

Perquimans: A Tool for Visualizing Patterns of Spreadsheet Function Combinations

Justin A. Middleton, Emerson Murphy-Hill
North Carolina State University, Raleigh, USA
{jamiddl2, ermurph3}@ncsu.edu

Abstract—Spreadsheet environments often come equipped with an abundance of functions and operations to manipulate data, which users can combine into complex formulae. However, anticipating these combinations is difficult, complicating matters for both researchers and practitioners who want to study formulae to improve spreadsheet practices. Therefore, we developed Perquimans, a tool that analyzes spreadsheet corpora to visualize patterns of function combination as an interactive tree, capable of representing both the most common and most anomalous patterns of formula construction and their contexts in actual workbooks. Using spreadsheets from the Enron corpus, we conduct both a case study and a user study to explore Perquimans’ various applications, particularly those in flexible smell detection and spreadsheet education.

I. INTRODUCTION

Spreadsheets surround us. They serve key roles in industry, where as much as 95% of U.S. financial firms use them daily [1], and academia, where teachers can use them to track research and students’ grades, not to mention many other applications [2]. It’s this flexibility that grants them their allure: while a novice can still work without much experience, spreadsheets offer hundreds of specialized functions to fulfill a wide range of advanced needs, from complex statistics to text manipulation [3]. As such, it should be no surprise that tens of millions of workers rely on these programs daily [4].

However, this ubiquity is not without danger; as more people adopt these tools and make larger and more complex sheets, the cost of failure grows too. To illustrate this, the European Spreadsheet Risks Interest Group (EuSpRIG) documents many horror stories of spreadsheets gone wrong¹. One story tells of a 2013 economics paper which drew connections between debt and national growth. Its findings shaped many political initiatives throughout the United States and Europe. However, other researchers soon discovered that a critical selection error in the research spreadsheets hampered the results and that, by correcting this error, the findings reversed completely! And this is only one of several accounts; even if most spreadsheet errors are relatively benign, poor spreadsheet practice can risk millions, if not billions, of dollars [5].

From these stories, we can see the dire importance of understanding how people actually use spreadsheets. Fortunately, spreadsheet researchers have supported this by amassing spreadsheet collections from diverse sources, industrial to academic. Collections like EUSES [6], Fuse [7], and the Enron

corpus [8] have already fueled productive research across the field, such as in Hermans’ [9] and Jansen’s [10] search for code smells in spreadsheet environments or Aivaloglou and colleague’s work on making a grammar to capture every possible spreadsheet program in Excel [11]. Additionally, some research has focused on comparing these collections, as Jansen did in 2015, to discover variation in spreadsheet techniques over time and location [12].

Considering the value of spreadsheets and all of these resources to describe their use, it becomes necessary that we design tools to better enable the exploration of these datasets and simplify the complex concepts that occur in spreadsheet design. One such concept is that of formula construction; functions are an important part of using spreadsheets efficiently, yet the number of potential combinations between them quickly becomes massive when you consider that there are hundreds of them. Tools, then, that empower people to explore questions about which functions are used together in practice have the potential to improve the current design of spreadsheets themselves and educate new generations of spreadsheets users on how to work best.

This paper contributes such a tool, Perquimans, that attempts to fulfill this need for better exploration by building on the aforementioned spreadsheet corpora. Working with spreadsheets in Excel, Perquimans focuses primarily on the functions, like SUM and IF and hundreds more, which are the building blocks of formulae that determine values across a spreadsheet. The tool creates an interactive, exploratory visualization which captures how people combine these functions in a selected collection of spreadsheets, quantifying the broad patterns of function nesting while also being specific enough to find anomalous formulae and link them back to the specific cell in spreadsheets where they originate.

Alongside the tool, we discuss several of the key decisions we faced during design, such as what to do with redundant formulae in a sheet or how to represent optional arguments, and we describe how our overall design goals both helped and hindered this process. We then apply the tool to a number of case studies to evaluate how much it could contribute to several different contexts, most notably code smell detection and spreadsheet education. To better understand how people might use Perquimans, we also conducted a user study to judge how usable and intuitive the tool actually is. This grounds the discussion of its potential uses while also underscoring some of its inherent limitations and setting the way for future

¹<http://www.eusprig.org/horror-stories.htm>

extensions and improvements upon the concept.

II. RELATED WORK

Visualizations excel for their ability to communicate information quickly and efficiently [13]; the visualization of spreadsheets, therefore, has offered much room for research. Several previous tools work within a spreadsheet, seeking to clarify the connections between the visible values in cells, the formulae that produce them, and the dependencies between cells that inform them. Igarashi and colleague’s fluid visualizations [14], for example, do this by imposing lines, color, and animation over the spreadsheet to visually explain these tangled connections. Likewise, Clermont explored ways of grouping cells by color and border that were related through similar functions, neighbors, or references [15], and Hipfl extended this work by incorporating the layouts and labels of spreadsheets [16]. Other tools focus on creating visualizations external to the sheets. Hermans and colleagues address a spreadsheet programmer’s information needs by making dataflow diagrams from individual sheets through the tools GyroSAT [17] and Breviz [18]. Perquimans is among the latter class, creating standalone visualizations about spreadsheets instead of drawing connections inside the spreadsheet itself. In contrast to the other visualization work, our work focuses on representing functions and how they combine into complex formula, rather than exploring the data structures of any particular spreadsheet.

Many other tools inspect the structure of formulae but often from the perspective of finding bad design. Following Fowler’s initial description of code smells in object-oriented design [19], many researchers have applied similar observations to spreadsheets and have cataloged classes of problematic formulae [9] [20] [21], often accompanying them with detection tools [22] and investigations into real datasets [10]. For example, Hermans, leveraging her work with the aforementioned dataflow diagrams, has worked with assessing common inter-worksheet smells, such as feature envy and inappropriate intimacy, wherein references between worksheets (rather than cells) in a file suggest a problem [23]. Other tools, like Badame’s Excel refactoring [24], are concerned more with understanding the formula in service of changing them. However, these studies define standards of poor design and orient their searches around them. Though Perquimans supports the search for bad design, as we will see, the tool itself takes a much more agnostic approach in presentation, offering examples without regard for design quality.

Implicit in this study is an exploration of the Excel API and how people use it. Previous research, such as the first study on the Enron spreadsheets [8] or in its comparison with the EUSUS corpus [12], quantifies how often users employ certain functions but not how they combine them. Researchers have applied such questions to other contexts as well, such as Murphy and colleague’s study into how Java developers use Eclipse and what commands they use most often [25]. Others focus on the documentation of the API itself: Robillard and DeLine, for example conducted a series of surveys and

interviews to diagnose common problems with learning APIs, and they found that code examples, one of the focuses of this tool, is one of the most important aids to have in learning a new system [26]. Though this paper applies the tool to the Enron corpus specifically, the tool itself is not limited to this; it can be readily applied to any collection of Excel spreadsheets a user gives it.

III. APPROACH

A. Design Goals

In visualizing the spreadsheet data, we set out a few core goals for what the tool should accomplish. Furthermore, with these goals, we also considered the likely challenges of achieving those goals and particular outcomes which we considered beyond the scope of the research. We present both sides of these goals below:

- 1 **Provide an interactive environment for free exploration.** There are a lot of data in some of these spreadsheet corpora, and the user should be able to pick for themselves which to explore while ignoring the rest. Furthermore, this exploration should not be designed around answering one specific question but rather helping to answer a variety of questions.
- 11 **Do not make judgments about good and bad design.** Though users may certainly approach the tool with the intention of exploring particular formulae, a formula visualization tool will not prioritize any on metrics of good or bad practice.
- 2 **Emphasize the quantitative patterns in formula construction.** The tool should address the questions of how often the spreadsheet programmers used a certain function and where they used it. To do this, it must show metrics, such as frequency of use and depth of function nesting, of the dataset it conveys.
- 12 **Do not overwhelm with numbers.** For popular functions especially, we anticipate that we’ll have to show a lot of related data at once. Though everything should be accessible in accordance with Goal 1, we should design in a way that reduces noise.
- 3 **Promote a qualitative understanding of the patterns.** The tool should supplement its observations with concrete instances of relevant formulae from the corpus. Ideally, it should even direct users to the exact cell in the spreadsheets where the formula was used, contextualizing the functions.
- 13 **Do not attempt to explain formulae.** Though the tool will to foster understanding by linking pattern to example, it will not try to be an explanatory tool that articulates what a complex formula accomplishes. Rather, we will provide the structure and context, and the user must infer this on their own.

Though we kept these guidelines in mind through the development of Perquimans, we nevertheless reached a number of points in which these principles conflicted. For a discussion of these decisions, see Section III-E.

B. Walkthrough of the Tool

Before discussing the minutiae of tool's development, we will give a basic example of how to use the tool. For this, we will work from the visualization built on the Enron corpus to answer this question: *What kinds of functions do people use to define the condition in an IF function?*

First, a word on the IF function. In Excel, it serves as one of the logical functions: given a condition as the first argument that evaluates to either true or false, it takes on the value of either the second or third argument, respectively. Or, as the documentation writes out, "IF(Something is True, then do something, otherwise do something else)"². Furthermore, the third argument is optional; if left out, the function will return a default "FALSE" value if necessary. Examples of this function in practice can be seen in Figure 1.

	A	B	C
1		Formula	Result
2	10	=IF(A2 >= 10, "Red", "Blue")	Red
3		=IF(A2 < 10, "Red", "Blue")	Blue
4		=IF(A2 >= 10, "Red")	Red
5		=IF(A2 < 10, "Red")	FALSE

Fig. 1. Configurations of the IF function

When the user first approaches the tree for a given top-level function – that is, a function nested within none other – only a few nodes are visible, as shown in Figure 2.

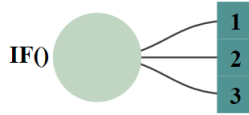





Fig. 2. How the IF tree looks at the start

The visualization so far comprises two types of nodes: the circle , which represents a discrete function in the formula and is size according to its frequency relative to the number of times to root function appeared; and the numbered squares , which represent the positions of arguments within its parent function. From this, we can confirm that, of the times it was observed, IF can have at most three arguments passed into it, which corresponds with its specifications in the API.

Knowing that it is the first argument which contains the conditionals, we click on the square labeled "1" to explore. To save space, when the tool finds more than 10 unique arguments in a position, it displays only the first ten, with an option to display the rest by clicking the arrow .

We see that IF contains a number of comparison operators as its first argument, such as = and ≤, and boolean-returning functions, like ISNA and AND, with simple equality being the most common and some use as ABS being the least seen of

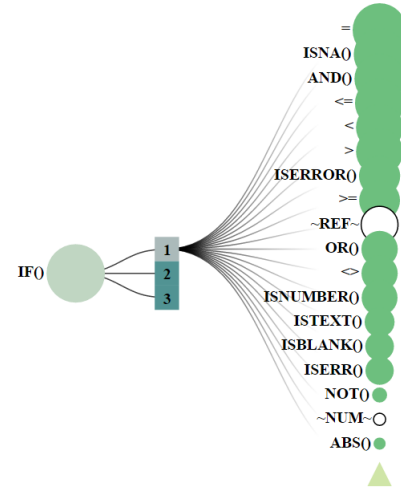




Fig. 3. First argument of the IF tree

everything actually used. From here, we can further explore the common options among these functions. Clicking on the "=" node will yield two arguments and expanding each of them will peer into the range of common values of equality comparison, which Figure 4 shows.

For both sides of the equal sign, the operator has certain types of arguments which predominate over the others: on the left side is most often a reference to another cell; on the right, a string or number literal, which makes sense for the case of confirming a value in another cell before assigning this one. Furthermore, a tooltip accompanies each function node in the tree, providing a concrete example of a function that uses this structure. If this single instance is not enough, then the user also has the option to double-click the individual function node, which will open up a new tab with a table of many more examples from dataset.

C. Glyph Glossary

From these images, we can provide a quick glossary of glyphs within the visualization to aid interpretation.

- **ABS()**  - **Function nodes** are green circles labeled with the function name. Their size is determined by their relative frequency, scaled logarithmically, to the frequency of the root node in the tree. They may have any number of arguments, including zero, as determined by the API. Users can select any of these nodes to view the examples from the provided dataset that use this function in the node's position in the tree.
- **~BOOL**  - **Value nodes** are white circles with a generic label. They represent elements of a formula which accept no arguments, like references (A1), ranges (A1:A10), numbers, boolean values, strings, and errors. However, Perquimans treats still functions with zero arguments, like NOW, as function nodes. Like function nodes, these also contain examples.

²<https://support.office.com/en-us/article/IF-function-69aed7c9-4e8a-4755-a9bc-aa8bbff73be2?ui=en-US&rs=en-US&ad=US>

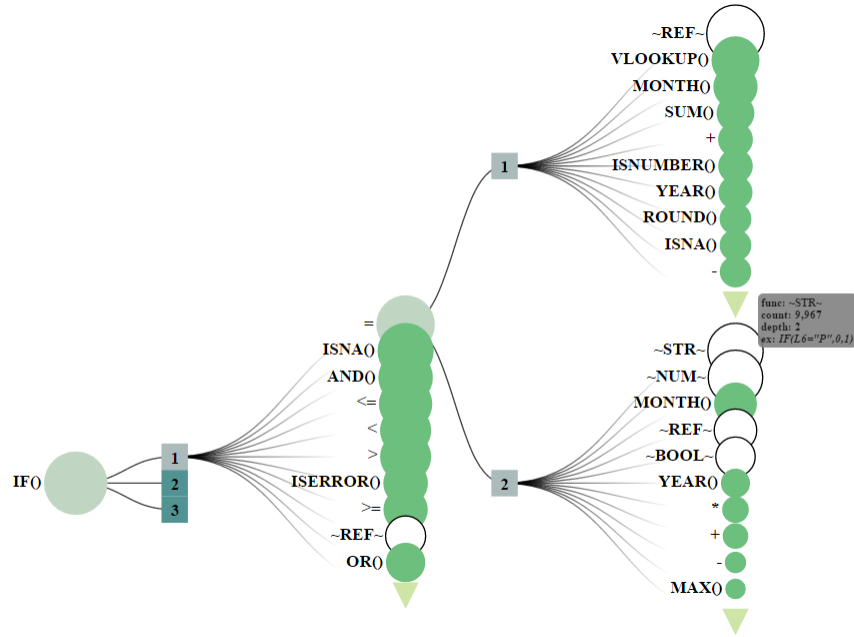


Fig. 4. A picture of Perquimans displaying the common arguments to the IF function's first parameter

- **1** - **Argument nodes** are dark blue squares labeled with a number. The number is the position of an argument within the function in the parent node. In Figure 3 for example, argument node 1 shows every function or value that was seen in the first argument.
- **Solid lines** represent a function's list of parameters. As such, they connect the function nodes to argument nodes.
- **Fading lines** represents how a formula author can use several different possible functions or values within a single argument position. As such, they connect argument nodes to function or value nodes.
- **Expansion arrows** appear within an argument node when there are over 10 possible functions or values in an argument position. By default, only the first 10 will be shown along with this arrow; clicking this will show the rest as well.
- **Optional argument trees** are variations of trees that show only formulae with a specific number of arguments. For example, the function AND can take any number of arguments, up to 255. By default, the tree shows data from AND functions with any number of arguments, but these trees, which have argument nodes of a lighter blue color, can show how AND was used when *only* two arguments were passed into it, or *only* four, and so on. See Figure 5 for how the data between tree types differs.

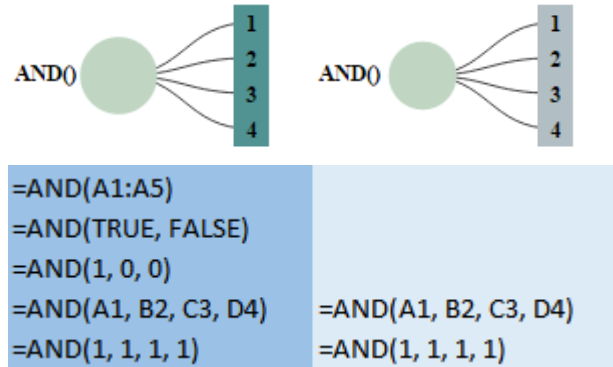


Fig. 5. The contents of the default tree (left) and the optional argument trees (right)

D. Implementation Details

The visualization is the product of two discrete processes:

- **Collection:** Given a set of Excel sheets, the tool, written in Java, uses Apache POI³ to identify and iterate over every cell containing a valid formula. Afterward, it calls POI's formula parser to break the formula text into an ordered set of individual tokens, which the tool then parses into the tree-like form. When all formulae have been analyzed like this, it produces JSON files for each top-level function in the set.
- **Presentation:** The JSON files, meanwhile, feed into the presentation code, implemented in Javascript with much

³<https://poi.apache.org/>

help from the visualization library D3⁴. We chose D3 primarily for its accessibility: given the JSON, the visualization can be simply embedded into a webpage accessible through a browser.

A demonstration of Perquimans can be found at <https://github.com/DeveloperLiberationFront/Excel-Function-Visualizer>.

E. Design Decisions

Early in the design, we chose the tree form for its inherent ability to represent the parent-children relationship of formulae as functions and their arguments, which could be yet more functions. By adapting this structure for a broad range of possibilities for nested functions, the branching factor depends alternatively on the number of arguments in a function and the number of possible functions observed as an argument in a function.

Another of our options was to represent the call trees as simple text hierarchies. Though this might work well for a single, uncomplicated call structure, we did not do this because our tool combined many of these call trees into a more complicated structure. To capture the different relationships in the tree and to quantify the frequency of arguments, we would need to be more verbose in our description. As such, we decided that visualizing some dimensions was quicker than writing them out.

Guided by the goals in Section III-A, we faced a number of decisions in how to visualize the data. Below, we've outlined those that had the largest impact in the values that appear in the tree.

- *Copied formulae*: Excel allows users to spread a formula over an area, repeating the same task in each cell with minor adjustments. Without checking for this, the analysis may not reveal the functions most commonly used together but rather the formulae most often applied to large areas. To combat this, we converted formulae from their native A1 format to the relative R1C1, in which copied formulae should be identical, and considered only each R1C1 formulae once per worksheet.
- *Importance of depth*: When a function appears within another, should it be analyzed only as a nested function or would it also be valid to analyze the nested function on its own?

For example, in the pictured IF function, we found that people often use another IF statement as the second or third arguments of the top-level IF. If we only consider functions exactly where they're found embedded in the formula, then information about the same function – IF, in this case – will be scattered across different trees with no way to aggregate them. If we record every instance of a function by ignoring their context – that is, including an IF embedded within a SUM function in the same node as the top-level IF – then the tool will represent some functions in multiple nodes to capture every possible level

of nesting. For now, we only include the first, with the latter to be added as an option in the future.

IV. CASE STUDY

The obvious question to pose to any visualization is this: What do the images tell us that the text could not? It is not enough to prove that something can be visualized; we must also demonstrate what we can be gained from any particular visualization. As such, we raised a few tasks in the introduction in which we thought the tool could help: detecting bad smells and guiding spreadsheet education. To demonstrate the tool's applicability, we sought out places in the tree which best exemplify these tasks.

A. Bad Smells

Fowler's description of code smells [19] underscored an important point of code quality: between elegant, efficient code and bug-crippled spaghetti, there is a spectrum of code designs which, by themselves, are not faulty but nevertheless suggest vulnerabilities in code design. Since then, researchers have applied these concepts to spreadsheet programming, as discussed in Section II. While some of the smells lie beyond the scope of the tool, such as those characterizing inter-worksheet connections, others have structures which create distinctive features within the tree, leading to easy detection through our visualization:

- *Multiple Operations*: A single formula comprises numerous functions and operators [9]. As a result, the formula tends to be prohibitively complex. In the visualization, since each nested and combined function creates yet another level of depth within the tree, these constructions can result in long, horizontal chains of nodes, as seen in Figure 6.
- *Long Parameter List*: A function uses numerous arguments, making it harder to understand [21]. This is not a problem for many functions which have a limited number of arguments that it accepts. However, for functions that accept arguments indefinitely, such as SUM and CONCATENATE, it creates tall towers of argument nodes from a single function node.
- *Conditional Complexity*: A logical function, particularly IF, nests several other logical functions inside of it, reducing code readability [9]. These can be traced manually in the trees for the logical functions. IF, for example, will have several more IF function nodes within its second or third arguments, which in turn might have more of the same nested within them.

Some code issues are meaningful not for the space they occupy but for how they clash with a function's expectations. For example, Excel offers a number of functions that accept any number arguments given to them, up to a resource-defined limit. SUM, for example, simply adds every argument given to it. This also means that it can accept only one argument, and when the user does so, they pass in a range of cells over 90% of the time. However, using the tool, we isolated an instance where the programmer

⁴<https://d3js.org/>

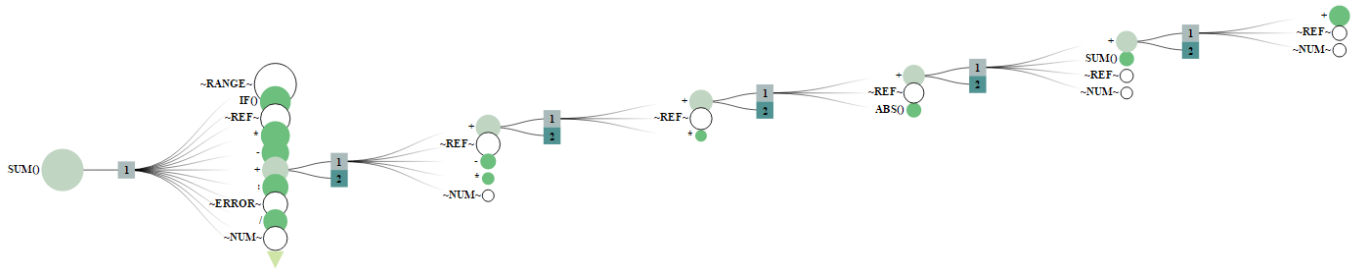


Fig. 6. The horizontal length of a tree may indicate complex or redundant design

used a single-argument SUM where the argument was a series of 32 contiguous cells added with the + operation – “SUM(C6+C7+C8+C9+C10+C11+C12+C13+...+C37)” – representing a technically valid but unusual and problematic design.

However, because Perquimans makes no judgments beforehand about which designs to emphasize as good or bad, the tool can be used to find strange or suboptimal designs that exist outside these readily visible categories. Consider the second argument of the “=” operator, already shown expanded in Figure 4: among the top five argument types for the position in an IF function were boolean values. This corresponds to designs in which conditions already in a boolean form were then checked against “=TRUE” or “=FALSE”, such as in the formula *IF(Formulas!C77=TRUE, "Yes")*, which appears in one of the sheets. Though this practice does not break anything in itself, it nevertheless represents redundant operations in formula design and indicates a possible misunderstanding of how the IF function works over the hundreds of examples of this boolean comparison that our tool can return.

B. Education

When Robillard and Deline researched common obstacles for programmers learning new APIs, they concluded that one of the most important elements of a good API was the use of code examples to demonstrate function use [26]. Examples in APIs, furthermore, come in a variety of forms: small snippets or tutorials that show only the intended function, sample applications that incorporate the function in a broader context, or even production code that employs the function but was not initially intended to be an illustrative example. Of these categories, Perquimans aligns entirely with the last; when a user chooses to explore a particular function node, they will see examples of that formula as it was used in a working environment, with the specifics depending on the dataset the tool is using.

Furthermore, Robillard and Deline’s study makes the case for examples that show “API usage patterns involving more than one method call” [26]. Examples that show only a single function, they find, are too simple, whereas those demonstrating the interaction of functions will equip users for more complex tasks. Perquimans is especially suited for this focus on combination; consider again the question in the walkthrough (Section III-B), asking which functions and

operations are used as conditions in IF. The design of this tool emphasizes the connection, then, between what functions like ISNA and AND return and what IF accepts, and specific examples for any of these combinations are only a click away.

For a deeper example, the LOOKUP functions are some of the most popular in Excel yet come with a number of important but silent requirements for proper use, and, as such, they have warranted some extra attention with regards to spreadsheet design. In short, these functions are for “when you need to look in a single row or column and find a value from the same position in a second row or column”⁵. Examples of their use can be found in Figure 7, and we will cover each type in more depth to better understand the visualizations for these functions.

	A	B	C	D	E
1	Table of Values			Formula	Result
2	1 Monday			=LOOKUP(3, A2:A6, B2:B6)	Wednesday
3	2 Tuesday			=LOOKUP(3, A2:B6)	Wednesday
4	3 Wednesday			=VLOOKUP(3, A2:B6, 2)	Wednesday
5	4 Thursday			=VLOOKUP(6, A2:B6, 2, TRUE)	Friday
6	5 Friday			=VLOOKUP(6, A2:B6, 2, FALSE)	#N/A

Fig. 7. Demonstrations of LOOKUP and VLOOKUP

LOOKUP has two forms: vector and array. In either case, the first argument is the value which you are trying to match in another column. If the formula is in the vector form, that column is the second argument, so in Figure 7, the formula in cell D2 (*=LOOKUP(3, A2:A6, B2:B6)*) will search for the value of 3 between cells A2 and A6. The value the formula returns then comes from the corresponding cell in the optional third argument’s column; since the lookup values matches the value in cell A4, it returns the value from cell B4. The array form of the LOOKUP works the same way, except that the second argument is a two-dimensional table where it matches values in the table’s first column and returns values from the last. Also, depending on the dimensions of the lookup table, the function may substitute rows for columns.

VLOOKUP works closely with this array form, except the user defines in its third argument which column from which

⁵<https://support.office.com/en-us/article/LOOKUP-function-446d94af-663b-451d-8251-369d5e3864cb>

to return values. In `=VLOOKUP(3, A2:B6, 2)`, the argument “2” tells to return the value from the second column, which is `B2:B6` here. Furthermore, it also accepts a boolean value for an optional argument: when set to `FALSE`, it returns only exact matches, and when `TRUE` or left out, it approximates the match to the closest value beneath it. We demonstrate this in Figure 7 in the bottom two `VLOOKUP` functions, one returning “Friday” and the other an error. `HLOOKUP` works identically but focuses on rows instead of columns.

All of these variations may seem daunting to a beginner, but Perquimans can help. Because of its design, users can distinguish between forms of the same function, as seen in Figure 8 where the one can explore both the frequency with which the spreadsheet programmers used these different forms – three-argument vector form much more than the array form – and then retrieve examples of every configuration in the dataset. The same goes for the `V/HLOOKUP` functions, as shown partially in Figure 9.

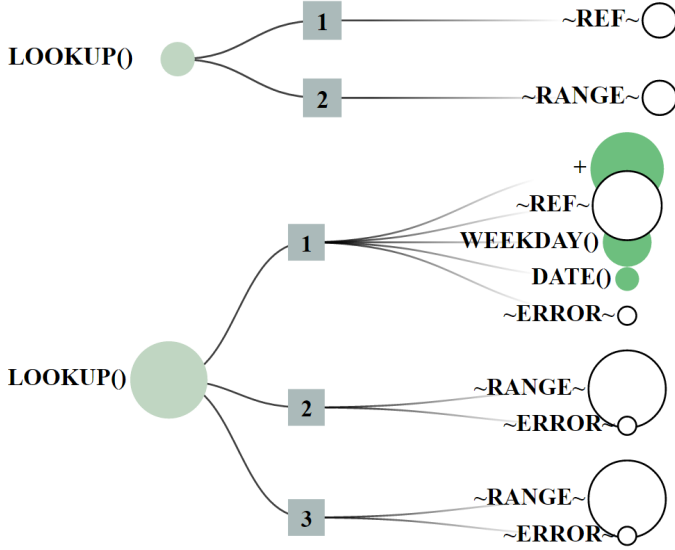


Fig. 8. LOOKUP with two and three arguments

Furthermore, these examples are good as well for exploring how it might bridge issues of bad design with education. In a recent study, Hermans, Aivaloglou, and Jansen probed the Enron dataset for uses of `VLOOKUP` and `HLOOKUP` specifically. The issue at hand was the optional fourth argument, which requires that rows are sorted lest it return inaccurate results [27]. For someone seeking to increase awareness of this problem, it first allows them to answer the question of significance – “How often do spreadsheet programmers use this function, with these particular parameters?” Though Perquimans does not discern whether neighboring columns are sorted, it can nevertheless guide the educator to several examples in production where this problem surfaces.

V. USER STUDY

During development, we conducted a brief, four-participant user study to detect conflicts between our design and the goals

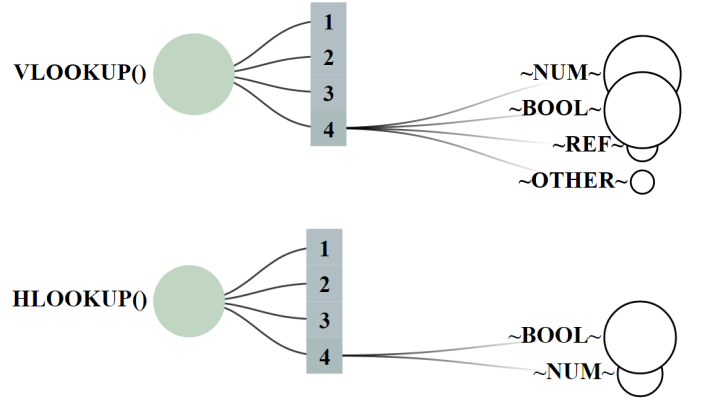


Fig. 9. VLOOKUP and HLOOKUP with four arguments

in Section III-A. We designed the study to be exploratory; given trees based in the Enron dataset and at least twenty minutes, we asked the participants to adopt the persona of a consultant evaluating a company’s spreadsheet practice, allowing for questions like which functions on which the employees most depended or which sheets or employees presented the most anomalous or dangerous designs. Though we instructed them on how to use the tool and suggested that they visit one of the most populous trees in the set, we put aside any specific tasks or questions and let them choose their own paths. Though interpretation of the phrase “spreadsheet practice” can certainly vary from participant to participant, we readily accepted this interpretive flexibility since we wanted a range of views and backgrounds despite the persona. We clarified, furthermore, that their observations could be directed either at the quality of the data conveyed by the tool or at the tool’s design itself. We present an overview of responses below, with the four participants recorded simply as P1 through P4.

A. Use in Smell Tracking

The participants were most vocal about their findings when they discovered, by purpose or accident, instances of heinous design in the dataset. Many times, they noted these examples shortly after opening a new tree, suggesting that the distinctive visual signatures as discussed in Section IV-A was a salient force in their exploration. For example, when P3 encountered the initial design of the `SUM` tree, as seen in Figure 10, they readily diagnosed that either a spreadsheet author was “totally incompetent, or [the formula was] just something that’s weird.” Even though the visualization struggles to scale well for this formula, it calls clearly to a problem in the underlying spreadsheets – awkward formulae make awkward trees. Other than these visual cues, value errors, prefixed with `#`s, also appear in the tree, which P4 said could be useful for tracking these problems if marked well.

Additionally, because the Enron files had names with the author as a prefix, P2 commented that companies could use the tool to follow up with repeat offenders. For instance, they first encountered a particular author’s name when investigating

an AVERAGE function with 18 distinct arguments for which our participant could not discern any logical order even after opening the source spreadsheet; the same name popped up again as P2 looked at a RATE function relying on several hard-coded values. P2 said that, if they were a manager or project leader, this recurrence was a sign to talk to the author personally and figure out why these problems were there, as to prevent more in the future. They also added that these problems would grow worse if this particular author left the company and no one remained who understood these formulae, a concern that aligns with Hermans' transfer scenarios [17].

The detection of bad design, however, is certainly not limited to a visualization tool. Some users remarked that a tool which printed a list of errors could work just as well for that purpose, and smell checkers can and have been directly built into spreadsheets to point out bad design. However, users also said that this visual interface is better when searching for new smells. Because the exploratory design makes no qualitative judgment and visualizes benign designs with the problematic, it allows for flexible interpretation of what a smell is; that is, a user might not realize a certain design is poor until they see it in the tree and, at the point, find specific examples of where it occurs in the spreadsheets.

B. Use in Education

Users found Perquimans' inclusion of examples to be especially useful since none of them considered themselves to be experts of Excel, their self-

Fig. 10. An abundance of parameters in SUM, which was a commonly noted smell in the user study

reported proficiencies ranging from "fairly familiar" (P2) to "not extremely familiar" (P4). For example, as P1 explored the VLOOKUP function, they said they could use the tool to collect more examples than the documentation offers even though they knew the documentation more verbosely explained its function signature. Furthermore, in the process of exploring trees, P1 and P3 also gravitated towards some functions they had not used before, such as PV and IPMT, looking for new features in Excel to explore and learn.

Additionally, Perquimans offers a simple way of finding examples where certain functions were used together, demonstrated when P4 took special interest in how people frequently used MATCH as the second argument of INDEX or how they used date functions like DATE and MONTH as lookup values in VLOOKUP. Though a standard text-search tool might yield the same results for a function alone, combinations can require more complex text queries, whereas here, the information is already captured in nodes.

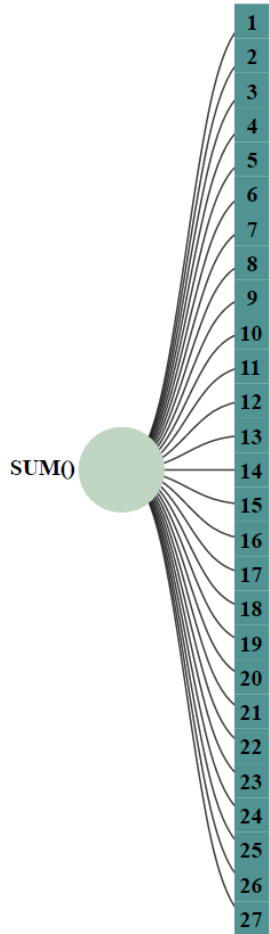
However, we found that even though a user can explore all of a function's configurations, this does not mean that they will learn exactly what it does. P1, examining unfamiliar functions like KURT and PV, could describe precisely what types of arguments it accepted and how many. But even after exploring the spreadsheets for context, they could not accurately describe what the functions produced without consulting the official documentation. Whether through reticence of the tool or obscurity of the functions themselves, the exploratory environment is not enough to teach users *when* to use a function. However, we could address this in future designs, perhaps, by linking directly to such documentation from within the tool without violating any design concerns in Section III-A.

C. Study Limitations

Though we did not start the study by telling that the data source came from Enron, two users studied the file names to deduce its roots in finance, if not Enron itself. Because of these notorious connotations, then, they might have been inclined from this information to orient their exploration around finance-related functions, potentially limiting their findings or perceived users for the tool. However, one participant also said that, without this essential context, they could not have intelligently explored a dataset in the first place. Comments like these point out the trade-offs of unguided exploration, too: though it might not restrict them to a single purpose, it might, at the same time, not afford them any mindset at all with which to interpret the data.

Furthermore, the data which users explored was processed and created before we had fully ensured that the tool could extract all of the useful data from the spreadsheets, meaning some of the counts and patterns in the trees were inaccurate. However, we decided that this was not a pressing concern, being that we were primarily concerned with whether any interesting reports could be made at all, not with whether these reports were 100% accurate assessments of reality.

Throughout the study, we noticed that users misunderstood some of the icons and, as such, their early discoveries were inaccurate. For example, P1 interpreted the numbers on the argument boxes to mean that all of the box's children had exactly that many arguments – that is, clicking on the dark blue "1" would return all the single-argument functions instead of the first argument of a function – and P2 initially took the solid lines to mean different paths in formula construction rather than different arguments of the same function. Though the users naturally did not explicitly report misinterpreting the icons, these misunderstandings became clear in their early



evaluations of the spreadsheet practice. Though we clarified the meanings when these misunderstandings became apparent, these events point to a failure in the tool to indicate every function clearly.

VI. LIMITATIONS

We began these studies with the intention of evaluating our progress towards the goals in Section III-A. Working from these results, we noted many places where the tool aligned well or fell short.

A. Unbiased Exploration

The first goal – that of full exploration – is threatened by the presence of certain formulae that the tool does not display, such as those with nonstandard functions. Because the data collection depends on POI’s formula parser, it does not allow for any partial parsing of a formula; it either processes a formula perfectly or throws it out. As such, the visualization does not display anything with syntactical errors or third-party functions that POI cannot parse. This poses larger problems, however, when POI does not support the parsing of certain functions, such as EOMONTH, preventing the healthy growth of those trees.

Other than that, we did avoid designing anything that intentionally evaluated formula designs. Nevertheless, Perquimans inadvertently emphasizes bad design of certain types, such as all of those in Section IV-A marked by their visual signatures. Even so, our participants found the discovery of bad smell to be the most interesting aspect about it, to the point where they could imagine business scenarios in which micromanagers use it to ensure precise design parameters across a department’s spreadsheets! To design in that direction, however, would mean a reevaluation of this design goal, since intentionally guiding users toward known smells may guide them away from new, unmarked ones.

B. Uncluttered Quantification

We realized early that some of the popular functions would have thousands of variations in large datasets, and showing all of these variations at once would hopelessly overwhelm the user. We therefore made a number of choices, such as the expansion arrows and the use of generic types in place of specific primitive values, that would reduce the variation to something more manageable.

Nevertheless, during the user study, P3 remarked that they specifically avoided the most popular functions, anticipating a flood of nodes from which they could salvage nothing interesting. P2 corroborated this by explaining how they gravitated toward exploring specific examples in particular value nodes over navigating the full, crowded tree, but they complicate it further by also saying that the tool at its best when it shows either every possibility of an argument side-by-side (for comparison) or nothing on that branch at all, a balance that is hard to strike with node-dense trees.

A threat to our goals, then, arises from the problem of too much data, particularly in the popular functions, like SUM and

IF. Despite our precautions, balancing the desire to show every single possibility of design with the desire not to overwhelm remains a challenge.

C. Informative Qualification

As we found in the case study, the tool excels at making formula examples available throughout a tree. However, the benefits described in the previous sections imply a hidden complication: if the tool educates through example but does not explicitly distinguish between good design and bad design, how can we be sure that people will not inadvertently learn bad design from it? In the user study, we discussed its use in education and smell detection by bringing up the issues surrounding the LOOKUP functions; this discussion, though, presupposes a distinguishing eye that knew which examples practiced good design and which exhibited the common errors. A beginner might not know the difference. Robillard and Deline, in their study, remarked that good API examples should demonstrate best practices, but, right now, we have no way to assure this with Perquimans. As with the problems in achieving unbiased exploration, correcting for this danger may entail a reevaluation of design goals.

VII. FUTURE WORK

For these user and case studies, we relied solely on Enron’s spreadsheets. However, Enron’s focus on finances and energy represents only one context in which people use spreadsheets. Other corpora, like EUSES and Fuse, draw from other domains and industries, and, as Jansen found in his comparison of spreadsheets Enron and EUSES [12], different companies rely on different functions. Though the use of a single corpora nevertheless suffices for evaluation, we may yet be able to find more interesting applications and uses for the tool in other types of spreadsheet.

Additionally, Excel is only one of many different spreadsheet products available, chosen for this project because of its prevalence. But other spreadsheets, such as Gnumeric⁶ or Google Sheets⁷ represent other approaches to spreadsheet systems. Even within identical domains, there’s no guarantee that practices and functions will hold across these varied offerings. This, then, warrants further analysis, in which good visualization might serve well.

Though our focus was specifically on function combination, there are several other elements of a formula’s context that we do not currently consider. For example, Perquimans does not currently capture argument combination; in Figure 11, it is impossible to state how often the function MATCH occurred in both the second and third arguments or whether they were more often paired with references. Furthermore, it is easy to open a tree and see what is used inside of a specific function, but finding information on what a function is used inside of takes considerably more work – we see again in Figure 11 that MATCH is used inside INDEX, but we cannot know which functions have INDEX inside them without searching every

⁶<http://www.gnumeric.org/>

⁷<https://www.google.com/sheets/about/>

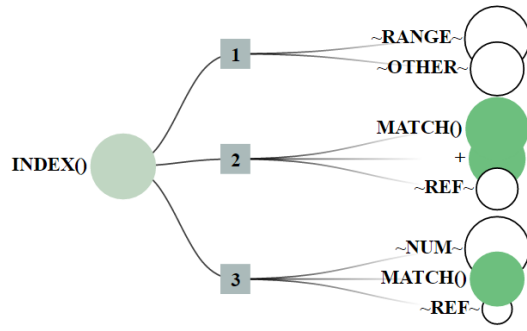


Fig. 11. A difficult question: how often is MATCH used in both the second and third arguments?

other tree. More distant concerns might be exploring which functions often occur in adjacent cells in the sheet – whenever INDEX occurs, which functions are seen most often in the cells around it?

VIII. CONCLUSION

This paper presents a tool to support the exploration of function combinations throughout a given spreadsheet dataset. By taking an agnostic approach to design quality, it attempts to convey the dataset’s spreadsheet practices as is: the common along with the anomalous, and the well-designed along with the odorous. As seen in the user and case studies, this allows it to take on several potential roles at once, such as an environment for investigating code smells as well as a repository for examples for learning new techniques.

The design of the tool still has much room for improvement. Though the exploratory philosophy fostered certain goals well, such as the ability to discover new problematic smells without knowing beforehand what they are, it hindered others. Some users, for example, found the trees of popular functions to be too crowded to explore well, or that their intention to use the tool to examine the good or the bad design exclusively was not fully supported by a tool that claimed to know neither. Many of the problems, however, were not essential to this design conflict and will be overcome in future iterations of design by refining icons and improving maneuverability.

Either way, the visualization of these large datasets represents an important step in improving practice overall. By taking these voluminous oceans of data offered in spreadsheet corpora and rendering them comprehensible through visualization, we seek to draw attention to valuable information that would otherwise go unnoticed.

ACKNOWLEDGMENT

This material is based upon work supported in whole or in part with funding from the Laboratory for Analytic Sciences (LAS). Any opinions, findings, conclusions, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the LAS and/or any agency or entity of the United States Government. I also thank the anonymous reviewers who advised the direction of this paper.

REFERENCES

- [1] R. R. Panko and N. Ordway, “Sarbanes-oxley: What about all the spreadsheets?” *arXiv preprint arXiv:0804.0797*, 2008.
- [2] A. J. Ko, R. Abraham, L. Beckwith, A. Blackwell, M. Burnett, M. Erwig, C. Scaffidi, J. Lawrance, H. Lieberman, B. Myers *et al.*, “The state of the art in end-user software engineering,” *ACM Computing Surveys (CSUR)*, vol. 43, no. 3, p. 21, 2011.
- [3] B. A. Nardi and J. R. Miller, *The spreadsheet interface: A basis for end user programming*.
- [4] C. Scaffidi, M. Shaw, and B. Myers, “Estimating the numbers of end users and end user programmers,” in *Visual Languages and Human-Centric Computing, 2005 IEEE Symposium on*. IEEE, 2005, pp. 207–214.
- [5] S. G. Powell, K. R. Baker, and B. Lawson, “Impact of errors in operational spreadsheets,” *Decision Support Systems*, vol. 47, no. 2, pp. 126–132, 2009.
- [6] M. Fisher and G. Rothermel, “The euses spreadsheet corpus: a shared resource for supporting experimentation with spreadsheet dependability mechanisms,” in *ACM SIGSOFT Software Engineering Notes*, vol. 30, no. 4. ACM, 2005, pp. 1–5.
- [7] T. Barik, K. Lubick, J. Smith, J. Slankas, and E. Murphy-Hill, “Fuse: a reproducible, extendable, internet-scale corpus of spreadsheets,” in *Proceedings of the 12th Working Conference on Mining Software Repositories*. IEEE Press, 2015, pp. 486–489.
- [8] F. Hermans and E. Murphy-Hill, “Enron’s spreadsheets and related emails: A dataset and analysis,” in *Proceedings of the 37th International Conference on Software Engineering—Volume 2*. IEEE Press, 2015, pp. 7–16.
- [9] F. Hermans, M. Pinzger, and A. van Deursen, “Detecting code smells in spreadsheet formulas,” in *Software Maintenance (ICSM), 2012 28th IEEE International Conference on*. IEEE, 2012, pp. 409–418.
- [10] B. Jansen and F. Hermans, “Code smells in spreadsheet formulas revisited on an industrial dataset,” in *Software Maintenance and Evolution (ICSME), 2015 IEEE International Conference on*. IEEE, 2015, pp. 372–380.
- [11] E. Aivaloglou, D. Hoepelman, and F. Hermans, “A grammar for spreadsheet formulas evaluated on two large datasets,” in *Source Code Analysis and Manipulation (SCAM), 2015 IEEE 15th International Working Conference on*. IEEE, 2015, pp. 121–130.
- [12] B. Jansen, “Enron versus euses: a comparison of two spreadsheet corpora,” *arXiv preprint arXiv:1503.04055*, 2015.
- [13] R. Baeza-Yates, B. Ribeiro-Neto *et al.*, *Modern information retrieval*. ACM press New York, 1999, vol. 463.
- [14] T. Igarashi, J. D. Mackinlay, B.-W. Chang, and P. T. Zellweger, “Fluid visualization of spreadsheet structures,” in *Visual Languages, 1998. Proceedings. 1998 IEEE Symposium on*. IEEE, 1998, pp. 118–125.
- [15] M. Clermont, *A scalable approach to spreadsheet visualization*, 2003.
- [16] S. Hipfl, “Using layout information for spreadsheet visualization,” *arXiv preprint arXiv:0802.3939*, 2008.
- [17] F. Hermans, M. Pinzger, and A. Van Deursen, “Supporting professional spreadsheet users by generating leveled dataflow diagrams,” in *Proceedings of the 33rd International Conference on Software Engineering*. ACM, 2011, pp. 451–460.
- [18] F. Hermans, M. Pinzger, and A. van Deursen, “Breviz: Visualizing spreadsheets using dataflow diagrams,” *arXiv preprint arXiv:1111.6895*, 2011.
- [19] M. Fowler, *Refactoring: improving the design of existing code*. Pearson Education India, 2009.
- [20] J. Cunha, J. P. Fernandes, H. Ribeiro, and J. Saraiva, “Towards a catalog of spreadsheet smells,” in *Computational Science and Its Applications—ICCSA 2012*. Springer, 2012, pp. 202–216.
- [21] A. Asavametha, “Detecting bad smells in spreadsheets,” 2012.
- [22] R. Abreu, J. Cunha, J. P. Fernandes, P. Martins, A. Perez, and J. Saraiva, “Smelling faults in spreadsheets,” in *2014 IEEE International Conference on Software Maintenance and Evolution (ICSME)*. IEEE, 2014, pp. 111–120.
- [23] F. Hermans, M. Pinzger, and A. v. Deursen, “Detecting and visualizing inter-worksheet smells in spreadsheets,” in *Proceedings of the 34th International Conference on Software Engineering*. IEEE Press, 2012, pp. 441–451.
- [24] S. Badame and D. Dig, “Refactoring meets spreadsheet formulas,” in *Software Maintenance (ICSM), 2012 28th IEEE International Conference on*. IEEE, 2012, pp. 399–409.

- [25] G. C. Murphy, M. Kersten, and L. Findlater, "How are java software developers using the eclipse ide?" *Software, IEEE*, vol. 23, no. 4, pp. 76–83, 2006.
- [26] M. P. Robillard and R. Deline, "A field study of api learning obstacles," *Empirical Software Engineering*, vol. 16, no. 6, pp. 703–732, 2011.
- [27] F. Hermans, E. Aivaloglou, and B. Jansen, "Detecting problematic lookup functions in spreadsheets," in *Visual Languages and Human-Centric Computing (VL/HCC), 2015 IEEE Symposium on*. IEEE, 2015, pp. 153–157.