ABSTRACT

Data analysis is at the core of scientific studies, a prominent task that researchers and practitioners typically undertake by programming their own set of automated scripts. While there is no shortage of tools and languages available for designing data analysis pipelines, users spend substantial effort in learning the specifics of such languages/tools and often design solutions too project-specific to be reused in future studies. Furthermore, users need to put further effort into making their code scalable, as parallel implementations are typically more complex.

We address these problems by proposing an advanced code recommendation tool which facilitates developing data science scripts. Users formulate their intentions in a human-readable Domain-Specific Language (DSL) for dataframe manipulation and analysis. The DSL statements can be converted into executable Python code during editing. To avoid the need to learn the DSL and increase user-friendliness, our tool supports code completion in mainstream IDEs and editors. Moreover, DSL statements can generate executable code for different data analysis frameworks (currently we support Pandas and PySpark). Overall, our approach attempts to accelerate programming of common data analysis tasks and to facilitate the conversion of the implementations between frameworks.

In a preliminary assessment based on a popular data processing tutorial, our tool was able to fully cover 9 out of 14 processing steps for Pandas and 10 out of 16 for PySpark, while partially covering 4 processing steps for each of the frameworks.

1 INTRODUCTION

Data analysis studies involve many steps of data manipulation and analysis. Typically, software tools with fixed processing workflows are not flexible enough to cover a large variety of scenarios encountered in research, and so some form of programming is mandatory. Consequently, users frequently create project-specific analysis pipelines using various frameworks and tools. These range from data-flow programming environments like KNIME to interactive data processing frameworks like JupyterLab (with Pandas, Scikit-Learn, TensorFlow etc.) to frameworks capable of massively parallel data processing like Apache Spark.

Most approaches are characterized by an inherent trade-off between ease-of-use and flexibility or performance. For example, due to the low development effort, Matlab is popular in industry and science to prototype data-centric applications. However, for the production scenario or to process massive data sets, such prototypes need to be rewritten from scratch into C/C++ or distributed computing frameworks like Apache Spark. In general, researchers and practitioners are still faced by multiple challenges at the intersection of data science and software engineering:

Programming barrier. Proprietary data formats and specific requirements can imply a substantial amount of project-specific script programming. This seriously increases the duration and cost of data analysis projects, and makes it substantially harder for domain specialists (frequently with limited programming skills) to interact with the data directly.

Reuse problem. A majority of the above-mentioned programming effort is put into adjusting code to the specifics of the project and its data sets. New and more widely applicable algorithms and libraries are frequently result of an additional coding effort performed only as a “side-effect” of a project. This creates an unfavorable overall ratio between reusable (library-like) and project-specific code bases.

Scalability problem. Implementing sequential versions of algorithms and software pipelines can be already quite challenging, yet their scalable (massively parallel) versions for large data sets are typically significantly more complex. Moreover, scalable versions require other data structures, libraries, and even programming paradigms (such as DAG operation graphs in Apache Spark), and so significant costs are needed (typically complete re-implementation) to provide scalable versions of software pipelines. Therefore, users frequently work with sequential scripts even if parallel processing would be beneficial, which can limit the considered data sizes and slow down the execution.

Multiple efforts have been undertaken to address these challenges, including novel human-in-the-loop approaches like Predictive Interaction [19], development of new programming languages like Julia [6], and research on advanced methods like program synthesis for data analysis [17], [2], [21]. Nevertheless, many of these techniques address only selected special cases, are still in the research phase, or might require to migrate to a new platform or a programming environments. To our knowledge, for a majority of application scenarios there are still no comprehensive and effective solutions, or solutions which are compatible with ‘legacy’ software (i.e. frameworks, libraries, and programming languages), which
would complement or support existing software ecosystems instead of trying to replace them.

We propose an approach which supports the development of data science scripts during the editing process. In essence, our approach can be understood as advanced code recommendations, where users formulate their intention in an abstract and user-friendly Domain Specific Language (DSL) for dataframe (table) manipulation and analysis. Such DSL statements are directly translated into executable Python code while DSL can remain in the scripts as comments.

Two elements of our solution are essential in addressing the above-mentioned challenges. First, we provide intelligent editing support for the DSL (code completion). Together with a self-explaining design of our DSL this substantially lowers the initial effort to command the DSL and reduces the adoption barrier. Furthermore, the very same DSL can generate code according to user settings - code for various frameworks (“targets”). Our prototype currently offers code generation for Pandas (a popular Python library for in-memory processing and analysis of time series and tables), and for Apache PySpark (Python bindings for Spark, a framework for distributed processing of massive data sets). Generating code for multiple targets supports converting of Pandas scripts to Spark in scenarios where users first experiment and prototype on small data sets (using Pandas) but later need a scalable solution based on Spark (or vice-versa).

DSLs are becoming increasingly popular in software solutions [12], [24], [7], [5], [9], as they raise the abstraction level of code and facilitate communication with domain experts. So-called external DSLs are completely independent languages, with code typically not mixed with other languages. While such DSLs allow high syntactic flexibility, adjustment to the target domain, and IDE support, the effort of implementing functionality beyond the original DSL intention can be substantial. Typically, functionality extensions are only possible via custom User Defined Functions (UDFs) or by embedding the DSL into a general-purpose language via strings or separate files (similarly to how SQL is used from C++ or Java). In such cases, developers must learn and use additional APIs to interact between two languages. In addition, debugging as well as (static) code analysis become cumbersome.

Another approach is to use internal DSLs which are essentially libraries written in general-purpose programming languages with flexible syntax, e.g. Ruby, Scala, Kotlin, or F#. Such DSLs are easier to implement and avoid the interoperability issues, but have only a constrained syntax and no IDE support (Intellisense etc.). In all cases, using a DSL can lead to a lock-in effect and might be a barrier to new developers on a project.

In our solution we use an external DSL yet attempt to circumvent the above-mentioned issues for such languages by allowing a “no-barrier” coexistence of the DSL and the generated code. First, developers can complement and modify the generated code directly during editing, which prevents the problem of lacking DSL functionality. Our DSL is intended to provide support only for common, frequently used operations, while more specific requirements are implement in the target language. Furthermore, developers are free to decide on how to use our DSL: it can serve only as “active help” during editing; it can be used as comments/explanations for the generated code; or it can serve as primary source code for simpler scenarios. We believe that this flexibility can be helpful in the adoption of our solution and reduce the lock-in effect. An obvious disadvantage of our proposal is that the DSL code and the generated code might become out-of-sync during editing, in worst case leading to a misleading code description (similarly to an outdated documentation). We will address this issue in further research, e.g. by automatically flagging DSL code which no longer fits to the generated target code.

This paper is organized as follows. Section 2 describes the details of the approach. Section 3 outlines the implementation. We present the preliminary evaluation in Section 4 and discuss related work in Section 5. Section 6 describes conclusions and future work.

2 APPROACH

Our approach supports script developers via an IDE-supported DSL for generating Python code for common data science tasks. Users enter DSL statements as pseudo-comments while being assisted by code completions (Figure 1), and can choose to insert executable code generated from these DSL statements. It is also possible to specify the type of generated code, or the type of the target framework (currently Pandas or PySpark). Apart from the changed editing experience (noticeable only in lines starting with the DSL prefix code, here `#`), there is no difference to a normal development and execution process. By placing DSL code in comments, normal execution and testing flow is not influenced and does not need to be changed. As noted in the introduction, users can deploy our tool in any editor/IDE supporting the Language Server Protocol, which currently covers all major IDEs. Consequently, we estimate the barrier to the adoption of the tool to be low.

The utility of this approach is largely determined by the design of the DSL, in particular, the power of the DSL (or its “expressiveness”) in terms of common operations for the target frameworks. To ensure a high level of DSL coverage, we have analyzed several popular “cheat-sheets” for Pandas and PySpark, as well as some tutorials for these frameworks. Based on this analysis we designed a DSL which attempts to cover most of the elements found in these sources, see Table 1. It should be noted that we purposefully do not attempt to cover all of the functionality in our DSL. This would largely increase the effort of the implementation (DSL grammar design and code generation), and would make the DSL fragile to changes in the targeted frameworks. Instead, we assume that developers will implement more specific functions directly in the Python code.
2.1 DSL for dataframe operations

Our DSL attempts to be easy-to-understand (or, in the best case, even self-explanatory) yet concise. Thanks to code completion, long keywords are acceptable, and so we preferred better readability in the DSL design than compact but ambiguous keywords. The hurdle of learning and understanding the DSL is further reduced by explanations of the commands provided in the list of suggestions (see Figure 1).

Table 1 gives an overview of the essential parts of our DSL. It covers functionality for data I/O, simple selection, deleting rows or columns, aggregation, multiple types of data transformations, and essential data inspection. In addition, we provide operations which are suitable only for Spark code generation (in Pandas mode, these emit empty code). The DSL has also a meta-command target_code which specifies for which framework code should be generated.

Many modern data science libraries allow the Fluid API coding style, i.e. chaining of method calls like in var . func_A() . func_B() to avoid need for intermediate variables (in R, similar effect is achieved by the "pipeline" operator `%>%`). Our DSL also allows this style, with "\" chosen as the "pipeline" operator (this can be easily changed). Furthermore, to specify the dataframe on which the operation chain is to be performed, we use on dataframe syntax. In Table 1, this is used in several examples (e.g. line 2).

2.2 Generated code

As explained in Section 3.1, DSL code is translated into executable (Python) code by our tool when a user requests a code completion action and the current DSL statement is syntactically correct. We show in Table 2 some examples of generated code. Typically, the DSL code and the target code have similar structure, e.g. order of parameters. Therefore, mapping of the DSL code to the target code is relatively easy. For example, in most cases we can map a DSL syntax node (or grammar rule) to the target code without considering other syntax nodes.

3 IMPLEMENTATION

3.1 Architecture

Figure 2 outlines the architecture of our prototypical implementation. To reach developers with various preferred code editors or IDEs, we use a Language Server Protocol (LSP) [8]. LSP decouples a particular editor/IDE from the "coding services" (including code completion, linting and basic refactoring) via a JSON-RPC interface. Editors/IDEs supporting LSP (clients) include Visual Studio (Code), JetBrains products (PyCharm, Ryder, IntelliJ IDEA,...), Eclipse (Che), Vim, Emacs, and others. Similarly, there exist a large number of language servers for major programming languages.

Table 1: DSL overview. Keywords are in bold, choices from a list are underlined, and other parameters are emphasized.

| Category    | DSL examples (prefix ## is omitted) |
|-------------|-------------------------------------|
| I/O operations | result = load as json 'some_path.json' on df: save as csv to 'some_path.csv' |
| Selection    | result = on df: select_cols a, b, c ... select_cols col1 == m or col2 < 3 ... select_cols col1 > 0 and col3 in [v1, v2, v3] |
| Deletion     | result = on df: drop_rows x, y, z ... drop_rows col1 > 0 and col2 not in [v1, v2] |
| Aggregation  | result = on df: group_by col1 apply sum ... group_by col1, col2 apply min |
| Transform    | result = on df: on_missing fill with value ... on_missing drop rows ... replace old_value by new_value ... apply_fun function on cols ... apply_fun function on rows ... append_col col_name ... sort_by col_name ... drop_duplicates ... rename_cols c1 to p, c2 to q |
| Inspection   | on df: show ... on df: describe ... return_top_N 10 ... select_rows col1 == m : count |
| Spark only   | start_session named 'session_name' stop_session s = schema col1 of int, col2 of str result = load 'some_path.txt' with_schema s |
| Pandas only  | ... append_row col_name default default_val |
| Options      | target_code = spark target_code = pandas |

Table 2: Examples of generated target code. In the column Type, 'P' indicates Pandas code, and 'S' Spark code.

| Type | Code (for DSL, prefix ## is omitted) |
|------|-------------------------------------|
| P    | load as csv some_path p = pd.read_csv(some_path) |
| S    | load as csv some_path with_schema S x = spark.read.csv(some_path, schema=S) |
| P    | on y: select_cols a, b, c: count y = y[[’a’, ’b’, ’c’]].count() |
| S    | x = y.select(’a’, ’b’, ’c’).count() |
| P    | on y: select_rows col1 == m and col3 in [v1, v2, v3] y = y[col1 == m] & (y.col3.isin([v1, v2, v3])) |
| S    | x = y.filter((y.col1 == m) & (y.col3.isin([v1, v2, v3]))) |
| P    | on y: rename_cols c1 to p, c2 to q y = y.rename(columns=[’c1’: ’p’, ’c2’: ’q’]) |
| S    | x = y.withColumnRenamed(’c1’, ’p’).with...(’c2’, ’q’) |
Our tool emulates a Language Server via a thin layer ("Hub") which is responsible to dispatching client requests to sub-modules, and forwarding responses from these sub-modules to the client. The dispatch mechanism essentially analyzes a code completion request (in LSP, `textDocument/completion` request) whether it has been issued in a code line containing DSL-code, or not. In the DSL case, a request is handled by our DSL-based Recommender (see Figure 2), otherwise forwarded (unchanged) to a regular language server (for Python, our prototype uses a server by Palantir Technologies\(^1\)). Few other LSP requests are duplicated to all sub-modules to ensure coherency of workspace/file caching, in particular `DidChangeEventDocument`.

The DSL-based Recommender uses `textX` [9] and `textX-LS`\(^2\) to implement code completion suggestions for our DSL grammar. `textX` is a Python library for defining and implementing DSLs, and `textX-LS` is a generic language server implementation which provides syntax checking and code completion for any language defined with `textX`. A response from `textX-LS` is a list of ranked recommendations as shown in Figure 1. We add to this list a preview of the generated target code (if DSL syntax is valid) with high rank, i.e., at position 1. In this way, a user can insert the generated code without breaking the editing flow.

### 3.2 Code generation

Code generation is implemented as a set of few classes on top of the `textX` library. Upon start of our tool, the DSL definition is parsed and remains in memory as a meta-model (note that contrary to other DSL construction tools like `xtext` or `mips`, grammar is parsed dynamically, without generating code for a parser/lexer). For each LSP request with a DSL in the current editor line we use `textX` to parse this line with the prepared meta-model. Upon success, `textX` returns a tree of Python objects corresponding to an Abstract Syntax Tree (AST).

To generate code, we essentially parse this tree using recursion, iteration and if/else statements, and collect the generated code using a string buffer. Figure 3 shows an example AST for the DSL `x = on y : select_cols a, b, c : group_by b apply unique : show`. A Python method processes the AST-node `LineOperation` by inspecting a corresponding Python object `obj` dynamically generated by `textX`. For example, if a property assignment of `obj` is not null, we add the variable name stored in property assignment .name (on the r.h.s. in the DSL) and `="` to the generated code. Further on, if the property `chainOps` of `obj` is not null, then we iterate over a list stored in this property. For each list element we call a method to recursively handle each sub-type of a `ChainOperation` AST node.

After acquiring some familiarity with the `textX` framework it becomes a relatively straightforward tasks to implement new DSL elements. Also the required (Python) code has reasonable size. In detail, code generator for our current DSL comprises about 240 LOC (Lines of Code, including comments) and 3 Python classes.

Different target frameworks are handled as sub-classes of a class for framework-agnostic code generation. Such sub-classes are typically small, which ensures that code generation for additional frameworks can be easily implemented. In our case, a subclass for Pandas code generation has 55 LOC and 12 short methods, and the subclass for Spark has 51 LOC and 11 methods.

### 4 PRELIMINARY EVALUATION

A proper evaluation of the usefulness of our approach would require a well-designed user study with a sufficient number of participants. Due to time constrains, we refrain from performing such analysis and focus instead on assessing the coverage of our initial DSL implementation. To that aim, in this preliminary evaluation we answer the following question: Given a real-usage scenario, what fraction of the analysis and data processing steps are covered by our current DSL design?

We first need to select a scenario that represents a typical data analysis task. Due to the popularity and demand for data analysis in current scientific landscape, tutorials are very common in the web. For our evaluation, we select a popular DataCamp tutorial "Apache Spark Tutorial: ML with PySpark"\(^3\) that provides a high-quality use-case for using PySpark dataframes for data processing and data analysis. This tutorial has multiple topics, ranging from Spark installation to the application of conventional machine-learning methods for Big Data. For this initial assessment, we focus only on the topics within the scope targeted by our DSL: data exploration and data pre-processing. The two topics in this tutorial contain a total of 16 processing steps. We define a processing step loosely as the smallest part of the code that can be executed on its own (typically single-liners), or in a single block of code in this tutorial.

To evaluate our DSL in context of Spark, we use unchanged source code from the tutorial. For Pandas, we manually translate each processing step into Pandas code, which yields only 14 processing steps, as some steps (such as creating RDDs to populate dataframes) are specific to PySpark. We do not use (another) tutorial directly for Pandas as it was impossible to find a tutorial with similar purpose/scenario as to the one for Spark. Moreover, many introductory tutorials for Pandas explain functions related to selecting individual values (e.g., `.loc` and `.iloc`), and functions related to the (row) index data structure of Pandas. Such functions make Pandas code fundamentally difficult to translate to other programming paradigms or frameworks (e.g. SQL, Spark), and typically make the code non-scalable. In our scenario, we assume that a developer considers the scenario of massive data sets and will avoid such functions right from the onset.

In our evaluation we attempt to express a basic processing step with our DSL. For each such step, we estimate whether it can be expressed in the DSL completely, whether DSL needs additional (Python) code, whether we need to substantially change the generated code, or if our DSL cannot express this step at all. We present in Table 3 the aggregated results of this initial assessment. Overall, our DSL fully covers 64.2% of Pandas processing steps and 62.5% of PySpark processing steps in the tutorial. In 4 processing steps for Pandas and PySpark, the translated code did not completely match the expected goal and users would have to add Python code (either as new parameters or function call) to fulfill their initial intention.

We find no case where the generated code needs to be rewritten but

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\(^1\)https://github.com/palantir/python-language-server
\(^2\)https://github.com/textX/textX-LS
\(^3\)https://www.datacamp.com/community/tutorials/apache-spark-tutorial-machine-learning
three processing steps (one in Pandas and two in PySpark) could not be expressed or translated by our DSL (see NS in Table 3).

In Table 4, we detail the processing steps our DSL fail to cover in its completion (CA) or could not support at all (NS). From the 11 partially failed steps, 6 were only covered by a similarly equivalent function (L1). In this particular case, our DSL generated the code to retrieve the top N rows in a dataframe through the head function call, while in the tutorial the show function is preferred. Both functions are similar in practice, but show prints the top N rows in the standard output, while head returns top N rows as a new dataframe. In another case (L2), when sorting a dataframe, our DSL assumes the sorting in the ascending order, hence omitting the optional parameter for descending sorting (ascending=False). The L3 evidences one limitation of our DSL, the lack of context awareness. In the current implementation, the DSL does not index or complete code from functions defined by the programmer and hence should not be used as a code recommender. The last case (L4), is the support for lambda functions not yet implemented in our tool.

### 5 RELATED WORK

Domains relevant to our work are low-code data analysis, accelerated scripting and coding, and Domain Specific Languages.

**Low-code data analysis.** Multiple research fields tackle the challenge of making the process of data analysis and transformation more user-friendly and accelerating scripting and automation of processing. The essential directions are: visual analytics [28], mixed-initiative systems [20], [29], facilitating user involvement in the data analysis or processing activities [10], [30], learning data transformations by examples [26], [33], [21], [32], and data wrangling in various flavors [31], [23], [35], [19], [30].

Data wrangling (or data munging) refers to the process of interactive data transformations on structured or unstructured data. The most mature tool in this domain is Wrangler [23] which was commercialized by Trifacta [27], and recently offered by Google as the Google Cloud service [13]. Another popular tool is OpenRefine [36] (originally GoogleRefine) which allows batch processing of tabular data by menu selection and a Domain Specific Language (DSL) named GREL. Albeit similar to Wrangler, it has more restricted functionality and offers no support for very large data sets.

The concept behind these tools is Predictive Interaction [19]. Its key elements are: (i) real-time preview of effects of code on a processed data set, (ii) code recommendations based on the context of user interactions and data, and (iii) a DSL to describe data transformations in a way easily accessible to users. A disadvantage of the Wrangler tool is the fact that it is a closed (and commercial) eco-system. This creates a serious barrier for interoperability with mainstream libraries or frameworks. Moreover, its DSL has a limited expressiveness (focusing on data preparation only), and extending this DSL requires developing User Defined Functions.

Learning data transformations by examples [26], [33], [21], [32] is a special case of the program synthesis techniques. Such approaches (while still immature) offer a promise to greatly facilitate complex data analysis, especially for users with no or little programming skills. The (quite sophisticated) methods here include constraint-based program synthesis, program sketching [34], version space algebra [15, 26], or searching in a state space graph [21]. In context of data extraction, transformation, and analysis, several interesting applications have been proposed [17], including extracting relations from spreadsheets [2], data transformations [21], or synthesizing regular expressions. So far, only the FlashFill approach [16] has been practically relevant and available to many users (as a component of Excel 2013 and ConvertFrom-String cmdlet in PowerShell). We consider program synthesis as a possible extension of our work.

**Accelerating scripting and coding** (and as a special case, end-user development/end-user programming) comprises a multitude of approaches from software engineering. The most visible progress in
In the context of data analysis, dataflow languages [14, 22] have gained some popularity via tools such as [1] or KNIME [4]. Such approaches can greatly accelerate the creation of small data processing pipelines and have also proven suitable for educational purposes. On the other hand, they tend to slow down more experienced programmers (even smallest operation like “+” must be selected from menu/palette and connected to other blocks), do not provide an intuitive support for controls structures, and lack interoperability with other tools or libraries. For these reasons, they are rarely used in larger projects.

Domain Specific Languages (DSLs) [12, 24, 9], have proven useful in a multitude of medium to large-scale projects by introducing highly readable and concise code with support for higher-level operations. While the underlying “theory” and scientific interest is still modest [24], [11], [18], DSLs are becoming increasingly popular in industry (for example, the industrial-grade database management system SAP HANA uses internally over 200 DSLs).

A particular flavor of DSLs are internal or embedded DSLs which can seamlessly inter-operate with the underlying (typically general-purpose) language. However, internal DSLs offer only limited range of syntax and are typically not supported by IDEs. Contrary to this, external DSLs admit almost any syntax, and modern DSL engineering tools (like MPS [7], Xtest [5], textX [9], or Spoofax [24]) provide “automatic” editing support tools (syntax checking and code completion) for them. The disadvantage of external DSLs is the difficulty of interaction with (general-purpose) languages. Paired with this is increased development effort in a scenario where DSL capabilities are not sufficient, and e.g. writing project-specific User Defined Functions become necessary.

In our approach we generate code for a general-purpose language from an external DSL during the editing process, which largely eliminates the interoperability barrier. We also implemented a special Language Server to provide coding assistance to both our DSL and the “embedding” general-purpose language (here Python).

6 CONCLUSIONS AND FUTURE WORK

We proposed a DSL-based approach to support data scientists in writing code for common tasks related to table analysis and processing. We use external DSL to express such operations in a human-readable form, and generate executable Python code directly during editing. In this way we circumvent the frequently encountered problem of insufficient expressiveness of a DSL, since developers can directly use Python code to address more special cases (outside the power of the DSL). Our prototype works with a large number of IDEs and editors (all supporting the Language Server Protocol), and provides editing support (code recommendations) for the DSL.

Moreover, users can generate code for Pandas “data wrangling” library, or for Apache Spark. This facilitates a transition from low-effort yet typically non-scalable scripts (in Pandas) suitable for smaller data sets to highly scalable scripts in Spark. Our preliminary evaluation shows that for typical data pre-processing tasks, our DSL is capable of generating complete code in 10 out of 16 cases for Apache Spark, and in 9 out of 14 cases for Pandas.

Despite of these promising results, there is still a lot of work to be done to understand and to address the challenges of our approach, and to provide tools of practical value. Our future work will include a controlled user study with interviews in order to identify such challenges, and verify our hypotheses on user behavior. We will also implement more code generation targets for our DSL, including R (with dplyr/tidyR) and Matlab. Another option is to provide and evaluate a DSL for deep learning frameworks like TensorFlow, Microsoft Cognitive Toolkit, or PyTorch.

Further work related to the editing support will include mechanisms for synchronizing DSL and the generated code, e.g. by marking DSL code which is no longer in-sync with the Python code. Another option here is to add support for “type providers” known from .NET languages, i.e. editor/compiler recommendations for column names and types of the actual data sets processed in a script.

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Table 4: Examples of DSL limitation in fully translating our studied tutorial into PySpark code. The “Cat” column references the categories of Table 4. The expected code written in red and bold is currently not supported by our DSL.

| ID | Cat. | Limitation | DSL code (# is omitted) | Generated code | Expected generated code |
|----|------|------------|-------------------------|----------------|-------------------------|
| L1 | CA   | Target function not supported | on df: return top_N 10 df.head(10) df.show(10) | df.show(10) | 6 |
| L2 | CA   | Parameter not supported | on df: sort_by col df.sort('col') | df.sort('col', ascending=False) | 2 |
| L3 | NS   | Custom user-functions not supported | – | df = convertColumn(df, columns, FloatType()) | 2 |
| L4 | NS   | Lambda functions not supported | – | df = rdd.apply(lambda x: x / 10).toDF() | 1 |
