Spreadsheet Data Extractor (SDE): A Performance-Optimized, User-Centric Tool for Transforming Semi-Structured Excel Spreadsheets into Relational Data

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Abstract

Spreadsheets are widely used across domains, yet their human-oriented layouts (merged cells, hierarchical headers, multiple tables) hinder automated extraction. We present the Spreadsheet Data Extractor (SDE), a user-in-the-loop system that converts semi-structured sheets into structured outputs without programming. Users declare the structure they perceive; the engine broadcasts selections deterministically and renders results immediately. Under the hood, SDE employs incremental loading, byte-level XML streaming (avoiding DOM materialisation), and viewport-bounded rendering.

Optimised for time-to-first-visual, SDE delivers about **70×** speedup over Microsoft Excel when opening a selected sheet in a large real-world workbook; under workload-equivalent conditions (single worksheet, full parse) it remains about **10×** faster, while preserving layout fidelity. These results indicate SDE's potential for reliable, scalable extraction across diverse spreadsheet formats.

CCS Concepts

• **Applied computing** → **Spreadsheets**; • **Information systems** → **Data cleaning**; • **Software and its engineering** → **Extensible Markup Language (XML)**; • **Human-centered computing** → *Graphical user interfaces*; • **Theory of computation** → Data compression.

Keywords

Spreadsheets, Data cleaning, Relational Data, Excel, XML, Graphical user interfaces

ACM Reference Format:
Anonymous Author(s). 2026. Spreadsheet Data Extractor (SDE): A Performance-Optimized, User-Centric Tool for Transforming Semi-Structured Excel Spreadsheets into Relational Data. In *Proceedings of Conference on Human Factors in Computing Systems (ACM CHI '26)*. ACM, New York, NY, USA, **??** pages. https://doi.org/10.1145/XXXXXXX.XXXXXXX

ACM CHI '26, Barcelona, Spain

ACM ISBN
https://doi.org/10.1145/XXXXXXX.XXXXXXX

1 Introduction

Spreadsheets underpin workflows across healthcare [**?**], nonprofit organizations [**? ?**], finance, commerce, academia, and government [**?**]. Despite their ubiquity, reliably analyzing and reusing the data they contain remains difficult for automated systems. In practice, many real-world spreadsheets are organized for human consumption [**?**] and therefore exhibit layouts with empty cells, merged regions, hierarchical headers, and multiple stacked tables. While such conventions aid human reading [**?**], they hinder machine readability and complicate extraction, integration, and downstream analytics.

The reliance on spreadsheets as ad-hoc solutions poses several limitations:

- **Data Integrity and Consistency:** Spreadsheets are prone to errors, such as duplicate entries, inconsistent data formats, and inadvertent modifications, which can compromise data integrity. [**? ?**]
- **Scalability Issues:** As datasets grow in size and complexity, spreadsheets become less efficient for data storage and retrieval, leading to performance bottlenecks. [**? ?**]
- **Limited Query Capabilities:** Unlike databases, spreadsheets lack advanced querying and indexing features, restricting users from performing complex data analyses.

Transitioning from these ad-hoc spreadsheet solutions to standardized database systems offers numerous benefits:

- **Enhanced Data Integrity:** Databases enforce data validation rules and constraints, ensuring higher data quality and consistency.
- **Improved Scalability:** Databases are designed to handle large volumes of data efficiently, supporting complex queries and transactions without significant performance degradation.
- **Advanced Querying and Reporting:** Databases provide powerful querying languages like SQL, enabling sophisticated data analysis and reporting capabilities.
- **Seamless Integration:** Databases facilitate easier integration with various applications and services, promoting interoperability and data sharing across platforms.

Given the abundance of spreadsheet data and the clear advantages of database systems, there is a pressing need for tools that bridge these formats. Automated, accurate extraction from spreadsheets into relational representations is essential.

Prior work introduced a tool for extracting data from Excel files [**?**]. While effective, that system exhibited performance issues on large workbooks and imprecise rendering of cell geometry, which limited usability for complex, real-world files. The user interface was also fragmented, requiring context switches between hierarchy definition and output preview.

This paper presents the *Spreadsheet Data Extractor (SDE)*, which transforms semi-structured spreadsheet content into machine-readable form. Users declare structure directly via cell selections—no programming required. The design addresses the above limitations and supports large, irregular spreadsheets with predictable, interactive performance.

1.1 Contributions

(1) **Unified interaction.** We integrate the selection hierarchy, worksheet view, and output preview into a single interface, reducing context switches and lowering the number of required interactions.
(2) **DOM-free, byte-level worksheet parsing.** We implement a custom parser that operates directly on the XLSX worksheet bytes, avoiding DOM construction and regex over decoded strings. This greatly reduces memory footprint and improves robustness on large/“bloated” sheets.
(3) **Incremental loading.** Worksheets are loaded and parsed on demand from the XLSX archive, enabling near-instant open times and interactive latency on large files (quantified in §??).
(4) **Excel-faithful rendering.** We recover row heights, column widths, and merges from XML to render worksheets closely to Excel, including text overflow behavior, which improves user orientation.
(5) **Viewport-bounded rendering.** The renderer draws only cells intersecting the viewport; selection queries are pruned with cached axis-aligned bounding boxes. Together these keep per-frame work proportional to what is visible rather than to sheet size.

2 Related Work

The extraction of relational data from semi-structured documents, particularly spreadsheets, has garnered significant attention due to their ubiquitous use across domains such as business, government, and scientific research. Several frameworks and tools have been developed to address the challenges of converting flexible spreadsheet formats into normalized relational forms suitable for data analysis and integration as summarized in Table **??**.

2.1 Aue et al.'s Converter

Aue et al. [**?**] developed a tool to facilitate data extraction from Excel spreadsheets by leveraging the Dart *excel* package [**?**] to process .xlsx files. This tool allows users to define data hierarchies by selecting relevant cells containing data and metadata. However, the approach faced significant performance bottlenecks due to the *excel* package's requirement to load the entire .xlsx file into memory, resulting in slow response times, particularly for large files.

In addition to memory issues, the tool calculated row heights and column widths based solely on cell content, ignoring the dimensions specified in the original Excel file. This led to rendering discrepancies between the tool and the original spreadsheet. Furthermore, the tool rendered all cells, regardless of their visibility within the viewport, significantly degrading performance when handling worksheets with large numbers of cells.

2.2 DeExcelerator

Eberius et al. [**?**] introduced **DeExcelerator**, a framework that transforms partially structured spreadsheets into first normal form relational tables using heuristic-based extraction phases. It addresses challenges such as table detection, metadata extraction, and layout normalization. While effective in automating normalization, its reliance on predefined heuristics limits adaptability to heterogeneous or unconventional spreadsheet formats, highlighting the need for more flexible approaches.

2.3 XLIndy

Koci et al. [**?**] developed **XLIndy**, an interactive Excel add-in with a Python-based machine learning backend. Unlike DeExcelerator's fully automated heuristic approach, XLIndy integrates machine learning techniques for layout inference and table recognition, enabling a more adaptable and accurate extraction process. XLIndy's interactive interface allows users to visually inspect extraction results, adjust configurations, and compare different extraction runs, facilitating iterative fine-tuning. Additionally, users can manually revise predicted layouts and tables, saving these revisions as annotations to improve classifier performance through (re-)training. This user-centric approach enhances the tool's flexibility, allowing it to accommodate diverse spreadsheet formats and user-specific requirements more effectively than purely heuristic-based systems.

2.4 FLASHRELATE

Barowy et al. [**?**] presented **FLASHRELATE**, an approach that empowers users to extract structured relational data from semi-structured spreadsheets without requiring programming expertise. FLASHRELATE introduces a domain-specific language, **FLARE**, which extends traditional regular expressions with spatial constraints to capture the geometric relationships inherent in spreadsheet layouts. Additionally, FLASHRELATE employs an algorithm that synthesizes FLARE programs from a small number of user-provided positive and negative examples, significantly simplifying the automated data extraction process.

FLASHRELATE distinguishes itself from both DeExcelerator and XLIndy by leveraging programming-by-example (PBE) techniques. While DeExcelerator relies on predefined heuristic rules and XLIndy incorporates machine learning models requiring user interaction for fine-tuning, FLASHRELATE allows non-expert users to define extraction patterns through intuitive examples. This approach lowers the barrier to entry for extracting relational data from complex spreadsheet encodings, making the tool accessible to a broader range of users.

2.5 Senbazuru

Chen et al. [**?**] introduced **Senbazuru**, a prototype Spreadsheet Database Management System (SSDBMS) designed to extract relational information from a large corpus of spreadsheets. Senbazuru

Name	Technologies	Output	Accessibility	Frequency
DeExcelerator	heuristics	relational data	partially open source no access to GUI code	last publication 2015
FlashRelate	AI programming-by-example	relational data	proprietary, no access	last publication 2015
Senbazuru	AI	relational data	partially open source no access to GUI code	last commit 2015
XLindy	AI	relational data	no access	discontinued
TableSense	AI	diagrams	proprietary, no access	last commit 2021
Aue et al. (converter)	User-centric Selection-Workflow	relational data	no public repository	last publication 2024

Table 1: Spreadsheet Data Extractor counterparts

addresses the critical issue of integrating data across multiple spreadsheets, which often lack explicit relational metadata, thereby hindering the use of traditional relational tools for data integration and analysis.

Senbazuru comprises three primary functional components:

(1) **Search**: Utilizing a textual search-and-rank interface, Senbazuru enables users to quickly locate relevant spreadsheets within a vast corpus. The search component indexes spreadsheets using Apache Lucene, allowing for efficient retrieval based on relevance to user queries.
(2) **Extract**: The extraction pipeline in Senbazuru consists of several stages:
   - **Frame Finder**: Identifies data frame structures within spreadsheets using Conditional Random Fields (CRFs) to assign semantic labels to non-empty rows, effectively detecting rectangular value regions and associated attribute regions.
   - **Hierarchy Extractor**: Recovers attribute hierarchies for both left and top attribute regions. This stage also incorporates a user-interactive repair interface, allowing users to manually correct extraction errors, which the system then generalizes to similar instances using probabilistic methods.
   - **Tuple Builder and Relation Constructor**: Generates relational tuples from the extracted data frames and assembles these tuples into coherent relational tables by clustering attributes and recovering column labels using external schema repositories like Freebase and YAGO.
(3) **Query**: Supports basic relational operations such as selection and join on the extracted relational tables, enabling users to perform complex data analysis tasks without needing to write SQL queries.

Senbazuru's ability to handle hierarchical spreadsheets, where attributes may span multiple rows or columns without explicit labeling, sets it apart from earlier systems like DeExcelerator and XLIndy. By employing machine learning techniques and providing user-friendly repair interfaces, Senbazuru ensures high-quality extraction and facilitates the integration of spreadsheet data into relational databases.

2.6 TableSense

Dong et al. [?] developed **TableSense**, an end-to-end framework for spreadsheet table detection using Convolutional Neural Networks (CNNs). TableSense addresses the diversity of table structures and layouts by introducing a comprehensive cell featurization scheme, a Precise Bounding Box Regression (PBR) module for accurate boundary detection, and an active learning framework to efficiently build a robust training dataset.

While **DeExcelerator**, **XLIndy**, **FLASHRELATE**, and **Senbazuru** focus primarily on transforming spreadsheet data into relational forms through heuristic, machine learning, and programming-by-example approaches, **TableSense** specifically targets the accurate detection of table boundaries within spreadsheets using deep learning techniques. Unlike region-growth-based methods employed in commodity spreadsheet tools, which often fail on complex table layouts, TableSense achieves superior precision and recall by leveraging CNNs tailored for the unique characteristics of spreadsheet data. However, TableSense focuses on table detection and visualization, allowing users to generate diagrams from the detected tables but does not provide functionality for exporting the extracted data for further analysis.

2.7 Comparison and Positioning

A direct head-to-head comparison was not possible due to the lack of artifacts, because for the UI-oriented systems **FLASHRELATE**, **Senbazuru**, **XLIndy**, and **DeExcelerator**, we contacted the authors mentioned in the publications to obtain research artifacts (source code, UI prototypes). As of the submission deadline, we had either not received any responses or that the project was discontinued; we could not find publicly accessible UI artifacts or runnable packages.

Moreover, unlike the aforementioned tools that rely on heuristics, machine learning, or AI techniques—which can introduce errors requiring users to identify and correct—we adopt a user-centric approach that gives users full control over data selection and metadata hierarchy definition. While this requires more manual input, it eliminates the uncertainty and potential inaccuracies associated with automated methods. To streamline the process and enhance efficiency, our tool includes user-friendly features such as the ability to duplicate hierarchies of columns and tables, and to move them

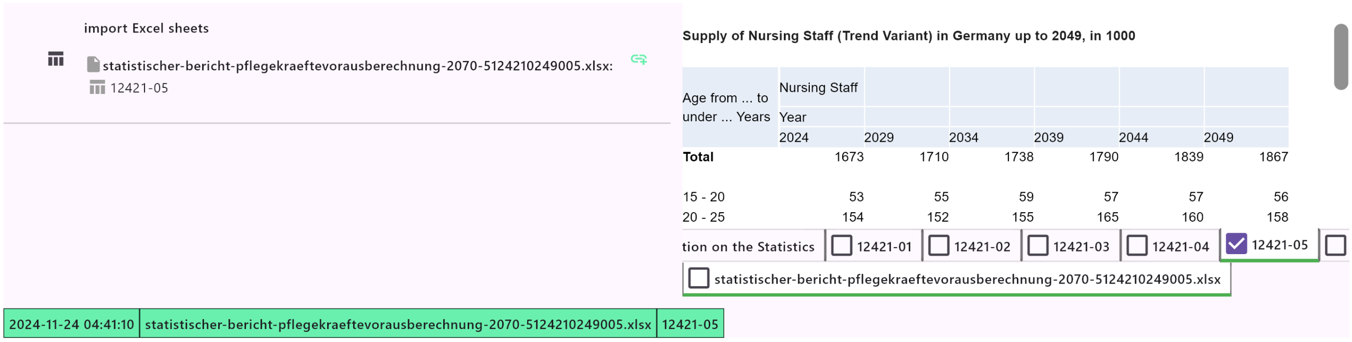


Figure 1: The SDE Interface Overview.

over similar structures for reuse, reducing the need for repetitive configurations.

By combining the strengths of manual control with enhanced user interface features and performance optimizations, our tool offers a robust and accessible solution for extracting relational data from complex and visually intricate spreadsheets. These enhancements not only improve performance and accuracy but also elevate the overall user experience, making our tool a valuable asset for efficient and reliable data extraction from diverse spreadsheet formats.

3 Design Philosophy

Spreadsheet tables are heterogeneous, noisy, and locally structured in ways that are hard to infer reliably with fully automatic extraction. Our goal is not to replace the analyst with an opaque model, but to *amplify* their judgment: the user points to the structure they already perceive (regions, labels, value columns), and the system guarantees a faithful, auditable transformation into a relational view. Instead of automatically extracting and then searching for mistakes, we invert the workflow: *select first, broadcast deterministically, render immediately*. This keeps discrepancies visible at the point of selection, where they can be corrected with minimal context switches.

We enforce three invariants: (i) **Provenance**: every emitted tuple is traceable to a set of visible source cells via an explicit mapping; (ii) **Stability**: small edits to selections induce bounded, predictable changes in the output (no global re-writes); (iii) **Viewport-bounded cost**: interactive operations run in time proportional to the number of cells intersecting the viewport, not the worksheet size. The parsing, indexing, and rendering subsystems are organized to uphold these invariants at scale.

User-Centric Data Extraction. The core interaction in the *SDE* lets users declare structure directly on the spreadsheet canvas and organize it into a hierarchy that drives a deterministic transformation into a relational view.

Hierarchy Definition. Users select individual cells or ranges (click, Shift-click for multi-selection). Each selection denotes either data (values) or metadata (labels/headers). Selections are arranged into a hierarchical tree: each node represents a data element; child nodes represent nested data or metadata. This hierarchy specifies how the SDE broadcasts selections into rows/columns in the output.

The interface supports flexible management: users drag-and-drop nodes to reparent or reorder the hierarchy when a different organization is more appropriate. Users can also introduce *custom nodes* with user-defined text to encode metadata that is implicit in the spreadsheet but absent from cell contents.

Reusability and Efficiency. To reduce repetitive work on sheets with repeated layouts, users can duplicate an existing selection hierarchy and apply it to similar regions. When moving a hierarchy, some cells may need to remain fixed (e.g., vertically stacked tables where only the topmost table repeats header rows). In `DuplicateAndMove` mode, the SDE provides a *lock* function: users freeze specific cells while relocating the rest of the hierarchy. Locks can be toggled via the lock icon at the top-left corner of a cell or next to the corresponding selection in the hierarchy panel; locked cells remain stationary while other selections shift accordingly (see Figure **??** in **??**). Already-locked selections are visually indicated and can be unlocked at any time.

4 Example Workflow

Consider a spreadsheet containing statistical forecasts of future nursing staff availability in Germany [?]. Figure **??** shows the SDE interface, which consists of three main components:

Hierarchy Panel (Top Left): Displays the hierarchy of cell selections, initially empty.

Spreadsheet View (Top Right): Shows the currently opened Excel file and the currently selected worksheet for cell selection.

Output Preview (Bottom): Provides immediate feedback on the data extraction based on current selections.

4.1 Selection of the First Column

The user adds a node to the hierarchy and selects the cell containing the metadata "Nursing Staff" (Figure **??**). This cell represents metadata that is common to all cells in this worksheet. Therefore, it should be selected first and should appear at the beginning of each row in the output CSV file.

Within this node, the user adds a child node and selects the cell *"Total"*, which serves as both a table header and a row label. This selection represents the table header of the first subtable. The user adds another child node and selects the range of cells containing

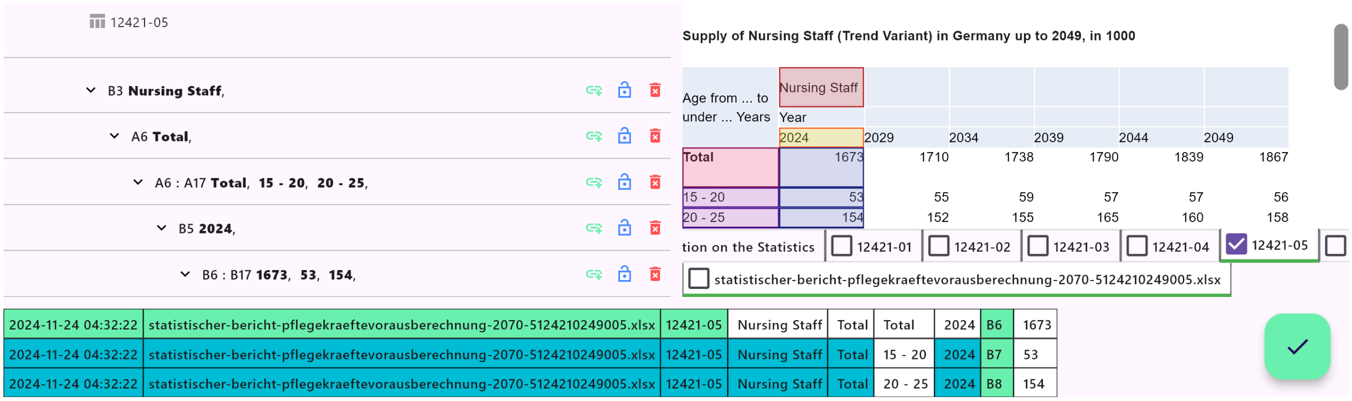


Figure 2: Selection of the First Column Metadata

row labels (e.g., *"Total", "15-20", "20-25"* and so forth) by clicking the first cell and shift-clicking the last cell.

A further child node is then placed under the row labels node, and the user selects the year *"2024"*. Subsequently, an additional child node is created beneath the year node, and the user selects the corresponding data cells (e.g., *"1673", "53", "154"*, etc.).

At this point, the hierarchy consists of five nodes, each—except the last one—containing an embedded child node. In the upper-right portion of the interface, the chosen cells are displayed in distinct colors corresponding to each node. The lower area shows a preview of the extracted output. For each child node, an additional column is appended to the output. When multiple cells are selected for a given node, their values appear as entries in new rows of the output, reflecting the defined hierarchical structure.

4.2 Duplicating the Column Hierarchy

To avoid repetitive manual entry for additional years, the user duplicates the hierarchy for "2024" and adjusts the cell selections to include data for subsequent years (e.g., "2025," "2026") using the "Move and Duplicate" feature.

To do this, the user selects the node of the first column "2024" and right-clicks on it. A popup opens in which the action "move and duplicate" appears, which should then be clicked, as shown in Figure ??.

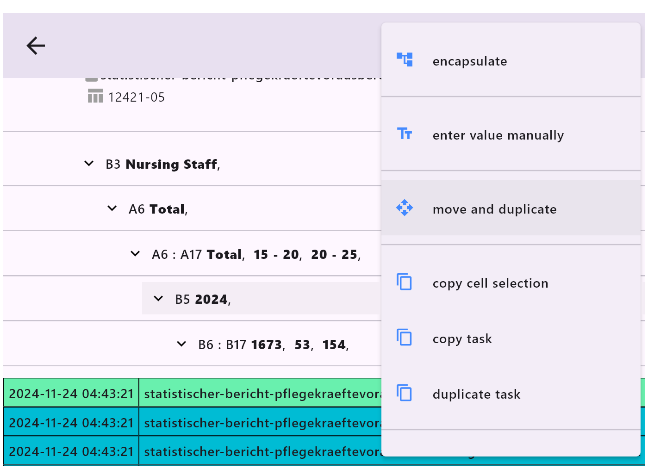


Figure 3: Invoking the "move and duplicate" feature on the 2024 column node.

4.3 Duplicating the Table Hierarchy

Subsequently, a series of buttons opens in the app bar at the top right, allowing the user to move the cell selections of the node as well as all child nodes, as seen in Figure ??. By pressing the button to move the selection by one unit to the right, the next column is selected. However, this would also deselect the first column since the selection was moved. To preserve the first column, the "move and duplicate" checkbox can be activated. This creates the shifted selection in addition to the original selection. The changes are only applied when the "accept" button is clicked. The next columns could also be selected in the same way. But this can be done faster, because instead of moving the selection and duplicating it only once, the "repeat" input field can be filled with as many repetitions as there are columns. By entering the number 5, the selection of the first

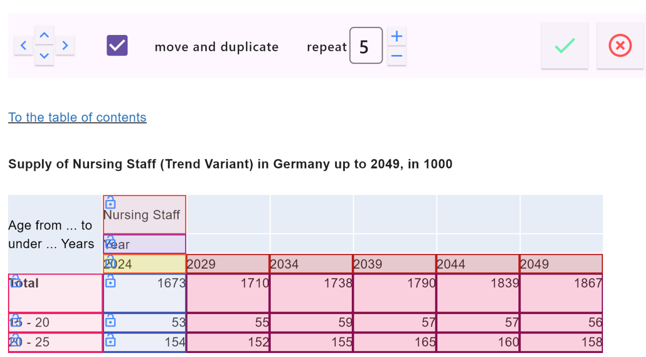


Figure 4: Moving the hierarchy one cell to the right while adjusting the number of repetitions to duplicate the column selection.

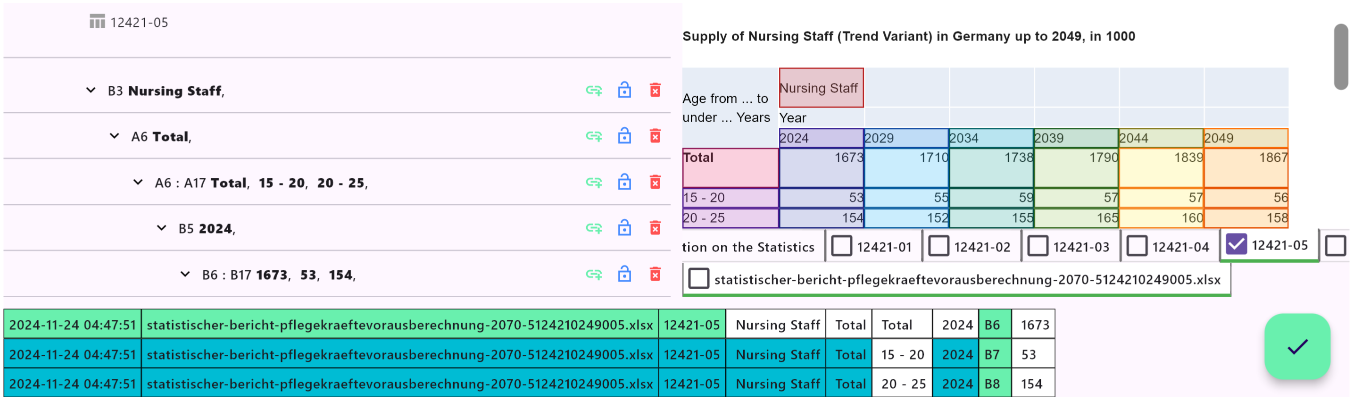
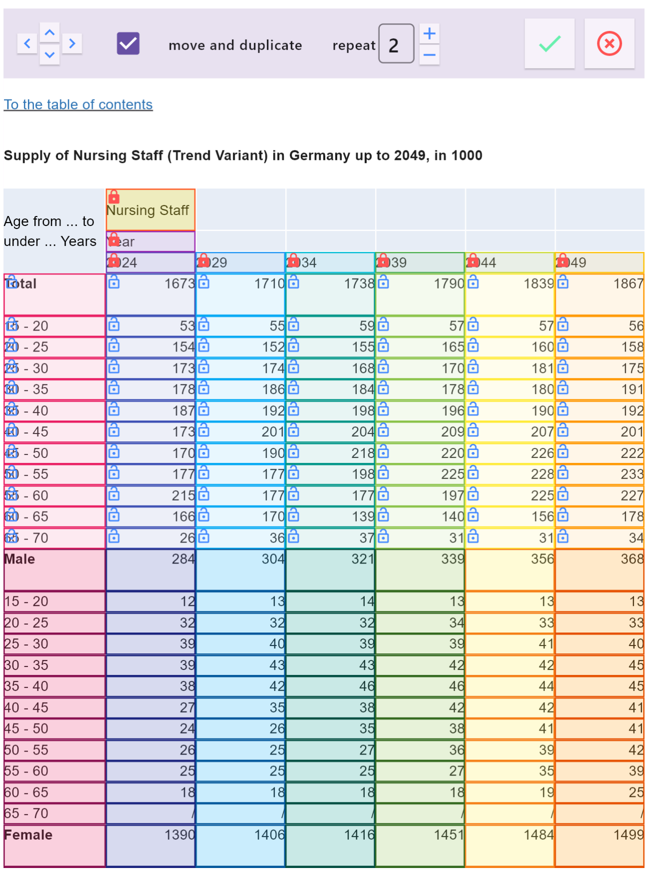


Figure 5: Resulting Hierarchy After Move and Accept

column is shifted 5 times by one unit to the right and duplicated at each step.

The user reviews the selections in the spreadsheet view, where each selection is highlighted in a different color corresponding to its node in the hierarchy. Only after the user has reviewed the shifted and duplicated selections in the worksheet and clicked the "accept"



Age from ... to under ... Years	Nursing Staff					
	Year					
	2024	2029	2034	2039	2044	2049
Total	1673	1710	1738	1790	1839	1867
15 - 20	53	55	59	57	57	56
20 - 25	154	152	155	165	160	158
25 - 30	173	174	168	170	181	175
30 - 35	178	186	184	178	180	191
35 - 40	187	192	198	196	190	192
40 - 45	173	201	204	209	207	201
45 - 50	170	190	218	220	226	222
50 - 55	177	177	198	225	228	233
55 - 60	215	177	177	197	225	227
60 - 65	166	170	139	140	156	178
65 - 70	26	36	37	31	31	34
Male	284	304	321	339	356	368
15 - 20	12	13	14	13	13	13
20 - 25	32	32	32	34	33	33
25 - 30	39	40	39	39	41	40
30 - 35	39	43	43	42	42	45
35 - 40	38	42	46	46	44	45
40 - 45	27	35	38	42	42	41
45 - 50	24	26	35	38	41	41
50 - 55	26	25	27	36	39	42
55 - 60	25	25	25	27	35	39
60 - 65	18	18	18	18	19	25
65 - 70	/	/	/	/	/	/
Female	1390	1406	1416	1451	1484	1499

Figure 6: Selection of All Cells in the Subtables by Duplicating the Hierarchy of the First Table

button are the nodes in the hierarchy created as desired. Figure ?? shows the resulting selection after the user approved the

The same method that worked effectively for duplicating the columns can now be applied to the subtables, as shown in Figure ??.

By selecting the node with the value "Total" and clicking the "Move and Duplicate" button, we can apply the selection of the "Total" subtable to the other subtables. This involves shifting the table downward by as many rows as necessary to overlap with the subtable below.

However, there is a minor issue: the child nodes of the "Total" node also include the column headers. If these column headers were repeated in the subtables below, shifting the selections downward would work without modification. Since these cells are not repeated in the subtables, we need to prevent the column headers cells from moving during the duplication process.

To achieve this, we can exclude individual nodes from being moved by locking their selection. This is done by clicking the padlock icon on the corresponding nodes, which freezes their cell selection and keeps them fixed at their original position, regardless of other cells being moved.

Therefore, we identify and select the nodes containing the column headers—specifically, the years 2024 to 2049—and lock their selection using the padlock button. By shifting the selection downward and duplicating it, we can easily move and duplicate the cell selections for the subtables below. By setting the number of repetitions to 2, all subtables are completely selected.

4.4 Path-wise Broadcasting

Figure ?? shows the selection hierarchy that users create on the spreadsheet. For readability, the example restricts itself to the first three columns and rows of the leftmost sub-table.

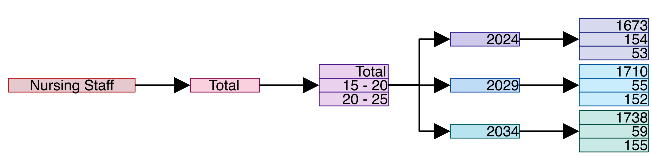


Figure 7: Selection hierarchy before path-wise broadcasting.

To produce a flat, relational table, the **SDE** performs *path-wise broadcasting*: for each root-to-leaf path $P = (v_0, \ldots, v_k)$ that ends in a list of N value cells $(x_1, \ldots, x_N)$, the SDE materializes N output rows by repeating or aligning the labels found along the path.

Concretely:

(1) **Broadcast singletons.** If a path node carries a single label (e.g., *Nursing Staff*, *Total*, or a single year), that label is replicated N times so each value cell inherits it.
(2) **Align equal-length lists.** If a path node provides a list of N labels, those labels are paired index-wise with the N value cells.
(3) **Emit one tuple per value cell.** For each $j \in \{1, \ldots, N\}$, emit a row that contains the labels gathered from the path at position j (broadcast or aligned) together with the value x_j.

The resulting hierarchy after broadcasting is illustrated in Figure **??**: upstream labels are repeated or aligned so that each numeric cell is paired with its full context, yielding one relational row per cell.

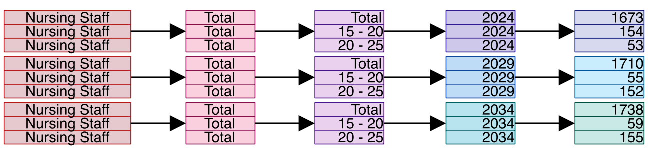


Figure 8: Selection hierarchy after path-wise broadcasting. Each value cell is paired with its repeated/aligned upstream context, producing one row per cell.

5 Interface Fidelity for Navigation

To ensure that users can navigate worksheets without difficulty, we prioritize displaying the worksheets in a manner that closely resembles their appearance in Excel. This involves accurately rendering cell dimensions, formatting, and text behaviors.

5.0.1 Displaying Row Heights and Column Widths. Our solution extracts information about column widths and row heights directly from the Excel file's XML structure. Specifically, we retrieve the column widths from the *width* attribute of the `<col>` elements and the row heights from the *ht* attribute of the `<row>` elements in the `sheetX.xml` files.

In Excel, column widths and row heights are defined in units that do not directly correspond to pixels, requiring conversion for precise on-screen rendering. Moreover, different scaling factors are applied for columns and rows. Despite extensive research, we were unable to find official documentation that explains the rationale behind these specific scaling factors. Based on empirical testing, we derived the following scaling factors:

- **Column Widths**: Multiply the *width* attribute by 7.
- **Row Heights**: Multiply the *ht* attribute by $\frac{4}{3}$.

5.0.2 Cell Formatting. Cell formatting plays a crucial role in accurately representing the appearance of worksheets. Formatting information is stored in the `styles.xml` file, where styles are defined and later referenced in the `sheetX.xml` files as shown in Figure **??**.

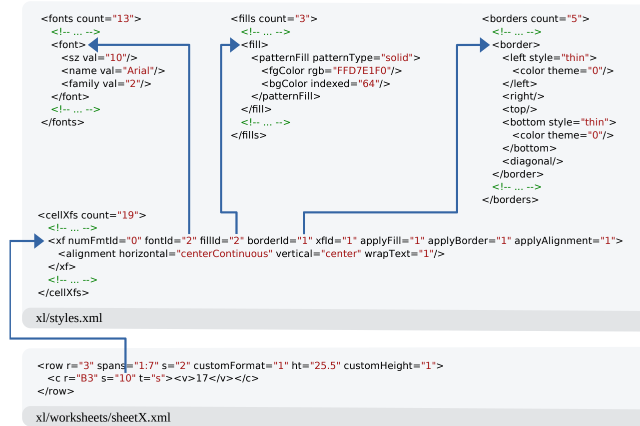


Figure 9: Illustration of the relationship between style definitions in xl/styles.xml (fonts, fills, borders, and cellXfs) and their application in a worksheet file (xl/worksheets/sheetX.xml).

Each cell in the worksheet references a style index through the *s* attribute, which points to the corresponding `<xf>` element within the `cellXfs` collection. These `<xf>` elements contain attributes such as *fontId*, *fillId*, and *borderId*, which reference specific font, fill (background), and border definitions located in the `fonts`, `fills`, and `borders` collections, respectively. By parsing these references, we can accurately apply the appropriate fonts, background colors, and border styles to each cell.

Through meticulous parsing and application of these formatting details, we ensure that the rendered worksheet closely mirrors the original Excel file, preserving the visual cues and aesthetics that users expect.

5.0.3 Handling Text Overflow. In Excel, when the content of a cell exceeds its width, the text may overflow into adjacent empty cells, provided those cells do not contain any data. If adjacent cells are occupied, Excel truncates the overflowing text at the cell boundary. Replicating this behavior is essential for accurate rendering and user familiarity.

We implemented text overflow handling by checking if the adjacent cell to the right is empty before allowing text to overflow. If the adjacent cell is empty, we extend the text rendering. If the adjacent cell contains data, we truncate the text at the boundary of the original cell.

Figure **??** illustrates this behavior. The text "Supply of Nursing Staff ..." extends into the neighboring cell because it is empty. If not for this handling, the text would be truncated at the cell boundary, leading to incomplete data display as shown in Figure **??**.

By accurately handling text overflow, we improve readability and maintain consistency with Excel's user interface, which is crucial for users transitioning between Excel and our tool.

6 Scalable Parsing, Indexing, and Rendering

This section describes how the SDE achieves interactive performance on large or bloated worksheets: (i) *incremental loading* of XLSX assets, (ii) a *byte-level worksheet parser* that avoids DOMs and

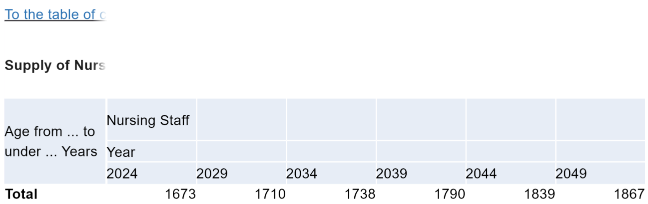


Figure 10: Incorrect rendering without overflow for cells adjacent to empty cells.

regex, (iii) compact *indexes* for merged regions and column geometry, (iv) *on-demand* streaming of rows and cells, and (v) *viewport-bounded* rendering.

6.1 Incremental Loading of Worksheets

Opening large Excel files traditionally involves loading the entire file and all its worksheets into memory before displaying any content. In files containing very large worksheets, this process can take several seconds to minutes, causing significant delays for users who need to access data quickly.

To facilitate efficient data extraction from multiple Excel files, we implemented a mechanism for incremental loading of worksheets within the SDE. Excel files (`.xlsx` format) are ZIP archives containing a collection of XML files that describe the worksheets, styles, and shared strings. Key components include:

- **`xl/sharedStrings.xml`**: Contains all the unique strings used across worksheets, reducing redundancy.
- **`xl/styles.xml`**: Defines the formatting styles for cells, including fonts, colors, and borders.
- **`xl/worksheets/sheetX.xml`**: Represents individual worksheets (`sheet1.xml`, `sheet2.xml`, etc.).

Our solution opens the Excel file as a ZIP archive and initially extracts only the essential metadata and shared resources required for the application to function. This initial extraction includes:

1. **Metadata Extraction**:
   We read the archive's directory to identify the contained files without decompressing them fully. This step is quick, taking only a few milliseconds, and provides information about the available worksheets and shared resources.
2. **Selective Extraction**:
   We immediately extract `sharedStrings.xml` and `styles.xml` because these files are small and contain information necessary for rendering cell content and styles across all worksheets. These files are parsed and stored in memory for quick access during rendering.
3. **Deferred Worksheet Loading**: The individual worksheet files (`sheetX.xml`) remain compressed and are loaded into memory in their binary unextracted form. They are not decompressed or parsed at this stage.
4. **On-Demand Parsing**:
   When a user accesses a specific worksheet—either by selecting it in the interface or when a unit test requires data from it—the corresponding `sheetX.xml` file is then decompressed and parsed. This parsing occurs in the background and is triggered only by direct user action or programmatic access to the worksheet's data.
5. **Memory Release**:
   After a worksheet has been decompressed and its XML parsed, we release the memory resources associated with the parsed data. This approach prevents excessive memory usage and ensures that the application remains responsive even when working with multiple large worksheets.

By adopting this incremental loading approach, users experience minimal wait times when opening an Excel file. The initial loading is nearly instantaneous, allowing users to begin interacting with the application without delay. This contrasts with traditional methods that require loading all worksheets upfront, leading to significant wait times for large files.

6.2 Parsing Worksheet XML with Byte-Level Pattern Matching

DOM-based parsers and regex-on-strings do not scale for very large worksheets: they require full decoding to UTF-16/UTF-8 and materialize enormous trees. In Dart, regular expressions cannot operate on byte arrays, so converting a gigabyte-scale `Uint8List` to a string alone can cost seconds. The SDE therefore parses *directly on bytes*, matching ASCII tag sentinels and reading attributes in place, decoding strings only on demand.

Parsing roadmap. Excel worksheets expose a stable top-level order: `<sheetFormatPr>`, `<cols>`, `<sheetData>`, `<mergeCells>`. We first anchor the end of `<sheetData>` by a backward byte search (Alg. **??**); then we parse metadata around it:

- `<mergeCells>` (after `</sheetData>`),
- `<sheetFormatPr>` (before `<sheetData>`) and
- `<cols>` (before `<sheetData>`)

and enter *sheet-data mode* only when rows or cells are actually needed.

Anchoring & metadata. We find the closing sentinel `</sheetData>` by scanning backward and validating the 12-byte pattern (Alg. **??**). This yields byte indices that bound all subsequent searches and lets us enumerate `<mergeCell ... ref="A1:B3">` elements linearly, converting each A1 pair to (r, c) and inserting the span into a compact index with binary-search probes and a prefix-maximum (used later by `spanAt`, Alg. **??**).

Defaults and column bands. We record the default row height H_d (attribute `defaultRowHeight`) and the default column width W_d (attribute `defaultColWidth`) in the `<sheetFormatPr ...>` node. From `<cols>` we parse each element of the form `<col min="i" max="j" width="w">`, which defines a *column band* $[i{:}j]$ with width w. Bands are stored in ascending order of `min`; queries such as retrieving the width at column c or the column at a given horizontal offset are answered via a linear or $O(\log B)$ search over these bands.

Streaming rows and accumulating offsets. Entering sheet-data mode, we stream `<row ...>` tags without decoding payloads. Within each opening tag we read `r="..."` (row index) and optional `ht="..."` (height). For each discovered row we cache its byte interval and

Algorithm 1: Backward search for </sheetData>

```
Input: b: bytes; [lo, hi): search window
Output: sheetDataCloseByte or −1
Function FindSheetDataEndBackward(b, lo, hi):
    pat ← bytes of </sheetData>
    m ← |pat|
    for i ← hi − m downto lo do
        if b[i] = pat[0] and b[i + m − 1] = pat[m − 1] and
        EqualAt(b, i, pat) then
            return i
    return −1
```

compute its top offset incrementally using explicit heights or the default H_d:

$$\mathrm{off}_1 = (r_1 - 1)\, H_d, \qquad \mathrm{off}_i = \mathrm{off}_{i-1} + (h_{i-1} \text{ or } H_d) + (r_i - r_{i-1} - 1)\, H_d.$$

See Alg. **??**.

Lazy cell parsing. Given a row byte interval $[s, e)$, cells are parsed on demand. We scan for `<c`, read attributes (`r="A123"`, `s="..."`, `t="..."`), and bound the cell interval by the next `<c` or the row end. Values are extracted *within* this interval from `<v>...</v>` or (for inline strings) `<is>...</is>`. See Alg. **??**. Because Excel enforces increasing row indices, we can stop row streaming as soon as we pass the requested row.

Merged regions. Merged areas are rectangles $[r_1, r_2] \times [c_1, c_2]$. We normalize and sort spans by (r_1, c_1), store parallel arrays $\mathsf{R}_1, \mathsf{C}_1, \mathsf{R}_2, \mathsf{C}_2$, and build a prefix-maximum PM over R_2. A point query `spanAt`(r, c) uses (i) a binary search on R_1 to cap candidates above r, (ii) a binary search over PM to drop candidates ending before r, (iii) a binary search on C_1 to find those with $c_1 \le c$, then a short local check; an origin map answers "is this cell the origin?" in $O(1)$. See Alg. **??**.

Scroll extents (without decoding payloads). We obtain $r_{\max}$ by scanning backward to the last `<row ... r="...">`. A single forward pass accumulates $\sum_{r \in E} \mathrm{ht}(r)$ and counts $|E|$; all other rows use H_d. In device units,

$$H_{\text{sheet}} = \sum_{r \in E} \mathrm{ht}(r) + (r_{\max} - |E|)\, H_d.$$

Horizontally, letting $c_{\max}$ be the largest covered column,

$$W_{\text{sheet}} = \mathrm{colOff}(c_{\max}) + w(c_{\max}).$$

These extents parameterize the viewport and drive scrollbar sizing in the UI.

Complexity and memory. All searches are bounded by structural sentinels (>, next `<row`, next `<c`, or `</sheetData>`). Anchoring `</sheetData>` is $O(N)$ with tiny constants; row streaming is $O(R)$ with $O(1)$ per-row offset updates; a targeted cell within a row scans only that row's interval; merge queries run in $O(\log M + \alpha)$ with a short local scan α. The representation is compact (byte slices + small numeric state), and strings are decoded only when needed.

6.3 Two-Dimensional Grid Viewport Rendering

Given a (potentially very large) worksheet with variable row heights, banded column widths, and merged regions, we lay out only tiles intersecting the current viewport. The renderer works in device pixels but derives all positions from the byte-level parser. Our goal is *frame-local* work proportional to the number of *visible* rows/-columns, independent of sheet size. Algorithm **??** summarizes the procedure. Throughout, index intervals are half-open $[a, b)$.

Algorithm 2: Stream rows & compute offsets

```
Input: b: bytes; window [o, c) with o = index after <sheetData...>, c =
       index of </sheetData>; default height H_d; pixel scale ρ
Output: sequence of ⟨r, [s, e), h, off⟩
Function RowsWithOffsets(b, [o, c), H_d, ρ):
    i ← o;  prevR ← ⊥;  prevH ← ⊥;  prevOff ← 0;  prevS ← ⊥
    while i ≤ c − 4 do
        if b[i..i + 3] = <row> then
            s ← i
            (r, h, j) ← ParseRowAttrs(b, i, c) // advances to just
              after >

            if prevR = ⊥ then
                off ← ρ · (r − 1) H_d
            else
                g ← r − prevR − 1
                H_prev ← (prevH or H_d)
                off ← prevOff + ρ · H_prev + ρ · g H_d
            if prevR ≠ ⊥ then emit
            ⟨prevR, [prevS, s), prevH, prevOff⟩
            prevR ← r;  prevH ← h;  prevOff ← off;  prevS ← s
            i ← j
        else
            i ← i + 1
    if prevR ≠ ⊥ then emit ⟨prevR, [prevS, c), prevH, prevOff⟩

Input: b: bytes; i: index at <row; c: close bound (sheet end)
Output: (r, h, j): row index r (or ⊥), optional height h (or ⊥), and j = first
        byte after >
Function ParseRowAttrs(b, i, c):
    r ← ⊥;  h ← ⊥;  j ← i + 4
    while j < c do
        if b[j] = > then
            j ← j + 1; return (r, h, j)
        if b[j] = r and b[j − 1] is space then
            k ← j + 1
            (s, e) ← GetInnerAttrInterval(k, c, b)
            if (s, e) ≠ ⊥ then r ← ParseIntAscii(b, s, e)
        if b[j..j + 1] = ht and b[j − 1] is space then
            k ← j + 2
            (s, e) ← GetInnerAttrInterval(k, c, b)
            if (s, e) ≠ ⊥ then h ← ParseDoubleAscii(b, s, e)
        j ← j + 1
    return (r, h, j) // malformed tail safely falls through

Input: i: scan index after the attribute name; n: hard bound; b: bytes
Output: (s, e) inner half-open interval, or ⊥ if not well-formed
Function GetInnerAttrInterval(i, n, b):
    while i < n and b[i] is space do
        i ← i + 1
    if i < n and b[i] = = then
        i ← i + 1
        while i < n and b[i] is space do
            i ← i + 1
        if i < n and (b[i] = " or b[i] = ') then
            q ← b[i]; i ← i + 1; s ← i
            while i < n and b[i] ≠ q do
                i ← i + 1
            return (s, i)
    return ⊥
```

Algorithm 3: Resolve cell by streaming the row

```
Input: b: bytes; row interval [S, E); target column c
Output: cell interval [s, e) or ⊥
i ← S
while i ≤ E − 2 do
    if b[i..i + 1] = <c then
        s ← i
        (c′, j) ← ParseCellCol(b, i, E)        // reads r="A123" and
            advances to just after >
        // end of this cell = next <c or E
        k ← j
        while k ≤ E − 2 and b[k..k + 1] ≠ <c do
            k ← k + 1
        e ← (k ≤ E − 2) ? k : E
        if c′ = c then
            return [s, e)
        i ← e
    else
        i ← i + 1
return ⊥
```

Inputs. Let x_0, y_0 be the horizontal/vertical scroll offsets (device pixels) and $W_{\text{vp}}, H_{\text{vp}}$ the viewport size. We use a small *cache extent* $\Delta > 0$ to pre-build tiles that will imminently enter view, rendering over $[x_0,\ x_0{+}W_{\text{vp}}{+}\Delta){\times}[y_0,\ y_0{+}H_{\text{vp}}{+}\Delta)$. Row geometry comes from the streaming parser: each row r has a top offset $\text{off}(r)$ and a height $h(r)$ (explicit `ht` if present, otherwise the default). Columns are given as ordered bands; for column c we can query its width $w(c)$ and cumulative offset $\text{colOff}(c)$. Merged regions are indexed by a structure that decides, in logarithmic time, whether a coordinate (r, c) is covered and, if so, by which span.

Visible set. We invert the cumulative-height/width functions:

$$r_\ell = \lfloor \text{rowIndexAt}(y_0) \rfloor, \quad r_u = \lceil \text{rowIndexAt}(y_0 + H_{\text{vp}} + \Delta) \rceil,$$

$$c_\ell = \lfloor \text{colIndexAt}(x_0) \rfloor, \quad c_u = \lceil \text{colIndexAt}(x_0 + W_{\text{vp}} + \Delta) \rceil.$$

Here `rowIndexAt`(y) and `colIndexAt`(x) are binary searches over cumulative extents built from parsed row heights and column bands, yielding $O(\log R)$ and $O(\log B)$ lookup time, respectively.

Cell coordinates and merge spans. A merged region is a closed rectangle $[r_1, r_2] \times [c_1, c_2]$ with $r_1 \le r_2$ and $c_1 \le c_2$. We sort spans by origin (r_1, c_1) and materialize parallel arrays $\mathsf{R}_1, \mathsf{C}_1, \mathsf{R}_2, \mathsf{C}_2$ plus a prefix-maximum array $\mathsf{PM}[i] = \max_{0 \le j \le i} \mathsf{R}_2[j]$. An origin map supports $O(1)$ checks that (r, c) is the top-left of a span. Membership "is (r, c) covered?" runs in three bounded steps:

(1) **Row window (binary search).** $hi = \text{ub}(\mathsf{R}_1, r)$; candidates lie in $[0, hi)$. Then $lo = \text{lb}(\mathsf{PM}[0{:}hi), r)$ discards all indices with $\mathsf{R}_2 < r$.
(2) **Column narrowing (binary search).** $k = \text{ub}(\mathsf{C}_1[lo{:}hi), c) - 1$ is the last origin with $c_1 \le c$.
(3) **Local check (constant expected).** Scan left from k while $\mathsf{C}_1[i] \le c$; accept if $r \le \mathsf{R}_2[i]$ and $c \le \mathsf{C}_2[i]$.

We use $\text{ub}(A, x) = \min\{i \mid A[i] > x\}$ and $\text{lb}(A, x) = \min\{i \mid A[i] \ge x\}$. This yields $O(\log M + \alpha)$ time, where α is a short local scan in practice.

Origin-first placement for merged regions. A naïve scan of $[r_\ell{:}r_u]\times[c_\ell{:}c_u]$ would instantiate merged tiles multiple times. Instead, we *pre-place* only spans whose origins lie outside the leading edges but whose rectangles intersect the viewport: probe the top border $(r_\ell, c_\ell{:}c_u)$ and the left border $(r_\ell{:}r_u, c_\ell)$, query $\text{spanAt}(r, c)$, and place the tile once at its origin (r_S, c_S). We maintain a burned set B to avoid duplicates in the interior.

Interior tiling. Traverse the visible grid and place a tile at (r, c) only if (i) no span covers it, or (ii) (r, c) is the origin of its span (checked in $O(1)$). Device positions are $x = \text{colOff}(c) - x_0$, $y = \text{off}(r) - y_0$.

Scroll extents. We size the vertical scroll domain from row attributes without decoding payloads. Anchored at `</sheetData>`, we scan backward to the last `<row ...>` to read $r_{\max}$ from `r="..."`. A single forward pass accumulates explicit heights $\sum_{r \in E} \text{ht}(r)$ and counts them as $|E|$; all other rows in $1..r_{\max}$ use the default H_d. With device pixels,

$$H_{\text{sheet}} = \sum_{r \in E} \text{ht}(r) + (r_{\max} - |E|)\, H_d.$$

Horizontally, with $c_{\max}$ the highest covered column,

$$W_{\text{sheet}} = \text{colOff}(c_{\max}) + w(c_{\max}).$$

These extents parameterize the viewport and drive scrollbar sizing/positioning (*two_dimensional_scrollables* [?]).

Correctness and complexity. Edge probes ensure any merged region intersecting the viewport but originating above/left is instantiated *exactly once* at its origin. The interior pass either places unmerged cells or the unique origin cell of each merged region. Let $R_{\text{vis}} = r_u - r_\ell + 1$ and $C_{\text{vis}} = c_u - c_\ell + 1$. Passes 1-2 cost $O(R_{\text{vis}} + C_{\text{vis}})$; Pass 3 costs $O(R_{\text{vis}}\, C_{\text{vis}})$ and does no work outside the visible rectangle. The burned set is updated at most once per span per frame.

6.4 AABB-Indexed Selection Lookup

Each selection source (a task or composed group) maintains a lazily computed, cached *axis-aligned bounding box* (AABB) that is invalidated on updates and recomputed on demand. When many such selection sourcess (grids) intersect the viewport, a linear scan over their bounding boxes can dominate latency. We therefore maintain a lightweight index over axis-aligned bounding boxes (AABBs) to answer point queries (x, y) in $O(\log G + \alpha)$ time, where G is the number of visible grids and α is the size of a narrow candidate window.

Each grid i exposes a bounding rectangle $[L_i, R_i] \times [T_i, B_i]$ in grid coordinates and a point predicate $\text{findCell}_i(x, y)$ that returns the cell at (x, y) or $\perp$. We build parallel arrays L, R, T, B (left, right, top, bottom) and a stable original-order index O (used to break ties consistently with the UI). Let σ be the permutation that sorts grids by nondecreasing T (top edge). In that order we form a prefix-maximum array $\text{PM}[j] = \max_{0 \le i \le j} B_{\sigma(i)}$. For a query row y, the candidate window is the tightest interval $[\ell, h)$ such that all boxes whose top $\le y$ and bottom $\ge y$ lie in that interval; we obtain $h = \text{ub}(T_\sigma, y)$ and $\ell = \text{lb}(\text{PM}[0{:}h), y)$ by binary search (ub: strict upper bound; lb: lower bound). We then prune by the x-interval condition $L \le x \le R$. Among the surviving candidates we test findCell in increasing O (original) order and return the first hit; if none match, the answer is $\perp$.

Algorithm 4: Viewport layout with merge-aware origin-first placement

```
Input: x₀, y₀; W_vp, H_vp; cache Δ; sheet accessors
       rowIndexAt, colIndexAt, off, colOff, h, w; merge index
       spanAt, isOrigin
Output: positioned tiles for current frame
// Visible indices
r_ℓ ← ⌊rowIndexAt(y₀)⌋, r_u ← ⌈rowIndexAt(y₀ + H_vp + Δ)⌉
c_ℓ ← ⌊colIndexAt(x₀)⌋, c_u ← ⌈colIndexAt(x₀ + W_vp + Δ)⌉
B ← ∅ // burned merged spans

// Pass 1: top border probes
for c ← c_ℓ to c_u do
    S ← spanAt(r_ℓ, c)
    if S ≠ ⊥ and S ∉ B and r_S < r_ℓ then
        place tile for S at (colOff(c_S) − x₀, off(r_S) − y₀)
        B ← B ∪ {S}
// Pass 2: left border probes
for r ← r_ℓ to r_u do
    S ← spanAt(r, c_ℓ)
    if S ≠ ⊥ and S ∉ B and c_S < c_ℓ then
        place tile for S at (colOff(c_S) − x₀, off(r_S) − y₀)
        B ← B ∪ {S}
// Pass 3: interior tiles
for c ← c_ℓ to c_u do
    x ← colOff(c) − x₀
    for r ← r_ℓ to r_u do
        y ← off(r) − y₀
        S ← spanAt(r, c)
        if S = ⊥ or isOrigin(S, (r, c)) then
            place tile at (x, y)

// ub(A, x) = min{i | A[i] > x}, lb(A, x) = min{i | A[i] ≥ x}.
Function spanAt(r, c):
    hi ← ub(R₁, r)
    if hi = 0 then
        return ⊥
    lo ← lb(PM[0:hi), r)
    if lo ≥ hi then
        return ⊥
    k ← ub(C₁[lo:hi), c) − 1
    if k < lo then
        return ⊥
    for i ← k downto lo do
        if C₁[i] > c then
            break
        if r ≤ R₂[i] and c ≤ C₂[i] then
            return span i
    return ⊥
```

The index builds in $O(G \log G)$ time and consists of six integer arrays plus the permutation π. It is invalidated on any structural change to the set of grids (move, resize, insert/delete) and rebuilt lazily on the next query. For small G (e.g., $G \leq 32$) we fall back to a linear scan; the cutover can be tuned empirically.

6.5 Lazy Output Flattening and Row Location

Large workbooks and selection hierarchies make fully materializing a relational view prohibitively expensive. Empirically, naive flattening leads to seconds or minutes of UI stalls on sheets with up to 10^6 rows (Excel's limit) and many columns. Our goal is to *render only what the user is about to see*, without precomputing the entire output.

Algorithm 5: AABB-indexed selection lookup over visible grids

```
Input: point (x, y); arrays L, R, T, B; permutation σ sorting by T; prefix max
       PM over B_σ(·); original-order O; accessor findCell_i(x, y)
Output: either ⟨i, cell⟩ or ⊥
// Binary-search helpers: ub(A, z) = min{i | A[i] > z},
   lb(A, z) = min{i | A[i] ≥ z}.
// 1) Y-narrowing: window of candidates whose top ≤ y and
   bottom ≥ y
h ← ub(T_σ, y)                         // first index with T_σ(h) > y
if h = 0 then
    return ⊥
ℓ ← lb(PM[0:h), y)                     // first prefix with bottom ≥ y
if ℓ ≥ h then
    return ⊥
// 2) X-pruning: keep only boxes covering x
C ← ∅
for j ← ℓ to h − 1 do
    i ← σ(j)
    if L_i ≤ x ≤ R_i then
        append i to C
if C = ∅ then
    return ⊥
// 3) Stable tie-break and confirmation
C ← sort C by increasing O_i           // preserve UI order/colors
foreach i ∈ C do
    ans ← findCell_i(x, y)
    if ans ≠ ⊥ then
        return ⟨i, ans⟩
return ⊥
```

Design overview. We model the visible table as a single *global row space* obtained by concatenating many small, contiguous *row blocks*. Each block is produced by streaming the hierarchy `files` → `tasks` → `sheets` → `cellTasks` in a deterministic order. The UI asks for a particular global row index r (e.g., the first row currently in the viewport); we then extend the stream just far enough so that r falls inside a cached block. This *on-demand flattening* avoids touching unrelated parts of the hierarchy.

Data structures. We maintain two parallel arrays: (i) `blocks` contains the realized row blocks (each stores `startRow`, `len`, `path`, `cells`, and the active workbook/sheet), and (ii) `starts` stores the corresponding `startRow` values. By construction, `starts` is strictly increasing. A FIFO queue Q holds pending `(task, path)` frames for a breadth-first streaming traversal. Traversal indices over files/sheet-tasks/sheets maintain the current context (`activeWb`, `activeSheet`). Optional caps $B_{\max}$ and $R_{\max}$ bound memory by pruning the oldest blocks.

Driver and lookup. When the UI requests row r, EnsureBuiltThroughRow extends the stream until *builtRows* $> r$ or the source is exhausted (Alg. **??**). We then locate the block via a binary search over `starts` (*upper bound* on r and step one back), yielding the block index and the local in-block offset (Alg. **??**, LocateRow). Both steps are $O(k)$ work to extend by k newly discovered rows plus $O(\log |starts|)$ for the lookup.

Streaming next block. NextBlock (Alg. **??**) emits the next contiguous block. If Q is empty we call FillQueueIfEmpty to advance to the next *source segment* (file, sheet task, sheet pair) with non-empty roots. Otherwise we pop a frame. If the popped task has no

Algorithm 6: Lazy row locator: driver and lookup (part A)

```
Input: hierarchy files→tasks→sheets→cellTasks; caps B_max, R_max
Output: on demand: for global row r, return (RowBlock, local) or ⊥
State: arrays blocks, starts; queue Q; indices fi, sti, si; curFile, curTask;
curSheets; (activeWb, activeSheet).
Function EnsureBuiltThroughRow(r):
    while builtRows ≤ r do
        rb ← NextBlock()
        if rb = ⊥ then
            break
        append rb to blocks; append rb.startRow to starts;
        PruneHeadIfNeeded()

Function LocateRow(r):
    EnsureBuiltThroughRow(r)
    if blocks = ∅ then
        return ⊥
    lo ← 0; hi ← |starts|
    while lo < hi do
        mid ← ⌊(lo + hi)/2⌋
        if starts[mid] ≤ r then
            lo ← mid + 1
        else
            hi ← mid
    idx ← lo − 1
    if idx < 0 then
        return ⊥
    b ← blocks[idx]; local ← r − b.startRow
    if 0 ≤ local < b.len then
        return (b, local)
    else
        return ⊥
```

children, its `sortedSelectedCells` form a new RowBlock (start = `builtRows`, length = number of selected cells) and we return it. If the task has children, we enqueue each child with the extended `path`. This BFS over the selection tree yields a deterministic, top-down order that matches the user's mental model.

Algorithm 7: Row block generation (part B): NextBlock

```
Function NEXTBLOCK:
    if ¬FillQueueIfEmpty() then
        return ⊥
    while true do
        if Q = ∅ then
            if ¬FillQueueIfEmpty() then
                return ⊥
            continue
        (t, path) ← pop-front Q
        if t.children = ∅ then
            cells ← t.sortedSelectedCells
            if |cells| = 0 then
                continue
            start ← builtRows; len ← |cells|
            return
            RowBlock(activeWb, activeSheet, path, cells, start, len)
        nextPath ← path ∪ {t}
        foreach u ∈ t.children do
            push-back (u, nextPath) into Q
```

Source advancement. FILLQUEUEIFEMPTY (Alg. **??**) advances through the outer hierarchy: it steps files (fi), sheet tasks (sti), then sheet pairs (si). For each sheet pair (wb, sh) it materializes the roots (`importExcelCellsTasks`) into Q and sets the active context used to form RowBlocks. If a segment has no roots, it is skipped. When the last file is exhausted and Q remains empty, the function returns **false** and the stream is complete.

Algorithm 8: Traversal feeding (part C): FillQueueIfEmpty

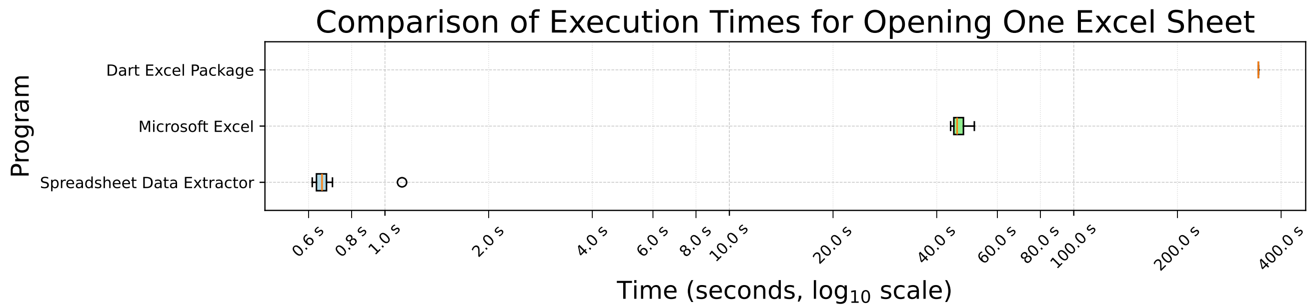
```
Function FILLQUEUEIFEMPTY:
    while Q = ∅ do
        if curTask = ⊥ then
            if fi ≥ |files| then
                return false
            curFile ← files[fi++]; sti ← 0
        if sti ≥ |curFile.sheetTasks| then
            curTask ← ⊥; continue
        curTask ← curFile.sheetTasks[sti++];   curSheets ←
        list(curTask.sheets); si ← 0
        while si < |curSheets| and Q = ∅ do
            (wb, sh) ← curSheets[si++];
            roots ← curTask.importExcelCellsTasks
            if |roots| = 0 then
                continue
            Q ← queue of (root, ∅) for each root ∈ roots
            activeWb ← wb; activeSheet ← sh
        if Q ≠ ∅ then
            return true
    return true
```

Cache pruning. PRUNEHEADIFNEEDED (Alg. **??**) trims the front of the cache to respect either (i) a block count cap $B_{\max}$, or (ii) a total cached row cap $R_{\max}$. Trimming removes the oldest blocks and their starts while preserving the invariant that `starts` remains strictly increasing and aligned with `blocks`. In practice we choose small caps that comfortably cover one or two viewport heights plus prefetch.

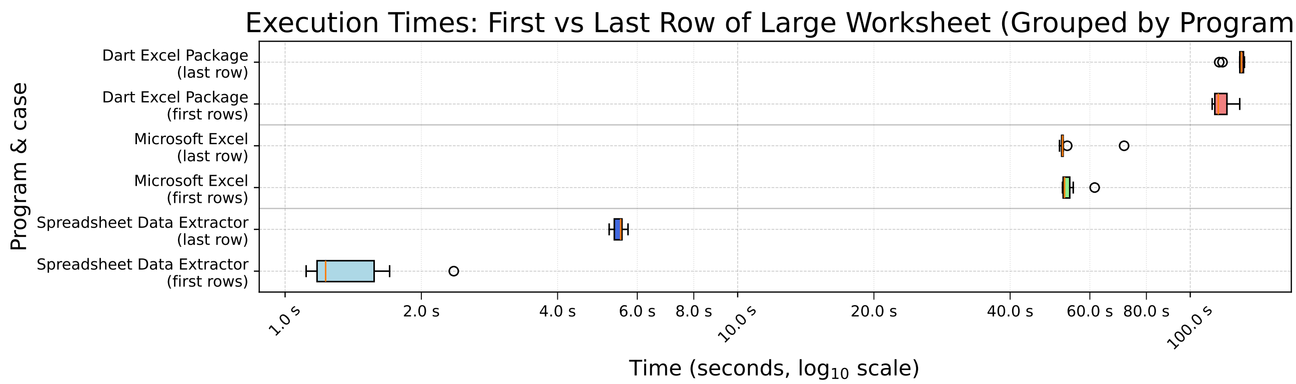
Algorithm 9: Cache pruning (part D): PruneHeadIfNeeded

```
Function PRUNEHEADIFNEEDED:
    rm ← 0
    if B_max ≠ ⊥ and |blocks| > B_max then
        rm ← |blocks| − B_max
    if R_max ≠ ⊥ then
        while rm < |blocks| do
            cached ← blocks[|blocks| − 1].startRow +
            blocks[|blocks| − 1].len − blocks[0].startRow
            if cached ≤ R_max then
                break
            rm ← rm + 1
    if rm > 0 then
        drop first rm from blocks and starts
```

Invariants and correctness. (1) **Monotone coverage:** every emitted block has `startRow` = $builtRows$ at creation time, and we update $builtRows \leftarrow builtRows$ + `len`; thus blocks are disjoint and cover $[0, builtRows)$ without gaps. (2) **Sorted index:** `starts` is strictly increasing; binary search always returns the last block whose start $\leq r$. (3) **Determinism:** the traversal order is completely determined by the order of files/sheet-tasks/sheets and by the top-down BFS over the selection tree; repeated runs produce identical global row layouts. (4) **Progress:** each child is enqueued at most once and each leaf produces at most one block; the stream terminates after a bounded number of steps.



(a) Large multi-worksheet workbook: opening one selected sheet (user-centred latency).



(b) Single-worksheet benchmark (1,048,548 rows): first vs. last row per programme.

Figure 11: Time-to-first-visual vs. full-parse costs across tools. (a) shows the practical benefit of initialising only the selected sheet in a multi-worksheet file; (b) isolates algorithmic differences under identical workload. Both plots aggregate 10 runs on a logarithmic time axis.

Complexity. Let N be the number of leaf tasks that produce non-empty `sortedSelectedCells`, and let $M = \sum \texttt{len}$ be the total number of output rows. Streaming is linear in the explored work: each internal node is visited once and each leaf contributes $O(1)$ metadata plus $O(\texttt{len})$ to copy/select references to its cells. A lookup for row r costs $O(k + \log |starts|)$, where k is how many *new* rows must be streamed to cover r (often $k = 0$ for warm caches). Memory is $O(|blocks|)$, bounded by $B_{\max}$ or by $R_{\max}$ rows of history.

UI integration. On each frame the viewport asks for the *leading* global row (top-left visible), calls LocateRow to obtain the block and local offset, and renders from there. We prefetch just beyond the viewport by requesting the row at $y_0 + H_{\text{vp}} + \Delta$, which amortizes the streaming cost without over-allocating memory. When the user scrolls back, previously cached blocks are reused; otherwise the binary search still runs in logarithmic time.

Failure modes. Segments with empty selections yield no blocks but are skipped efficiently. If the hierarchy ends before covering the requested row, the driver returns $\perp$; the UI interprets this as "no more data." All pruning policies preserve correctness: they only remove *past* blocks and never create gaps inside the realized suffix.

By applying this method, we render only the cells necessary for the current view, thereby optimizing performance and ensuring smooth user interactions even with large and complex worksheets.

7 Evaluation

The Spreadsheet Data Extractor (SDE) builds on the converter by Aue et al. [?], whose extraction effectiveness was evaluated on over 500 Excel files (331 files; 3,093 worksheets; mean 15 min per file, 95 s per worksheet). Our contribution focuses on *user experience* and *latency*: we render worksheets as they appear in Excel, reduce context switching by integrating selection hierarchy, worksheet view, and output preview, and engineer incremental loading, byte-level parsing and plus viewport-bounded rendering.

7.1 Acceleration When Opening Files

We quantify opening latency in two complementary scenarios: (i) a *user-centred* case that measures time-to-first-visual when opening a *selected worksheet* from a large, multi-worksheet workbook; and (ii) a *workload-equivalent* case that uses a single worksheet with 1,048,548 rows to align the amount of work across programmes (first rows vs. last row). Throughout, we report medians over repeated runs and show distributions as box plots on a $\log_{10}$ time axis.

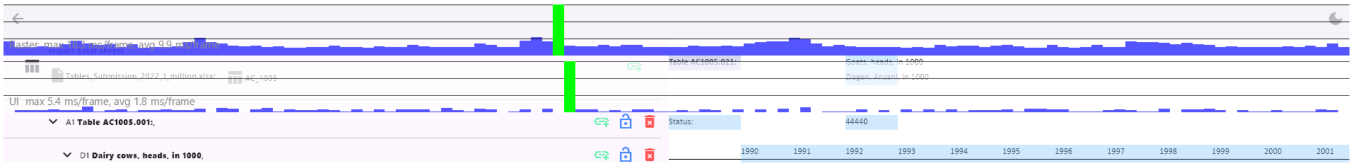


Figure 12: SDE performance profiling during scrolling. Timeline shows per-frame rendering costs (blue); average 18ms/frame and peak 54ms/frame.

Setup. We evaluate three programmes: the *SDE*, Microsoft Excel (automated via PowerShell/COM), and a Dart *excel* package. Each condition was repeated ten times *unless noted otherwise.*

User-centred latency: opening a selected worksheet. Opening a selected worksheet from a large real-world workbook [?], SDE initialises only the requested sheet and achieves a median of **0.657 s**, compared to **45.843 s** for Excel—a **69.8**× speedup (Fig. **??**). The Dart *excel* package completed only the first run at 343.568 s; runs 2-10 terminated with out-of-memory on our test machine (n=1). Based on that single run, SDE is **522.9**× faster in this scenario.

Controlling for workload comparability. The multi-worksheet experiment reflects an important user scenario (time-to-first-visual for a selected sheet), but it is not a like-for-like comparison: SDE initialises only the requested worksheet, whereas the baselines initialise the entire workbook. To control for this confound and establish workload equivalence, we construct a *single-worksheet* benchmark from the example in Section **??** (**??**) by pruning the workbook to one sheet and duplicating the table vertically until no additional table fits, yielding 1,048,548 rows of real data. The resulting file is ~ 35 MB on disk (XLSX ZIP container) and ~ 282 MB uncompressed. We then report two cases—*first rows* (time-to-first-visual) and *last row* (forces a full parse)—to align SDE's measured cost with eager parsers. Under these identical I/O and parsing conditions, SDE achieves **1.229 s** vs. **52.756 s** for Excel on first rows (**42.9**×), and **5.515 s** vs. **52.228 s** on the last row (**9.47**×).

Results (overview). Initialising only the selected sheet yields much lower time-to-first-visual (Fig. **??**); under identical workload SDE remains ~10× faster even when a full parse is enforced (Fig. **??**).

7.2 Interactive scalability

While the underlying extraction model remained effective, the previous prototype did not stay interactive on very large sheets. Empirically, on workbooks with hundreds of thousands of rows—and in particular near Excel's 10^6-row limit— two failure modes dominated:

(1) **Eager materialisation in views.** When the selection view or the output view attempted to realise large regions eagerly, per-frame times rose above 1 s, making panning and selection unusable.
(2) **Large selection hierarchies.** With many nested selections, highlight updates and duplicate/move previews performed work proportional to the total number of selected cells, causing multi-second pauses per interaction and making operations on large datasets impractical.

These observations motivated the engineering in **?? ??**: (i) byte-level, on-demand parsing of worksheet XML; (ii) viewport-bounded rendering that lays out only $[r_\ell{:}r_u] \times [c_\ell{:}c_u]$ (Algorithm **??**); (iii) AABB-based filtering of selection sources with cache invalidation (**?? ??**); and (iv) on-demand flattening of the output table (**?? ??**). Together these changes bound per-interaction work to the visible area rather than the sheet size.

On a sheet with 10^6 rows and a selection covering all cells, the UI remained smooth during scrolling, sustaining ≈ 2 ms per frame (Fig. **??**), which corresponds to ≈ 500 FPS. When dragging the scrollbar—filling the entire viewport at once with new content—frame times rose to about 60-80 ms (≈ 12-17 FPS), which remained acceptable for rapid navigation at that scale.

Benchmarking environment. All tests were conducted on a machine with an AMD Ryzen 5 PRO 7535U with Radeon Graphics (6-core CPU at 2.9 GHz), 31.3 GB RAM, and a hard disk drive (HDD), running Microsoft Windows 11 Enterprise (build 26100, 64-bit). The version of Microsoft Excel used was version 16.0.

8 Conclusion

In this paper, we introduced the Spreadsheet Data Extractor [?], an enhanced tool that builds upon the foundational work of Aue et al. [?]. By addressing key limitations of the existing solution, we implemented significant performance optimizations and usability enhancements. Specifically, SDE employs incremental loading of worksheets and optimizes rendering by processing only the visible cells, resulting in performance improvements that enable the tool to open large Excel files.

We also integrated the selection hierarchy, worksheet view, and output preview into a unified interface, streamlining the data extraction process. By adopting a user-centric approach that gives users full control over data selection and metadata hierarchy definition without requiring programming knowledge, we provide a robust and accessible solution for data extraction. Our tool offers user-friendly features such as the ability to duplicate hierarchies of columns and tables and to move them over similar structures for reuse, reducing the need for repetitive configurations.

By combining the strengths of the original approach with our enhancements in user interface and performance optimizations, our tool significantly improves the efficiency and reliability of data extraction from diverse and complex spreadsheet formats.

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