Exploring Organization of Computational Notebook Cells in 2D Space

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***Abstract*—Representing branching and comparative analyses in computational notebooks is complicated by the 1-dimensional (1D), top-down list arrangement of cells. Given the ubiquity of these and other non-linear features, their importance to analysis and narrative, and the struggles current 1D computational notebooks have, enabling organization of computational notebook cells in 2 dimensions (2D) may prove valuable. We investigated whether and how users would organize cells in such a "2D Computational Notebook" through a user study and gathered feedback from participants through a follow-up survey and optional interviews. Through the user study, we found 3 main design patterns for arranging notebook cells in 2D: Linear, Multi-Column, and Workboard. Through the survey and interviews, we found that users see potential value in 2D Computational Notebooks for branching and comparative analyses, but the expansion from 1D to 2D may necessitate additional navigational and organizational aids.**

***Index Terms*—data science, computational notebooks**

I. Introduction

Since computational notebooks, a popular data science tool [1], such as Jupyter [2] emerged, millions now use them for their work [3], including research communities [4]. Computational notebooks combine code, visualizations, and text in one document, enabling analysts to construct a *computational narrative* [3]. Computational notebooks also let analysts interleave results with code and edit code in-place, helping the iterative, exploratory process of data analysis [3], [5] to quickly test and refine models on their data and see results.

Current computational notebooks do not handle non-linearity well given the 1-dimensional (1D) layout of cells. Rule, Tabard, and Hollan [3] view support for non-linear narratives as a key design opportunity. We identify two common types of non-linearity: different operations on same data, and same operations on different data. The former may occur when an analyst tries different models, tweaks parameters, and compares results to iteratively refine their work on a single dataset. This is valuable for presentation to a technical audience interested in choosing an analysis method. The latter may occur when an analyst performs the same analytic steps on two different sets of data, such as separate subsets of a single, larger dataset; this is valuable for comparative analysis.

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Another limitation of current computational notebooks is navigating long notebooks with many cells, as scrolling up and down becomes tedious. To address this, some of the authors open the same computational notebook in multiple windows, with each one showing a different part of the notebook.

To better represent non-linearity and improve navigation in longer notebooks, the authors propose organizing computational notebook cells in 2 dimensions (2D); instead of ordering cells from top to bottom as an ordered list, a 2D environment may empower users to address non-linear narratives with non-linear configurations and enable additional methods of navigation in addition to scrolling vertically. 2D space may also empower users to encode meaning into space, like how analysts used extra space in Space to Think studies [6], [7].

This paper contributes to research on computational notebooks through exploring 2D organization of computational notebook cells and requirements gathering for designing 2D notebooks. We focused on the following research questions:

1) Given a notebook with non-linear features, would users utilize 2D space?
2) How would users organize notebook cells in 2D space?
3) How would users encode run order in a 2D layout?
4) What strengths and weaknesses might 2D notebooks have compared to 1D notebooks?
5) Would users want to use 2D computational notebooks?

II. Background and Related Works

A. Computational Notebooks

Computational notebooks, influenced by Knuth's *literate programming* [8] concept where authors weave "human language with live code and the results of the code" to produce a computational narrative [9], support incremental and iterative analysis, explanation of an analyst's thoughts and processes, and sharing of code, text, and visuals in one document [3].

However, Chattopadhyay et al. [10] found users struggle with computational notebooks. One struggle with the iterative process of exploration and analysis is messiness [3], [11], [12].

Analysts described notebooks and their code as ”ad hoc” or ”throw-away” [5], [13] and in need of cleaning [3] before presentation. Kery et al. [12] found data analysts, as part of the process of exploring alternatives, replicate code across many cells that must later be refactored, a process both tedious and error-prone [12], [14]. In short, exploration and analysis can complicate constructing clean computational narratives.

Some proposed solutions include forking and backtracking of stateful alternatives [14] and version control systems [15], [16]. Weinman's work on forking [14] introduces forking in 2D space, which supports using 2D to address computational notebook issues. Following best practices, such Rule et al.'s [3], [17], can also resolve many issues. We support such work; such guidelines are complementary to our work, and appropriate use of 2D space could be a future best practice.

B. Computational Narratives

Perez & Granger [9] note computational narratives are developed for a set of audiences and contexts; given different audiences and contexts, different storytelling strategies are necessary [18]. An audience only interested in results may find a linear narrative with only relevant cells helpful. However, some audiences may benefit from a non-linear narrative structure. Weinman et al. [14] note that ”the ability to proximally compare” different visual representations of data is critical to analysis processes. In addition, an audience that wants to understand and evaluate the entire analytic process may find a non-linear narrative structure better, as it can expose alternatives tried and compared to the final results used, enhancing reproducibility. Weinman et al. [14] found analysts used forking paths to compare results of machine learning models as part of their exploratory analysis; while they focused on analysis, seeing different options tried and their results in a proximally comparable way could aid understanding.

C. Space to Think

Andrews, Endert, and North [6] focused on large, high-resolution displays for sensemaking, and found additional space aided users in two ways: it enabled externalized memory, letting users focus on the task at hand rather than on recalling important info, and it enabled encoded meaning into space, such as by clustering similar items together. That work has been expanded through study of additional space provided by virtual reality [7], as well as collaborative uses of large spaces through increased and varied content contribution [19]. Similar works demonstrating benefits of space to programming tasks include Code Bubbles [20] and VisSnippets [21].

III. Methodology

This study consisted of a screening questionnaire, user study task, post-task survey, and optional interview. The user study task focused on research questions 1-3. The post-task survey and optional interview focused on research questions 4-5. 50 participants from two universities' academic listservs of students and faculty applied. 43 passed screening to ensure Python and computational notebook experience. 25 completed the user study and post-task survey; we interviewed 5 of them.

A. User Study Task

We created a computational notebook with analysis of publicly available COVID-19 data focused on Virginia and two of its counties: Fairfax and Henrico. Knowledge of Virginia was not expected from participants. The analysis contained non-linear features; it included three different charts for Virginia overall, showing the same data with different analyses, while the two counties had the same analyses done with different data; each county had 3 graphs. We divided the analysis into sections with markdown cells at the beginning of each section. We converted each notebook cell into an image and randomly placed it in a jumbled pile on a Miro Board [22], infinite 2D canvases that allow users to move images around at will, connect them with arrows, create labelled frames that images can be put into, and more. We used Miro Boards because of these additional features to explore what kinds of additional visual features might help in 2D computational notebooks.

Each participant got a personal copy of the Miro Board and were instructed to take 40 minutes to complete the task of organizing the cells. We designed the task to set presentation and development as key considerations. Due to COVID-19, we were unable to watch participants complete the task.

To analyze the visual layouts created, we took all the participants' layouts and their mini-maps and put them into a single Miro board for study. Comparison and pattern finding was done with an open coding approach with multiple coders.

B. Post-Task Survey and Optional Interview

Participants completed the post-task survey after they finished the user study task, which consisted of 19 seven-point Likert-Scale (strongly disagree to strongly agree) questions investigating participants' attitudes towards 2D Computational Notebooks' potential, as well as qualitative questions about the visual layout they created, their reasoning for it, and initial thoughts on 2D Computational Notebooks' potential. We analyzed qualitative data using open coding to identify themes, and Likert-Scale data using frequencies for each choice, condensed to agree, neutral, and disagree.

In the interviews, which lasted 45 minutes to 1 hour, we delved deeper into participants' qualitative survey responses. We transcribed them and used open coding to identify themes.

IV. Results

A. User Study Task Results

Most participants utilized 2D space, as seen in Fig 1 below, with the layouts grouped into 3 distinct approaches. Furthermore, the authors easily interpreted the run order of all participants' layouts except for the layout by participant P09.

1) High-Level Design Patterns: We identified 3 high-level organizational design patterns in 2D: Linear (7 instances), Multi-Column (8 instances), and Workboard (10 instances).

The **Linear** pattern uses one column as the layout's backbone and has three subgroups: Traditional, Split-Cell, and Split-Column. Traditional Linear (4 instances) is equivalent to a 1D Computational Notebook layout. Split-Cell Linear (2 instances), like Fig 2 has at least 1 cell in the column is “split”

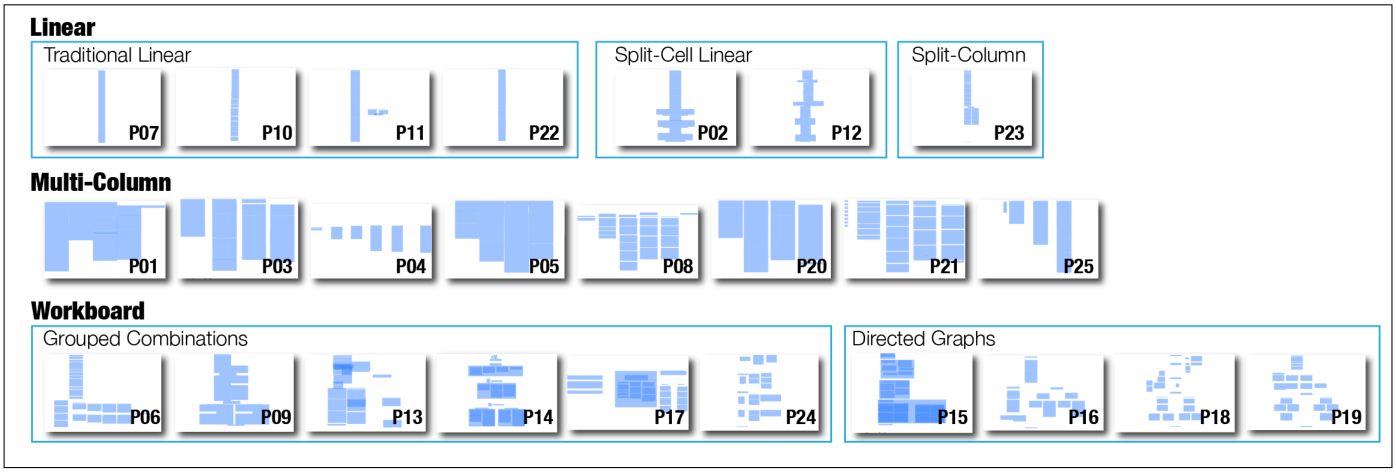

Fig. 1. Minimaps of User Study Task Results

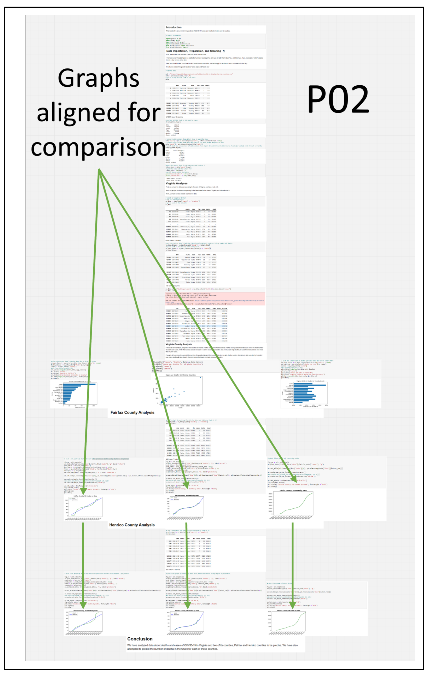

Fig. 2. Example Linear design pattern with 3 split cells.

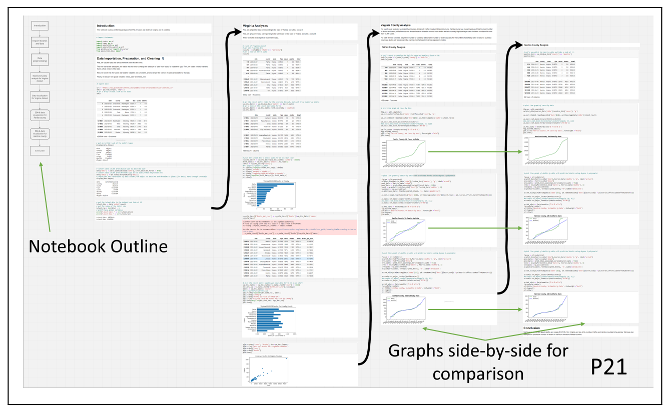

Fig. 3. Example Multi-Column design pattern with parallel counties.

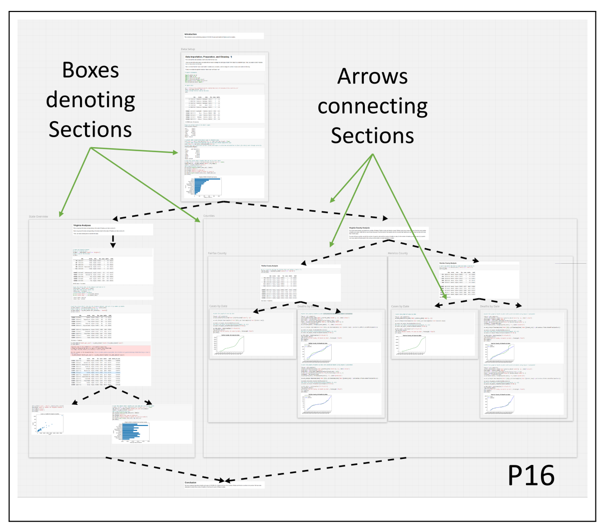

Fig. 4. Example Workboard approach using a Directed Acyclic Graph.

into a row of cells, like the Jupyter Notebooks Split Cells extension [23]. Split-Column Linear (1 instance) eventually splits the main column into two or more columns, like Fork-It [14]. Linear layout run orders were always top-to-bottom, with Splits being left-to-right. Running splits in parallel or any order could be possible and may represent cognitive branching.

The **Multi-Column** pattern arranges cells in columns run left-to-right and top-to-bottom in columns. The columns represent "chunks" or sections from the notebook, each chunk with its own semantic meaning. Unlike Split-Column Linear, all columns start at about the same vertical position instead of splitting from a main column. 5 users aligned the 2 county columns, pushing the second column lower, as in Fig 3.

The **Workboard** pattern had complex 2D layouts in two sub-groups: Grouped Combinations and Directed Graphs. Grouped Combinations (6 instances) organize notebook cells into sections which may differ in strategy (e.g. Linear, Multi-Column). For example, sections may be arranged vertically with each section being multi-column. Layout P09, the only confusing run order, was in this subgroup; they arranged sections vertically and may have meant for sections to run in a clockwise rotational manner. Directed Graphs (4 instances) use arrows to develop flowchart-like run orders (as in Fig 4) similar to node-link diagrams, which are useful in visual programming endeavors like the block-based programming work of Suzuki et al. [24]. Each Directed Graph used a top-down progression, with 2 also using left-to-right progression.

2) Representations of Non-Linearity: We noted whether and how participants utilized 2D space for non-linear features of the computational notebook. 20 of 25 users utilized 2D space for one or more kind of non-linearity mentioned in the introduction. For different data, same analysis, 15 layouts aligned similar charts for the county data subsets horizontally, as in Fig 3 and 4 layouts aligned these charts vertically, as in Fig 2. 7 of 8 Multi-Column pattern users aligned the charts horizontally. These users may have sought to ease comparisons between the counties. For same data, different analysis, 4 layouts aligned Virginia charts horizontally, as in Fig 2.

3) Low-Level Features: We also noted use of certain low-level features, such as columns of cells (25 layouts), rows of cells (19 layouts), and arrows to denote flow (9 layouts). Several cell grouping features were seen, such as boxes (4 layouts) around similar cells or spatial clustering of similar cells in the same general area, with clusters separated by white space. 4 users used Miro's [22] sticky notes feature to label different clustered sections or to help others understand their layout. Finally, 2 users left a few cells apart from the rest; this could illustrate scratch space or a discard pile.

B. Post-Task Survey Likert-Scale Results

TABLE I
2D NOTEBOOK SURVEY RESULTS WITH LIKERT-SCALE FREQUENCIES

Question	Agree	Neutral	Disagree
Better Info Layout than 1D	24	0	1
Easier to Navigate than 1D	18	2	5
More Beneficial than 1D	21	3	1
Made Meaningful 2D Layouts	20	5	0
Like Unrestricted Cell Placement	23	0	2
Infinite Canvas Useful	22	1	2
Better in 2D: Collaboration	19	1	5
Better in 2D: Presentation	20	1	4
Better in 2D: Exploring, Prepping Data	18	3	4
Better in 2D: Development, Analysis	15	3	7
Better in 2D: Debugging	12	2	11
Better in 2D: Branching Paths	20	3	2
Better in 2D: Sectioning Code	22	1	2
Better in 2D: Comparing Vis	25	0	0
Better in 2D: Comparing Parameters	23	2	0
Better in 2D: Comparing Data	23	2	0
Would Use 2D Notebooks	19	5	1

Users rated 2D notebooks' potential positively compared to 1D notebooks. Almost all survey questions had most votes on the Likert scale's "agree" side. According to the responses, summarized in Table I, the tasks most likely to be helped by 2D computational notebooks are comparison activities, such as comparing results with different model parameters, different data, or different visualizations. However, some users were skeptical about 2D computational notebooks' usability for debugging, analysis and development; others doubted navigation would be easier in 2D space.

C. Qualitative Survey Questions & Interview Results

We analyzed the qualitative responses and grouped themes into 4 categories: Benefits, Challenges, Features, and Preferences. The first two focus on potential benefits and design challenges of 2D Notebooks. Features focuses on features that helped users make a good layout. Finally, Preferences focuses on expressed preferences for 2D or 1D notebooks. Table II shows themes by category and summarizes each theme with a participant quote. The table notes the number of participants (users) whose comments expressed the same sentiment, either in the survey response or interview format, as each theme.

V. DISCUSSION

1D notebooks struggle with non-linearity and navigating longer notebooks, which prompted our work on 2D notebooks. Initial evidence suggests 2D space may provide the benefits found in Space to Think studies [6], [7], and future studies may validate benefits of discovered 2D notebook design patterns.

A. Organizing Notebooks in 2D

The Split-Cell extension [23], and Fork It [14], show how 1D notebooks can benefit users with limited 2D space. The prevalence of the Multi-Column approach among participants suggests that as a new notebook extension for 2D space usage.

Still, most users liked the flexibility of cell placement in the 2D computational notebook sketch using Miro [22]. Participants with Workboard layouts designed varied, creative flows to express different aspects of the notebook structure. Given this and the fact that 20 of the 21 2D layouts' run order were intuitive, a 2D Computational Notebook could be useful even given 1D notebooks with limited 2D capabilities.

B. Enabling Strengths of 2D Notebooks

Almost all participants thought the 2D Notebook environment would be useful for comparative analyses. Their layouts placed cells or sequences of cells side-by-side, such as in the two aligned columns in Fig 3. Thus, 2D computational notebooks should enable users to compare results from different cells or branches in flexible and easy-to-use ways; for multi-column designs, this might mean changing the order and alignment of columns easily to enable quicker comparisons.

The potential to run notebook segments in parallel is exciting. Layouts had parallel side-by-side branches in the cell layout, or with one-to-many arrows. Data analysts may try different machine learning models with a dataset for a classification task, and could run adjacent columns of code in parallel, getting results quicker to better compare model performance and choose which method to use in production.

Finally, more sophisticated controls for running cells in a 2D notebook may prove useful;a user may want to run a group of cells, such as those in a particular column or cluster.

TABLE II
QUALITATIVE THEMES IN SURVEY & INTERVIEW RESULTS REGARDING 2D NOTEBOOKS

Category	**Theme**	**Sample Quote**	**Num. Users**
Benefits	Comparison	”I think the 2D notebook will be super useful for any kind of comparison analysis.”	5
	Presentation	”This is a great tool for presenting data to layman audiences.”	4
	Organization	”The 2D board is definitely hugely beneficial to organize code in a meaningful manner.”	2
Challenges	Navigation	”The zooming in and out and continuous scrolling to reorganize the tiles seemed tedious.”	10
	Cognitive Load	”Organizing [notebook cells] might be a little tedious however, and needs to be planned in advance.”	2
Features	Arrows	”The arrows were very useful, as they helped direct the flow of the narrative.”	10
	Boxes or Frames	”The boxes also helped in grouping cells together.”	7
Preferences	Prefer 2D	”[2D Notebooks] felt like a great and much easier way to reorganize some of my Jupyter notebooks!”	3
	Prefer 1D	”In terms of [collaboration and development], I feel that the linear layout would still work best.”	2

This would require ways to designate groups of cells. Some participants used explicit grouping features, such as boxes or columns or rows, to express such semantic grouping.

C. Addressing Tradeoffs of 2D Notebooks

While the 2D Computational Notebook concept shows promise, the results indicate potential downsides. One downside some participants noted was tedious navigation. Given participants' survey and interview responses, aiding navigation in intuitive, efficient ways seems critical for 2D computational notebook design. Two ideas for dealing with this include sectioning code cells using boxes or frames and enabling quick jumps to different sections, and enabling search utilities for keywords in code and text. In addition, an interactive minimap with features like clicking on a cell and jumping to it may help improve navigation. Finally, certain headers in markdown cells should remain readable even when users zoom out.

Another consideration is more cognitive load; a user must organize cells during analysis. However, given how notebooks become “messy” [13] in 1D, it may be that considering cell organization during analysis could benefit users. There are also ways to address cell organization. First, a templating mechanism could be designed, in which users select from a set of common templates to pre-organize cells or provide initial structure. The templates should be based on data, such as the observed high-level strategies. After selecting a template, the notebook might provide visual affordances such as pre-labeled sections in 2D space, and interactive affordances to fill in cells in the template. For example, a multi-column template could provide a set of initial empty columns to fill in with cells. AI methods could also be developed to semi-automate cell organization through actions like suggesting templates based on code structure and static analysis [25], semantic interaction [26], and active placement of cells. An AI could spot non-linear branches of ‘same analysis with different data’ and suggest a parallel multi-column template. Wenskovitch et al.'s work [25] on visualizing dependencies and relationships between computational notebook cells uses a dynamic graph structure that might be built upon to enable such methods.

D. Assessing Interest in 2D Notebooks

The results of the user study task provide evidence that users are willing to organize computational notebooks in 2D. The fact that, out of 25 participants, only 4 opted to align the cells in 1D supports this idea. That 19 out of 25 participants agreed that they would like 2D Computational Notebooks in their analytic toolbox also supports this assertion.

E. Limitations

This study is limited by its task structure and medium. The task structure could require more panning and zooming than would be normal in a 2D notebook. This, combined with the fact that using Miro meant assuming a generic 2D canvas with standard pan/zoom 2D navigation may contribute to complaints of tedious navigation. While more structured forms of navigation may alleviate this, the fact that such tedium was noted by 10 participants (40%) suggests that navigation is a key design concern for 2D computational notebooks. Furthermore, Miro is not a 2D Computational Notebook prototype; care was taken in drawing conclusions about design requirements for 2D Computational Notebooks.

VI. CONCLUSION

Computational notebooks enable crafting of meaningful, replicable computational narratives. However, 1D computational notebooks make presenting certain narratives and performing some analyses difficult. Thus, we investigated 2D computational notebooks' potential to address non-linear narratives and improve upon 1D computational notebook design.

Our work shows users are interested in 2D computational notebooks' potential. The ability to easily compare results, show branching analyses, and present non-linear narrative structures in a semantic way seemed valuable to our participants. Participants' layouts were about evenly split between three strategies: primarily linear, multi-column, and workboard strategies. The workboard strategy included directed graph layouts and complex nesting of other strategies. Approximately half of the participants also made use of additional annotation features, such as arrows, labels, and boxing.

However, 2D computational notebooks have design challenges. Adding another dimension may complicate navigation. If 2D computational notebooks are to succeed, effectively aiding navigation is key. In addition, the increased complexity brought by organizing cell layout in 2D means layout aids such as templates may help minimize added cognitive load during analysis. Still, 2D computational notebooks could provide a potent ‘space to think’ for data scientists.

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