Capturing and Querying Structural Provenance in Spark with Pebble

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ABSTRACT

Analyzing and debugging Spark processing pipelines is a tedious task which typically involves a lot of engineering effort. The task becomes even more complex when the pipelines process nested data. Provenance solutions that track the derivation process of individual data items assist data engineers while debugging these pipelines. However, state-of-the-art solutions do not precisely track nested data items.

We demonstrate Pebble, a system for capturing and querying a new type of provenance on nested data in Spark called structural provenance. It captures access and modification of top-level as well as nested data items, and allows querying the provenance of nested items based on tree-pattern-matching. Implemented as a standalone library on top of Apache Spark, it seamlessly leverages the underlying infrastructure for scalability. Through the graphical user interface implemented in a Jupyter notebook we showcase ten debugging scenarios of Spark programs on real-world datasets.

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1 INTRODUCTION

Big Data analytics systems such as Apache Hadoop, Flink, and Spark have built-in support for processing nested data sources such as JSON, Protocol Buffers, and XML files. That is

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Figure 1: Screenshot of Pebble in a Jupyter notebook

why data engineers frequently choose these systems to process nested data in complex pipelines. However, analyzing and debugging these pipelines is tedious.

We demonstrate Pebble that supports data engineers in analyzing and debugging pipelines in Apache Spark. Pebble implements a novel type of provenance called structural provenance. In general, provenance describes the derivation process of data items [4] all the way from the source data to the result data. In addition to tracing the data itself, structural provenance also traces the access and structural manipulations of nested data items. Pebble collects structural provenance during Spark program execution and offers tree-patterns to query the collected provenance. These allow data engineers to precisely reference nested items and to put them into relation. Pebble implements a novel, scalable tree-pattern-matching (TPM) algorithm to match the tree-patterns on the data. To provide an interactive debugging experience, Pebble provides visual representations of the tree-patterns, the matching data, and operators.

Figure 1 shows a screenshot of Pebble, integrated in a Jupyter notebook. Colors highlight different components, which are subsequently discussed in more detail in this paper and the video (<https://youtu.be/YUSEyCKqCk>). Overall, Pebble implements the following research contributions and, to the best of our knowledge, demonstrates, for the first time, scalable provenance capture and querying for nested data.

Structural provenance capture. Pebble captures structural provenance for nested data items. Structural provenance records the access and manipulation of each potentially nested data item during processing. In the context of big data analytics, it is the first provenance approach that explicitly distinguishes between the access of a data item,

e.g., filtering of a value, and the manipulation of a data item, e.g., unnesting of a nested collection, or the re-assignment of a value. This is required to precisely and efficiently resolve data dependencies of nested items.

Tree-pattern-matching query. Existing Big Data analytics solutions provide no means to query individual nested data items. In order to address individual items or hand-picked combinations of them, Pebble implements tree-patterns and tree-pattern-matching [8] on top of Spark. To the best of our knowledge, it is the first solution to provide a distributed and scalable tree-pattern-matching solution.

Interactive exploration. In order to deliver an interactive exploration and debugging experience, Pebble is integrated in a Jupyter Notebook. It provides provenance views for programs, operators, and dataframes, which precisely visualize attributes relevant to a scenario under observation.

Related work. To put the above contributions in perspective to existing provenance solutions for Big Data analytics systems like Spark, we briefly review related work. Titian [6], Newt [7], and RAMP [5] only provide data provenance of flat data items. In contrast, Pebble provides structural provenance that suits both flat and nested data items. The only provenance solution supporting nested data items is Lipstick [1], which is only capable of tracing data values. In contrast, Pebble traces data values and data structures and offers a scalable solution by not relying on an in-memory provenance graph. In addition, Pebble is the only solution that offers a systematic, tree-pattern-based approach to query provenance based on items structure, e.g., the nesting order of attributes or the amount of nested lists.

Structure. Section 2 walks through an example debugging session to show Pebble’s features. In Section 3, we show how Pebble’s architecture transparently integrates in Spark. Section 4 covers the audience experience.

2 EXAMPLE SCENARIO

Let us consider a use case on Twitter data. An excerpt of the data, used as input in our example, is shown in Table 1. Our program groups tweets by distinct users, considering both tweets that users authored and tweets they were mentioned in (Figure 2). The result is shown in Table 2. We observe that the text *Hello World* occurs twice in the nested list of user *Lisa Paul*. To find the cause for the duplicate, we debug the program in a Pebble-enabled Jupyter Notebook.

Capture. To capture structural provenance, we simply replace Spark’s read method with Pebble’s Provenance.readJson(...) method (Figure 2, l. 1). It triggers Pebble to associate a unique identifier to each processed top-level data item. Pebble also records which attributes an operator accesses and how an operator modifies an input item to contribute to the output. When processing

	text	user		user_mentions	
		id_str	name	id_str	name
1	Hello @ls @jm @ls	lp	Lisa Paul	ls	Lauren Smith
				jm	John Miller
				ls	Lauren Smith
2	Hello World!	lp	Lisa Paul		
3	Hello World!	lp	Lisa Paul		
4	Hello @lp	jm	John Miller	lp	Lisa Paul

Table 1: Example input data

	user		tweets
	id_str	name	text
11	ls	Lauren Smith	Hello @ls @jm @ls
			Hello @ls @jm @ls
12	lp	Lisa Paul	Hello @ls @jm @ls
			Hello World
			Hello World
			Hello @lp
13	jm	John Miller	Hello @ls @jm @ls
			Hello @lp

Table 2: Example result data

nested collections, Pebble further keeps track of positions within the list, e.g., when the program flattens the nested *user_mentions* collection (Figure 2, l. 2). These recordings are based on inference rules defining the structural provenance. Similarly to [3], they extend operator semantics of the nested relational calculus.

Querying. Once Pebble has computed the program result – and the provenance behind the scenes – it can support data engineers in expressing their information need to explain the previously mentioned duplicate in form of a tree-pattern. Indeed, Spark does not provide built-in means to address individual items in nested collections.

A tree-pattern consists of nodes representing attributes in the schema and edges representing relationships between them [8]. Edges represent parent-child (PC) or ancestor-descendant (AD) relationships. The relationships impose structural constraints over the schema, because the tree-pattern only matches the result if all PC and AD relationships are satisfied. In addition, we may also associate nodes with value and cardinality constraints. Value constraints are satisfied if the value in the data matches the value associated with a tree-pattern node. Cardinality constraints define how many matching descendant nodes must be in the data. They are only applicable on nodes that match nested collections.

In our example, we define the tree-pattern visualized in Figure 3. It references the attribute *text* that has to be a descendant of the *tweets* attribute to satisfy the structural constraints. Further, it must have the value *Hello World* to satisfy the value constraint and it must occur twice to satisfy the cardinality constraint of the *tweets* node. Pebble’s scalable tree-pattern matching algorithm matches this tree-pattern to the dark-grey items in Table 2.

```

1 val tweets = Provenance.readJson(pathToDemoData, spark)
2 var mentioned = tweets.withColumn("mentioned_user", explode($"user_mentions"))
3 val extractedUsersMentioned = mentioned.select($"text", $"mentioned_user.id_str", $"mentioned_user.name")
4 val extractedUsers = tweets.select($"text", $"user.id_str", $"user.name")
5 val allUsers = extractedUsers.union(extractedUsersMentioned)
6 val restructuredUsers = allUsers.select(struct($"id_str", $"name").alias("user"), struct($"text").alias("tweet"))
7 val usersTweets = restructuredUsers.groupBy($"user").agg(collect_list($"tweet").alias("tweets"))

```

Figure 2: Example program that collects all tweets of an authoring or mentioned user in a nested collection

Figure 3: Tree-pattern that matches the dark-grey items in Table 2

```

[usersTweets]
|
5: GroupBy/Agg [1]
|
4: Project [2]
|
3: Union [2]
|
+---+
| 2: Project [0]
| |
| 1: Flatten [0]
| |
| [tweets] [0]
|
0: Project [2]
|
[tweets] [2]

```

Figure 4: Operator provenance graph

Operator

Type: GroupBy / Aggregation

Attributes Accessed:

1) user.id_str
2) user.name

Attributes Manipulated:

1) tweet.text ==> tweets.element[pos].text

Output (1 of 1 items displayed)

```

[34359738368] { user: { id_str: "lp", name: "Lisa Paul", tweets: { [...], [1]
  { text: "Hello World", [2] { text: "Hello World", ... } } } }

```

Input (2 of 2 items displayed)

```

[25769803776] { user: { id_str: "lp", name: "Lisa Paul", tweet: { text: "Hello World" } }
[25769803778] { user: { id_str: "lp", name: "Lisa Paul", tweet: { text: "Hello World" } }

```

Figure 5: Operator details for groupby and aggregation

Backtracing. As entry point to the backtracing, Pebble provides a `Provenance.structuralBacktrace(...)` method for matching the tree-pattern on the result and tracing the matched items back to the input. After backtracing, Pebble yields the dark-grey items in the input Table 1. They explain how the queried duplicate was obtained: *Lisa Paul* has tweeted *Hello World* twice.

Comparison to data provenance. In comparison, data provenance solutions, such as Titian [6], trace back the entire light-grey item of the result (Table 2) to the four light-grey items of the input (Table 1). Imagine *Lisa* has tweeted another hundreds of texts and got mentioned in few thousand tweets more. All these tweets would have contributed to the provenance of the light-grey result item. Further notice that the

data provenance consists of entire tweets. In our real world dataset these have roughly 1000 attributes. Consequently, existing data provenance solutions would overwhelm the data engineer with “imprecise” data provenance, consisting of a large number of wide data items. Note that in contrast, where-provenance [2] (a different kind of data provenance than the data provenance supported by data analysis systems) would return too little information to explain the duplicate. Details are omitted due to space constraints. Opposed to existing solutions, Pebble allows to precisely pinpoint nested source data items by leveraging structural provenance.

Provenance graph. To further improve the debugging experience in the Jupyter Notebook, Pebble offers a compact summary of the provenance, called provenance graph. Figure 4 shows the provenance graph of our running example. It consists of the program’s operator tree annotated with the number of top-level items traced back to the input (in square brackets). In our example, the graph reveals that no item went through the flatten operator. Consequently, no tweet that mentions *Lisa Paul* contributed to the result.

Detail views. Investigating the input data and the provenance graph may not be sufficient to identify unintended data manipulations. For that purpose, Pebble offers a detail view for each operator. Figure 5 shows the operator details of the *groupby* and *aggregation* operation. It reveals that the nested *user* attributes are accessed, but not manipulated unlike the *tweets.text* attribute. It becomes member of the nested *tweets* collection and gets a unique *position*. Thereby, Pebble can precisely track just the colored *text* items in Figure 5.

In conclusion, Pebble’s structural provenance implementation allows to precisely track and query nested data items in Spark programs for debugging purposes.

3 PEBBLE’S ARCHITECTURE

Pebble extends Apache Spark to provide the functionality described in Section 2. It also provides an HTML printer to generate output in the web-based notebooks. In Figure 6, we show Pebble’s modules (blue) on top of Spark (black), embedded in an Apache Toree kernel that runs in a Jupyter Notebook (grey). In the following, we sketch the modules’ internals.

Provenance capture. The *Pebble* module consists of two submodules. The first one is the *Capture* module. It extends Spark’s distributed dataframes and operators. The

Figure 6: Pebble's architecture

dataframes are bags of items that share the same schema and allow for nested bags and sets. The module associates a unique identifier to each top-level item in the dataframe. In addition, the *Capture* module extends and, thus, collects provenance for the following Spark operators: read, select, filter, join, union, groupby, aggregation, map with UDFs, flatten and nested queries. In case of a groupby, aggregation, or flatten operator, the module also records positions of the nested items being manipulated.

Provenance query. The *Query* module is *Pebble*'s second submodule. It is responsible for querying the captured provenance and consists of a *Backtracing* and a *Tree-Pattern-Matching (TPM)* module.

The *TPM* module implements tree-patterns and a Spark-tailored tree-pattern-matching algorithm, which has two major phases. Opposed to existing approaches that focus on semi-structured XML data [8], *Pebble* exploits the fact that Spark internally considers a structured nested data model. During the first phase, it matches the structure of the tree-pattern against the schema of the result dataframe. It yields a set of schema matches, which fulfill the structural constraints. During the second phase, the algorithm generates a filter statement that calls a user-defined function for each top-level item in the dataframe. The user defined function checks for each item whether it fulfills all structural, value, and cardinality constraints of the tree-pattern. The explicit separation into a schema matching and a data matching phase let the implementation scale with the Spark-cluster unlike other state-of-the-art approaches that rely on global data structures [8].

The *Backtracing* module implements the means to trace back items that match the tree-patterns. It joins the identifiers captured during program execution until the input is reached. The module extends Titian's backtracing on item identifiers [6] with conditions reflecting relevant nested data items, e.g., the positions of items in nested collections.

Pebble API. The *Pebble API* module masks the Spark extensions of the previous modules so that programming with *Pebble* looks and feels like standard Spark programming. It is the entry point to capturing and querying the provenance.

Printer. The *Printer* module provides the HTML views mentioned in the previous section. It requires an HTML renderer from a Jupyter or any other kind of notebook.

Architecture comparison. *Pebble* is a standalone library that does not require any modification of Spark's provided modules unlike existing solutions. Our experiments indicate that it is binary compatible between versions 2.1 (2016) and 2.4 (2019). Since *Pebble* only requires an HTML printer, it runs on Jupyter Notebooks with Apache Toree kernels or Almond-Spark kernels, and on Apache Zeppelin Notebooks. Thus, it runs in a wide variety of environments.

4 AUDIENCE EXPERIENCE

We run *Pebble* on a remote Spark cluster of six computing nodes. The cluster stores two real-world datasets: a 2 GB DBLP dataset (<https://dblp.org/>) and a 500 GB dataset containing Twitter tweets (<https://developer.twitter.com/>). For each of these datasets, we have prepared five debugging scenarios that include a Spark program and a tree-pattern expressing a data engineer's debugging interest. Besides demonstrating these prepared scenarios, we invite attendees to define their own programs and provenance questions.

5 CONCLUSION

This demonstration presents *Pebble*, a system that tracks structural provenance of nested data in Big Data analytics pipelines. This provenance can be queried using tree-patterns. These capabilities are integrated in a Jupyter notebook that supports data engineers in debugging their Big Data analytics pipelines. We demonstrate these features on ten different scenarios over two real-world datasets.

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