucket do
            this.template.UPDATE(MAP(kpath, null))
    function FLATTEN
        return this.tree.FLATTEN(this.ibucket, this.template)
    function LEAF(kdx, data, parent)
        if TYPE(kdx) = INT then
            leaf ← INDEXEDLEAF(kdx, data, parent)
        else leaf ← KEYEDLEAF(kdx, data, parent)
        this.depth ← MAX(this.depth, leaf.level)
        this.kbucket.ADD(leaf.KPATH())
        return leaf
    function BRANCH(kdx, data, parent)
        if LENGTH(data) ≤ 0 then
            return this.LEAF(kdx, null, parent)
        if TYPE(data) '= MAP then
            data ← ENUMERATE(data)
            if TYPE(kdx) = STR then
                branch ← KIB(kdx, MAP(), parent)
            else branch ← I2B(kdx, MAP(), parent)
        else if TYPE(kdx) = STR then
            branch ← K2B(kdx, MAP(), parent)
        else branch ← IKB(kdx, MAP(), parent)
        for all kdx, value ∈ data.ITEMS() do
            if TYPE(value) = ITER then
                node ← this.BRANCH(kdx, value, branch)
            else node ← this.LEAF(kdx, value, branch)
            branch.value.UPDATE(kdx, node)
        return branch
    function ROOT(data)
        if LENGTH(data) ≤ 0 then
            return null
        if TYPE(data) '= MAP then
            data ← ENUMERATE(data)
            root ← INDEXINGROOT(MAP())
        else root ← KEYINGROOT(MAP())
        for all kdx, value ∈ data.ITEMS() do
            if TYPE(value) = ITER then
                node ← this.BRANCH(kdx, value, branch)
            else node ← this.LEAF(kdx, value, branch)
            root.value.UPDATE(kdx, node)
        return root
```

3.6 Generator Alternative – Algorithm 6

To allow for the implementation flexibility of the index bucketing algorithm, ROOT and TREE class definitions are modified to transform the framework into a generator capable of delivering flattened data *incrementally* rather than in a single instance.

Instead of the ROOT node managing the index bucket within its FLATTEN method, this responsibility is shifted to the TREE class's FLATTEN method. Introducing a *count* field, initialized at 0, enables the tracking of index bucket progress. When the *count* reaches the end of the index bucket, it is reset to 0, and null is returned to signal completion. This generator-style implementation offers a controllable method to alleviate the adverse effects of duplication explosion which can otherwise overload memory usage. The adaptability of index bucketing as an algorithm allows for diverse implementations, offering various advantages to address challenges that stem from other recursion-intensive approaches.

Algorithm 6: Generator Implementation.

```
class INDEXINGROOT inherits Root
    function FLATTEN(ipath, template)
        idx ← ipath.AT(this.level)
        child ← this.value.GET(idx)
        flat ← template.COPY()
        flat.UPDATE(child.FLATTEN(ipath))
        return flat
class KEYINGROOT inherits Root
    function FLATTEN(ipath, template)
        flat ← template.COPY()
        for all child ∈ this.value do
            flat.UPDATE(child.FLATTEN(ipath))
        return flat
class TREE
    function TREE(kdx, data)
        this.count ← 0
        this.depth ← 0
        this.kbucket ← SET()
        this.tree ← this.ROOT(kdx, data)
        this.ibucket ← this.tree.IBUCKET(this.depth)
        this.template ← MAP()
        for all kpath ∈ this.kbucket do
            this.template.UPDATE(MAP(kpath, null))
    function FLATTEN
        if this.count ≥ LENGTH(this.ibucket) then
            this.count ← 0
            return null
        ipath ← this.ibucket.AT(this.count)
        this.count ← this.count + 1
        return this.tree.FLATTEN(ipath, this.template)
```

4 EVALUATION

To assess the efficacy of the index bucketing algorithm, we evaluate the performance measurements across two prominent question-answering datasets: QuAC (*QuAC, Question Answering in Context. https://quac.ai/*) and NewsQA (*NewsQA: A Machine Comprehension Dataset. https://www.microsoft.com/en-us/research/publication/newsqa-machine-comprehension-dataset/*). These datasets vary in file size: 74 MB and 151 MB respectively. Both datasets come with a myriad of restructuring challenges described below.

- QuAC dataset requires that the background attribute be prepended to each paragraph's context attribute, and data with "CANNOTANSWER" questions and questions without answers need to be filtered out (Fig. 3).

```
{"text": "Miami ... contributed to this report.",

"type": "train",
 "questions": [{
 "isQuestionBad": 0.0,
 "consensus": {
 "s": 15,
 "e": 32
 },
 "validatedAnswers": [{
 "count": 2,
 "s": 15,
 "e": 32
 }],
 "answers": [{
 "sourcerAnswers": [{
 "s": 15,
 "e": 32
 }]
 }],
 "q": "Who reportedly suffers a seizure?",
 "isAnswerAbsent": 0.0
 }],
 "storyId":
"./cnn/stories/6ebb8ab29b94430fa68f0e256c7703d9a41
f8bff.story"}…
```

Figure 3: QuAC question answering dataset structure.

- NewsQA dataset requires data extraction from start and end attributes, into a new answer attribute containing the indicated substring found in the text context, and data with "isQuestionBad" questions ne ed to be filtered out (Fig. 4).

```
{"text": "Miami ... contributed to this report.",
 "type": "train",
 "questions": [{
 "isQuestionBad": 0.0,
 "consensus": {
 "s": 15,
 "e": 32
 },
 "validatedAnswers": [{
 "count": 2,
 "s": 15,
 "e": 32
 }],
 "answers": [{
 "sourcerAnswers": [{
 "s": 15,
 "e": 32
 }]
 }],
 "q": "Who reportedly suffers a seizure?",
 "isAnswerAbsent": 0.0
 }],
 "storyId":
"./cnn/stories/6ebb8ab29b94430fa68f0e256c7703d9a41
f8bff.story"}…
```

Figure 4: NewsQA question answering dataset structure.

The index bucketing algorithm was juxtaposed against two alternative flattening implementations: one leveraging the Pandas Python API and another employing a basic solution that combines recursive and iterative techniques. Summarized in 0, Pandas Python is used as a benchmark for comparison, as it offers a competitive set of methods to flatten nested data collections, such as filling missing values, normalizing dictionaries into new columns, and exploding lists into new records. The basic implementation, on the other hand, serves to demonstrate the worst-case effects of each challenge. Evaluations span various subsets of each dataset incrementally from a Fibonacci-based sequence in the range of 0.1% to 100% to gauge scalability. Each subset underwent evaluations of the observed total time of initialization and execution runtimes. The average runtimes across the evaluations were recorded to ensure more robust assessments.

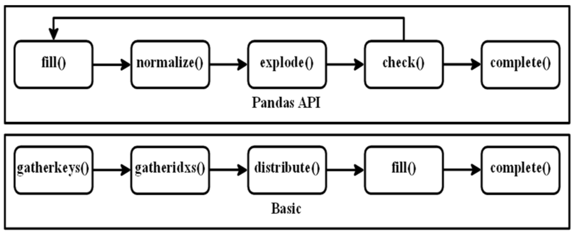

Figure 5: Pandas Python implementation & basic execution pipelines.

The ensuing graphs are organized by implementation and dataset, plotting subset size, measured in bytes, against runtime, measured in seconds. These evaluations were conducted on an Intel Core i7-8750H CPU, 32 GB RAM PC, clocking in at a base frequency of 2.20 GHz, and capable of reaching a maximum turbo frequency of 4.10 GHz. A stringent maximum time limit of thirty minutes was set to avoid prolonged executions, triggering a timeout exception if exceeded. Notably, the basic algorithm showcases an exponential growth pattern in total runtimes, vividly illustrating the cost escalations attributed to challenges that the index bucketing algorithm aims to address. Compared to Pandas Python implementation, our index bucketing framework shows a 24.7% faster total runtime with the QuAC dataset evaluations (0). With the NewsQA larger dataset, the Pandas Python encounters failures, which we suspect are attributed to duplicated data instances within the original dataset. While Pandas Python offers potential solutions to address these errors, implementing such remedies remains nontrivial to the best of our knowledge.

By preserving the original dataset structure, index bucketing eliminates the need for dataset reacquisition during subsequent executions. For instance, considering a scenario where the flattening process is repeated 100 times for each implementation, the index bucketing showcases substantial performance superiority. Although multiple iterations of flattening might not align with typical real-world scenarios, this comparison

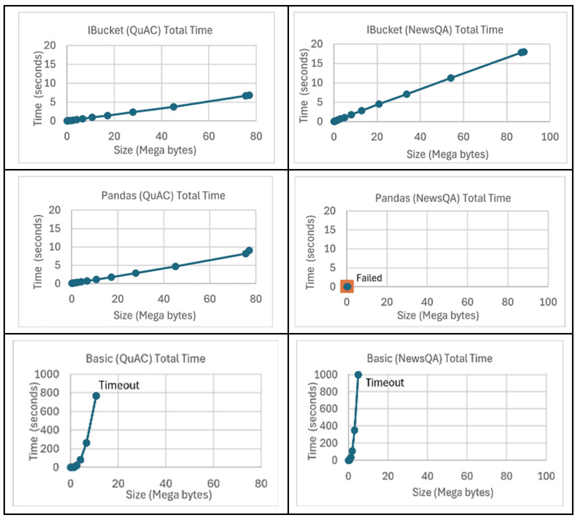

Figure 6: Total runtime evaluation.

demonstrates the index bucketing's efficiency in executing additional feature implementations beyond flattening. Tasks like conditional filtering or attribute selection can be executed notably more efficiently with index bucketing compared to other implementations. The performance results exemplify the enduring advantages of the index bucketing approach in handling repetitive operations and processing complex tasks.

5 RELATED WORK

We have discussed nearly related work on employing declarative querying APIs for integrating data query languages with host programming languages' data processing. Transforming nested queries into efficient forms using set-oriented operators has been investigated for decades in different contexts (Agrawal, 1988; Suciu, 1996). Work presented by (Ulrich, 2019) offers a review of query flattening and descriptions of query flattening in database theory. Obtaining flat outputs in the presence of collection queries was extended to multiset collections via normalization and conservative algorithms (Fegaras & Maier, 2000; Van den Bussche, 2001). Several applications of nested data models build on this calculus (Fegaras & Noor, 2018; Ricciotti & Cheney, 2021).

Another closely related work proposes a framework that translates nested collection queries into a semantically equivalent sequence of queries, where outputs may then be nested and efficiently evaluated (Smith et al., 2021). The framework flattens nested queries by utilizing a series of preprocessing and post-processing algorithms referred to as query shredding and query stitching. This has exhibited effectiveness in addressing information loss, duplication explosion, and irregular schema within the confines of traditional relational database environments.

For resiliency against skewed distribution in query processing, (Rödiger et al., 2016)introduce a distributed join algorithm that detects skewness for relational data by using small approximate histograms and adapting the redistribution scheme to resolve load imbalances. Nonetheless, alleviating performance inefficiencies of flattening nested collections with skew problems remains an open question in the context of query processing (Smith et al., 2020). Our framework addresses the aforementioned challenges which also arise when manipulating these large nested data structures, and has shown the potential to extend its scope to the realm of query processing.

6 CONCLUSIONS

We introduce a novel framework, index bucketing, that aims to address the irregular schema, skewed distribution, information loss, and duplication explosion challenges in the manipulation of nested data structures. Our contributions can be summarized as the following. Employing proactive processes, computational overheads that impede performance are effectively offloaded during initialization, hence enabling a controllable solution for data duplication (Challenge *A*). Addressing skewed data distribution (Challenge *B*) before manipulating the nested structure. This is achieved by aggregating index paths into an index bucket, a mechanism facilitating efficient indexed-hashing access for nested data and ultimately producing flattened records. Addressing irregular schema (Challenge *C*) in the initialization process that includes constructing a flat template—a critical step ensuring every flattened record encompasses all absent keys filled with null values. The architecture of index bucketing, rooted in a platform-independent, tree-based algorithmic structure, aligns seamlessly with the original nested data, preserving its inherent structure and circumventing potential information loss (Challenge *D*). The work explores an intuitive framework for mitigating these challenges assessed on prominent question-answering datasets such as NewsQA and QuAC. Performance is compared against a competitive Pandas Python API implementation and a basic recursive, iterative implementation. Index bucketing compares favorably against these alternatives, exemplifying the enduring advantages of the ability of the framework algorithm to handle repetitive operations and process complex nested data structures. Comparing the performance of index bucketing against larger datasets is a limitation of this study. More insights can be gleaned from further evaluations expanding to other datasets and implementations. Future work will, in part, explore the implications of index bucketing to handle repetitive operations and process complex nested data structures.

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