A Tool for Visualizing Patterns of Spreadsheet Function Combinations

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***Abstract*—Spreadsheet environments often come equipped with an abundance of functions and operations to manipulate data, but it can be difficult to understand how programmers actually use these in practice. Furthermore, users can combine several functions into a complex formula, complicating matters for both researchers and practitioners who want to study formulae to improve spreadsheet practices. Therefore, we developed a tool that visualizes patterns of function combination in spreadsheets as an interactive tree of possibilities. Using spreadsheets from the public spreadsheet corpora, we then apply to the tool to real datasets and demonstrate its ability to capture the most common and most anomalous patterns of function combination and their contexts in actual workbooks.**

I. Introduction

Spreadsheets surround us, ordering the ever-growing flood of data that we produce. 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 lines of work [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 every day [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 stress this, the European Spreadsheet Risks Interest Group (EuSpRIG) documents many horror stories of spreadsheets gone terribly wrong[1]. One such story tells of a 2013 economics paper which drew stark 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 coding error in the research spreadsheets hampered the results and that, by correcting this error, they completely reversed the findings! 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, if only to avoid disasters. 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] or Jansen's [10] search for code smells[2] 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 simply on comparing these collections, as Jansen did in 2015, to discover variation in spreadsheet techniques over time and location [12].

Considering the sheer value of spreadsheets and all of these resources to describe their use, it becomes necessary that we design tools to make sense of it all. Tools, then, that empower people to explore datasets are rife with 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 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 formula and programs which 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:

- API improvement
- Detection of code smells
- Spreadsheet education

To round out that discussion, 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

[1] http://www.eusprig.org/horror-stories.htm

[2] Or, instances of inelegant code that do not necessarily cause problems alone but nevertheless suggest a need for refactoring to prevent future problems. More on this in section IV.

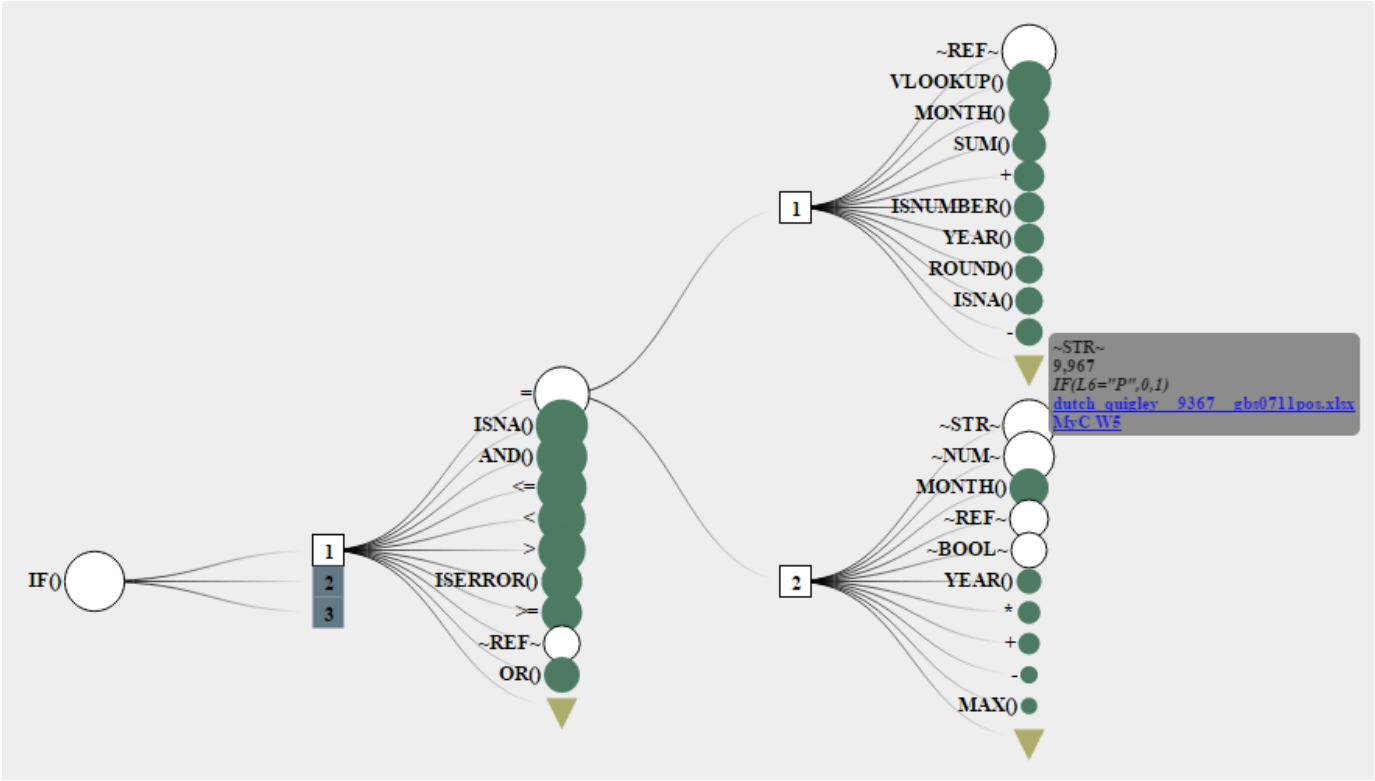


Fig. 1. A picture of the tool.

underscoring some of its inherent limitations and setting the way for future extensions and improvements upon the concept.

II. Related Work

Given humanity's affinity for visual information, visualizations have long been prized for their ability to communicate information quickly and efficient [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 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. In contrast to Hermans' work, though, our work focuses on representing functions and how they comprise complex formula, rather than exploring the data structures of any particular spreadsheet.

Many other tools inspect the structure of formulas 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 [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 Badam's Excel refactoring [24], are concerned more with understanding the formula in the 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], quantify how ofter 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/Methodology

A. Design Goals

In visualizing the spreadsheet data, I outlined a few core goals for what the tool should accomplish:

1 **Draw an interactive interface to explore observed function combinations.** The combination space for all Excel functions is massive, let alone the space for observed formulas. Working from data with actual referents in practice, the tool must aid the user in navigating this space.

2 **Emphasize the quantitative patterns in formula construction.** The tool, accommodating datasets of a few spreadsheets to millions, should address the questions of how often the end users employed a certain function and where they used it. In this way, it must show precise metrics, such as frequency of use and depth of function nesting, of the dataset it conveys.

3 **Promote a qualitative understanding of the patterns.** Lest these patterns remain abstract, the tool should supplement its observations with concrete instances of relevant formulas from the corpus. Ideally, it should even direct users to the exact cell in the spreadsheets where the formula was used, contextualizing the functions.

Likewise, to bound our scope, we outlined a few goals to specifically avoid accomplishing with this:

!1 **Do not try to directly explain what a function does.** Though the tool tries to foster tries understanding by linking pattern to example, it won't provide a precise description of what a function accomplishes. The tool's user must infer this.

!2 **Do not create new formulas.** This is essentially an exploratory tool, not a generative one. It should not produce any information other than new views of the original data.

!3 **Do not visualize individual formulas.** Though there is room to explore the place of a single function in the group, the tool must design the core visualization around the entire body of data, not the other way around.

B. Walkthrough of Tool

Before discussing the minutiae of how the tool was developed, it will help first to give a basic example of how the tool can be used and how to interpret its symbols. One such example might be to find the answer to this question: *What kinds of functions do people use to define the condition in an IF function?* The final visualization is available in figure 1; however, to understand the interaction, we will start rather from the beginning.

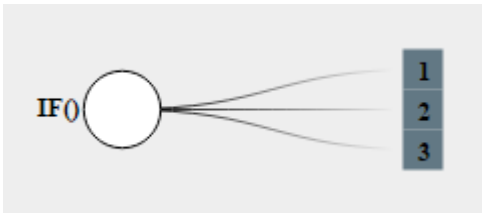
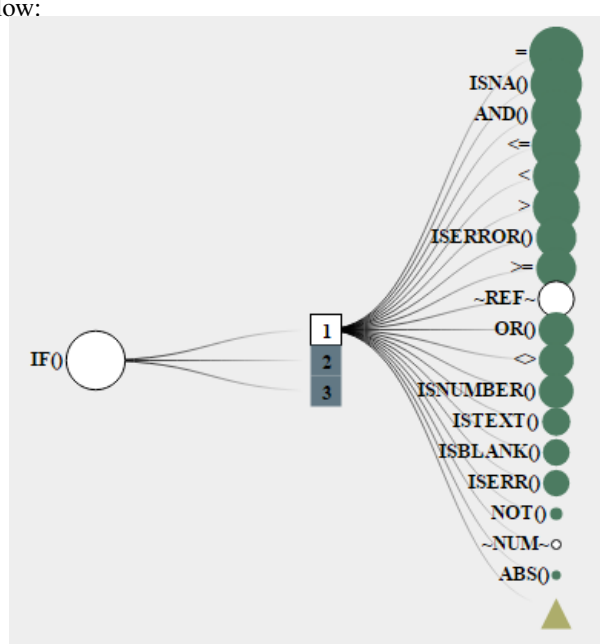


Fig. 2. How the IF tree looks at the start

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 III-B.

The visualization so far comprises two types of node: the circle, which represents a discrete function in the formula and is size according to its relative frequency (the top-level node, by definition, will be the largest); and the numbered squares, which represent the positions of arguments within its parent function. From this, we can infer 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.[3]

Knowing that it is the first argument which contains the conditionals, we click on the square labeled "1" to explore. To save space, when more than 10 unique arguments have been observed in any position, the tool displays only the first ten, with an option to display the rest. The results are shown below:



As expected, we see that IF contains as its first argument a number of comparison operators, 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 everything actually used.

[3]https://support.office.com/en-us/article/IF-function-69aed7c9-4e8a-4755-a9bc-aa8bbff73be2

From here, we can further explore the common options among these functions. Clicking on the "=" node will yield two arguments, it being a binary operator, and expanding each of them will peer into the range of common values of equality comparison, which Figure 1 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, if the concept is difficult to imagine is practice, a tooltip accompanies each function node in the tree, providing a concrete example of a function that uses this structure and where it can be found. 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. Design Decisions

Early in the process, we decided that the tree form would be a suitable fit to represent the parent-child or caller-callee relationships inherent in the data, given the composition of formulas as functions and their arguments (which could be yet more functions). By adapting this structure to accommodate a broad range of possibilities for nested functions, the branching factor depends on both the number of arguments in a function and the number of possible functions observed as an argument in a function.

Guided by the goals in section A, we faced a number of decision points, a sample of which we describe below, before we arrived at the design shown above.

- *Copied formulas*: 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 formulas most often applied to large areas. To combat this, we converted formulas from their native A1 format to the relative R1C1, in which copied formulas should be identical, and reduced the records to unique R1C1 formulas per sheet.
- *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. Both approaches have benefits and drawbacks, and so we included both.
- *Pattern density*: How should the tool quantitatively order its elements: by a function's raw frequency or by the unity of patterns it leads to? For example, if SUM has for its first argument two possibilities, one which itself contains 1000 unique argument possibilities with 1 occurrence each (high frequency, low pattern density) and another seen with 2 argument possibilities of 100 occurrences each (low frequency, high pattern density), which would be more interesting to emphasize? The answer depends on the nuances of the questions, but for simplicity, I've shown the former.
- *Non-functions*: How should the tool represent everything in the formula that isn't a function: numbers, string literals, errors, references, etc? Since these don't accept arguments, they will adorn the tree as leaves, and their precise content won't affect the functions around them as long as their types are known. As such, in the visualization, all of these nodes are replaced and aggregated under their types and represented as empty white nodes.
- *Optional arguments*: How should the tool handle functions which accept a variable number of arguments? SUM, for example, can have anywhere from 1 to 255, and IF can accept either 2 or 3. [4] Without prior evidence, it's possible that, when people use optional arguments, they use different kinds of types and functions for arguments versus the cases when they ignore optional arguments. To account for this, we separate and analyze the different quantities of arguments observed for each function; the tool, however, uses as default all of the options collapsed into a single representation.

D. Implementation Details

We can view the final visualization as the product of two discrete processes:

- *Collection*: Given a set of Excel sheets, the tool, written mostly in Java, uses Apache POI[5] 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 by which it is recorded. When all formulas 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 help from the visualization library D3[6]. We chose D3 primarily for its accessibility: given the JSON, the visualization can be rather simply embedded into a webpage accessible through a browser.

A demonstration of the tool can be found at [LINK HERE].

[4] https://support.office.com/en-us/article/Excel-functions-by-category-5f91f4e9-7b42-46d2-9bd1-63f26a86c0eb

[5] https://poi.apache.org/

[6] https://d3js.org/

IV. Case Study

The obvious question to pose to any visualization is this: Why does it matter that we see this way? In other words, it is not enough to prove that something can be visualized; instead 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: identifying places for API improvement, detecting bad smells or common programmer misunderstanding, and guiding spreadsheet education. To demonstrate the tool's applicability, then, we sought out places in the tree which best exemplify these respective concerns.

A. Bad Smells

Fowler's description of code smells [19] underscored an important point of code quality: between perfect code and bug-crippled spaghetti, there is a spectrum of code designs which, by themselves, are not faulty but nevertheless suggest problems and vulnerabilities in code design. Code smells, as we call them, soon commanded attention and earned wide-ranging applicability, eventually making it to the art of spreadsheet design.

Since then, spreadsheet researchers have taken the concept, if not the specific smells themselves, and applied them to spreadsheet programming [9] [20] [10] [21] . While some of the smells lie beyond the scope of the tool, such as those characterizing inter-worksheet connections, some have structures which create distinctive features within the tree, leading to easy detection through visualization:

- *Long Method*: Also called "Multiple Operations" in [9], this refers to situations where numerous functions and operators are used all within the same cell, creating a formula that tends to extend beyond a compact viewing space and makes it difficult to understand. 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 IV-A.
- *Long Parameter List*: [tall, vertical towers of blue nodes]
- *Conditional Complexity*: [IF nodes within IF nodes]

Some examples are meaningful not for the space they take up but for how they clash with the expectations around a function. For example, Excel offers a number of functions that accept any number arguments given to them, up to a resource-defined limit. SUM and CONCATENATE are two such functions: adding more arguments simply adds or appends that element in the same way as every previous argument. Strange cases were found, then, in the cases where these functions were used with only one argument.

Otherwise, the LOOKUP functions are particularly notorious for their confusing mechanisms and, as such, have warranted some especial attention with regards to spreadsheet design. 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: when omitted or set to TRUE, the function attempts to return a value from another column by matching two values approximately, but when set to FALSE, the match must be exact. Furthermore, exact matching works only with sorted columns or rows; if the programmer neglects to sort values before calling the *LOOKUP function, they may acquire inaccurate results [**?**].

Given access to the same dataset, how might this tool approach the issue? On the surface, the tool supports easy quantification through the tooltips displayed for each node, as shown in figure IV-A, answering the question, "How often do spreadsheet programmers use this function?". But, more to the point, the tool's distinction between the numbers of arguments for a single function lets the user compare frequencies of three-argument forms with the four-argument. The visualization does not, however, discern between the different values for booleans in the tree, much less whether the spreadsheet columns are ordered – but the linking of examples to patterns allows quick insight into which files are at risk for the problems they outlined.

Also at hand are issues with the standard LOOKUP function. Unlike the two variations above, LOOKUP accepts either two or three arguments, depending on which API-defined form the programmer uses: the vector form or the array form, the primary difference being whether the second parameter is a one-column/-row range or a two-dimensional array. The array form, as it happens, is strongly discouraged by the API in favor of the V/HLOOKUP, a notion that might also be leveraged in the pursuit in good spreadsheet design.

B. Education

Learning by example has long been a cornerstone of effective teacher techniques: by showing the student a concrete example of something, rather than dwelling in the realm of abstract description, comprehension increases [I'm sure there's a cite out there somewhere.] This is no different in software, where every explanation of a tricky programming concept is much untangled by the illustrative stub. Even APIs, researchers have found, by the inclusion of an in-practice example of the function described. Spreadsheet programming, then, should not be essentially different: examples of spreadsheet functions in use

V. User Study

Midway through production, we conducted a brief, four-participant user study in order to gauge how well we were capturing the initial design goals. The study was, in general, a flexible and exploratory affair: rather than giving the users any specific tasks or pointed questions, we asked instead that they choose for themselves which trees to explore and report anything that they deemed interesting. Specifically, given trees rooted in the Enron dataset and at least 20 to thirty minutes, the participants situated themselves within the persona of a consultant asked to evaluate a company's spreadsheet practice, which could be arranged around questions like which functions

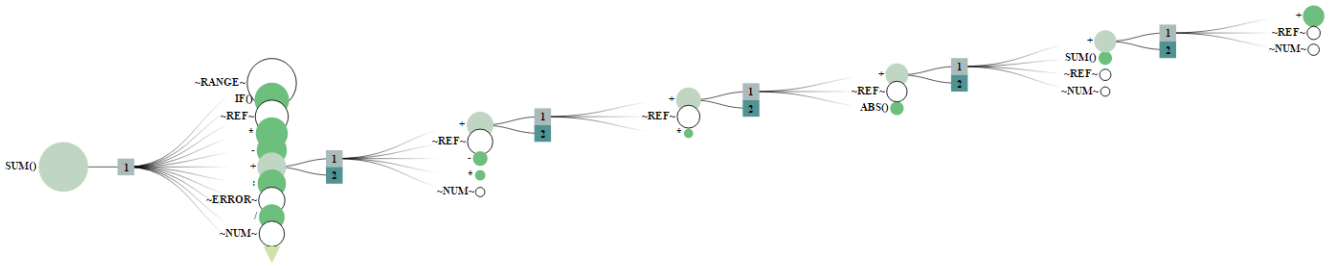


Fig. 3. The horizontal length of a tree may indicate complex or redundant design.

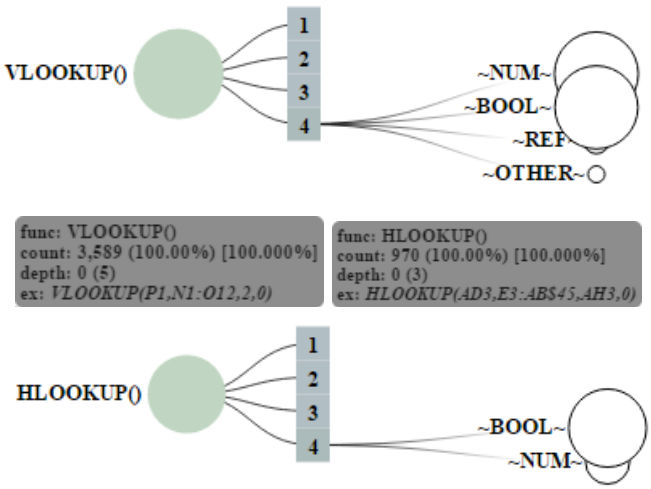


Fig. 4. VLOOKUP and HLOOKUP with four arguments. Numbers not expected to correspond perfectly with [**?**].

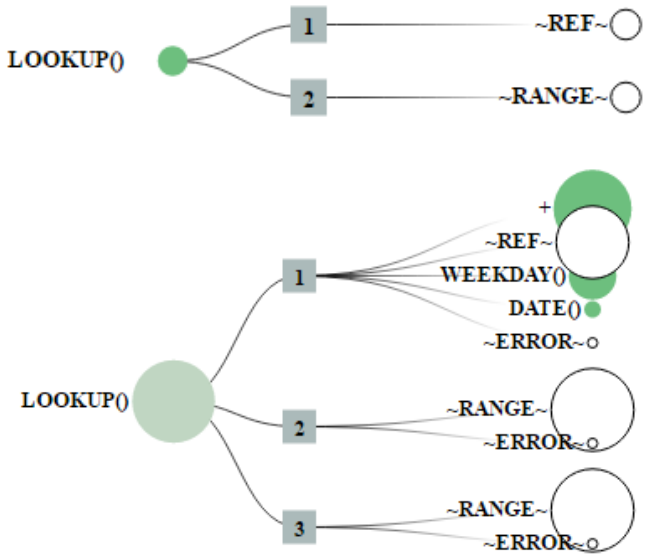


Fig. 5. LOOKUP with two (6 occurrences) and three (1648) arguments.

on which the employees most depended, which sheets presented the most anomalous or dangerous designs, and so on. Interpretation of "spreadsheet practice" can certainly vary from participant to participant, but since we wanted a range of views and backgrounds despite the persona, we readily accepted this interpretive wiggle room.

We clarified, furthermore, that these notes could be directed either at the quality of the data conveyed by the tool or at the tool's conveyance itself. Since the tool's philosophy was based in exploration, we decided that it would not have been appropriate to restrict what people were to look for, letting them find interesting stories of formula construction for themselves. Additionally, either kind of comment – on data or on tool – would direct us back to the central evaluation; a user's silence, or lack of any interesting findings, would tacitly indicate that perhaps the tool does not convey information well enough.

Still, several limitations cropped up during the study that complicate the evaluation. For one thing, though the source of the data was not explicitly stated at the outset of the session, several users studied the file names (unchanged as they were) to deduce its roots in finance, if not Enron itself. Because of these notorious connotations, then, some were inclined from this moment of discovery to orient their exploration around finance-related functions, potentially limiting their findings or perceived users for the tool – though some also said that, without this essential context, they could not have properly 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. Another potential problem is that the data which users explored was processed and created before we had fully completed the tool, 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 with whether any interesting reports could be made at all, not with whether these reports were 100% accurate assessments

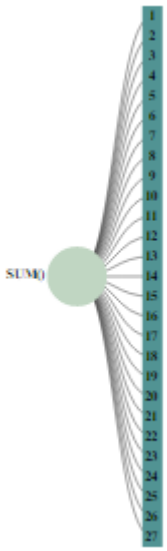
of reality.

Nevertheless, these user studies were a formative moment in evaluating the tool's performance, generating a number of directions or corrections in the process. We present an overview of responses below, with the four participants recorded simply as P1 through P4.

A. Positive Responses

The inclusion of formula examples, grounded in and linking back to the originating spreadsheets, proved to be an especial draw to the tool. After all, none of the participants professed themselves to be experts with Excel, their self-reported proficiencies ranging from "fairly familiar" (P2) to "not extremely familiar" (P4); even if they were experts, it would likely be unreasonable to expect an evenly distributed familiarity with the 100+ function trees available. Nevertheless, the list of actual formulas accessible through a node's double-click allowed the users a way to find examples of formulas with exactly the configuration they wanted. For example, as P1 explored the VLOOKUP function, even though they knew the official API more verbosely explained its signature, they said they could use the tool to collect more examples than the documentation offers.

Furthermore, it offers a simple way of finding examples where certain functions were used together. 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. [This paragraph contrasts it with previous approaches, but lacks compelling evidence – a lot of "mights"]



The discovery of errors and bad design, whether by purpose or accident, produced the more jarring events of the study, and as such, most users commented on the tool's ability to locate these problems in spreadsheet design. This was often supported by the distinctive visual signatures of certain bad practices: multiple arguments produce towers of nodes, deep function nesting stretches the tree horizontally, and so on. As such, the participants remarked on the problems quickly after opening: P3, exploring the example for a 27-argument SUM (with SUM's initial appearance pictured left), diagnosed the situation with either incompetency or just plain weirdness; P2, meanwhile, decided that the spreadsheet's author "was having a bad day" when writing an AVERAGE with 18 distinct arguments. Aside from these implicit cues, there are also nodes which refer to formula errors, prefixed with #s, which P4 said could be useful if marked well. Furthermore, once these errors are found, the participants could then open the offending spreadsheets, discovering that, even in context, some of these formulas remained incomprehensible, posing problems for the spreadsheet transfer scenarios as outlined by Hermans [17]. The tool, then, aggregates these issues in a single place, accessible to either the unguided user and the ones who know exactly where to find these issues.

The detection of bad design, however, is certainly not limited to a visualization tool, and some users remarked that a tool which printed a list of errors could suffice just as well for that purpose. However, they also remarked that this visual interface better supports the case when searching for new and unknown brands of bad smell.

Because the exploratory design makes no qualitative judgment and visualizes benign designs with the problematic, it therefore allows for flexible interpretation of what is an issue; that is, a user might not realize a certain design is suboptimal until they see it in the tree and, at the point, find every instance of it.

B. Negative Responses

Some interaction with the tool underlined how a lack of contextual information may limit the tool. For example, the benefits described in the previous sections imply a hidden complication: if the tool educates through example but doesn't explicitly distinguish between good design and bad design, how can we be sure that people won't inadvertently learn bad design from it. Right now, we can't be sure; the tool would have to be supplemented with a distinguishing eye, informed on bad design already, and supplying the tool with this would take it beyond a design-agnostic view. [More on this in the conclusion.]

Furthermore, just because a user can exhaustively explore every variation of how a function was used doesn't mean they will learn exactly what it does. P1, in their exploration, examined functions that they hadn't used before, such as KURT and PV, and described precisely what types of arguments it accepted and how many. However, even after exploring the spreadsheets, 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 for independent education. However, unlike the previous problem, this can be addressed, perhaps, by guiding the user directly to such documentation from within the tool without violating any design concerns.

A threat to the exploratory philosophy may also mount from the problem of too much data, particularly in the popular functions, like SUM and IF. We had added some precautions before the study: for any position in the tree, for example, only the ten most common functions were displayed without clicking on the expansion arrow ▼. Nevertheless, P3 remarked that they specifically avoided the most popular functions, anticipating a flood of nodes from which they could salvage nothing interesting – which might not have been a bad prediction, considering that the SUM is built from 910 nodes and IF, at least 18000 [double-check these with refined data]. P2 corroborated this by explaining how they gravitated toward specific examples over the plane of nodes but complicates it further by also deeming the tool at its best when it shows

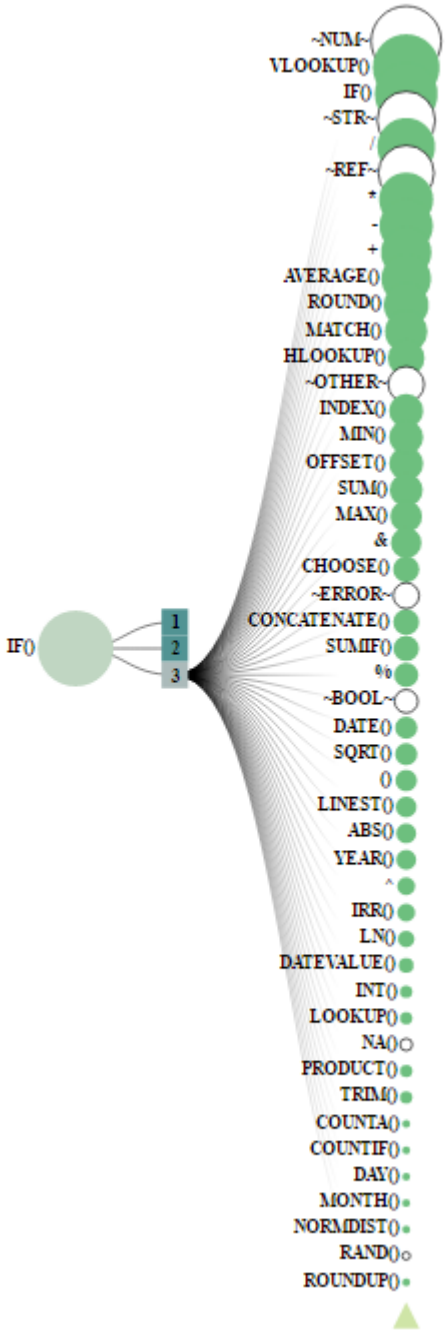
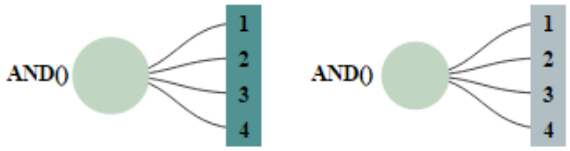


Fig. 6. The many possibilities of IF, argument 3, demonstrate the problem of having too many options.

either every possibility of an side-by-side (for comparison) or nothing on that branch at all, a balance that is hard to strike with node-dense trees.

Throughout the study, it became apparent that some of the concepts, particularly optional arguments, were easily lost in the representation. To illustrate this, consider the following two trees:



The difference is, perhaps, too subtle: on the left, the tree contains instances of AND functions with any number of arguments, up to four; on the right, the tree contains only instances with exactly four arguments. In other words, an instance of ”=AND(A1, B2, C3, D4)” would be found in both trees, while ”=AND(A1, B2)” would be found in only the left. Though the users naturally did not explicitly report misinterpreting the icons, it became clear in their out-loud thoughts that they viewed each box as a fundamentally different set of possibilities in formula construction rather than just a specific parameter. Though we clarified the meanings when these misunderstandings became apparent, these events point to a failure in the tool to properly indicate every function with clarity.

VI. Limitations

Beyond the negative responses in the user study, a few more inherent limitations beset the tool. These largely resulted from trade-offs in which we found no acceptable way to win the best of both worlds, and necessary compromises were made.

Because the data collection depends on POI’s formula parser, it affords no leeway or partial information from a formula; it either processes it perfectly or throws it out. As such, the visualization inhibits insight into anything with syntactical errors or third-party functions that can’t be evaluated without additional tools. Note, however, that this does not include standard Excel errors like #REF! and #DIV/0, which the parser handles well. This poses more egregious problems, however, when POI does not support the parsing of certain functions, such as EOMONTH (as obscure as it may be), preventing the healthy growth of those trees.

Many functions have an expected order of arguments, but some, like SUM and MATCH, can be reordered in various ways and maintain their value. However, the representation that this tool uses reinforces for all functions that the order is important, even in these exceptions. Future work could design a new family of tree to accommodate these loose cases, however, by bucketing order-insignificant arguments together; this, of course, would still have to address the profusion of co-presented data.

A larger and related problem is the loss of argument combination. For example, figure VI shows the situation of the INDEX tree, wherein each argument position has a few distinct possibilities. While it is easy to break down, for each position, which argument types are most common (ranges, MATCH, and numbers, respectively), the tree is silent on whether MATCH functions are used together in the second and third arguments, among other concerns. Though these argument combinations could be pieced together by manually

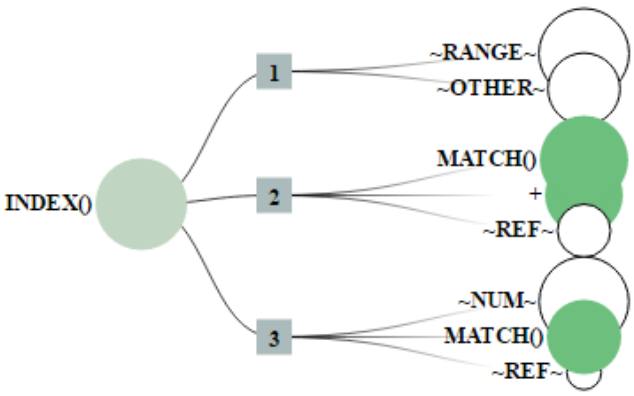


Fig. 7. A difficult question: how often is MATCH used in both the second and third arguments?

inspecting the lists of examples, it is nevertheless inconvenient, though not outside the realm of future improvement.

VII. Future Work

For these user and case studies, we relied solely on Enron's spreadsheets to find our results. 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, 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 Gnumeric[7] or Google Sheets [8] 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.

VIII. Conclusion

This paper presents a tool to support the exploration of function combinations throughout a given spreadsheet dataset. By taking a 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 search out bad code smells as well as a repository for examples for learning new techniques.

To be sure, we still have a lot of 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 also hindered the project in 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 images, we seek to draw attention to valuable information that would otherwise go unnoticed.

[7]http://www.gnumeric.org/

[8]https://www.google.com/sheets/about/

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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 elipse 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.