ABSTRACT

For more than a century, scientists have been collecting behavioral data—an increasing fraction of which is now being publicly shared so other researchers can reuse them to replicate, integrate or extend past results. Although behavioral data is fundamental to many scientific fields, there is currently no widely adopted standard for formatting, naming, organizing, describing or sharing such data. This lack of standardization is a major bottleneck for scientific progress. Not only does it prevent the effective reuse of data, it also affects how behavioral data in general are processed, as non-standard data calls for custom-made data analysis code and prevents the development of efficient tools. To address this problem, we develop the Behaverse Data Model (BDM), a standard for structuring behavioral data. Here we focus on major concepts in behavioral data, leaving further details and developments to the project’s website [https://behaverse.github.io/data-model/].

Keywords behavioral data · standards · open science · task-pattern

1 Introduction

Experimental psychologists have been collecting behavioral data for over a century now. As psychological sciences and related fields are maturing, it has become increasingly clear that the field needs to establish and converge on standards and standard operating procedures.

Data is essential to science. The recent rise of the open science movement and the increased propensity to share and reuse data, as well as the need to integrate results across multiple studies (e.g., within meta-analyses) has revealed many shortcomings in the way we currently process our datasets and has motivated several initiatives aiming to make these datasets easier to find and use. Prominent examples include BIDS (Brain Imaging Data Structure,
Behavioral data, however, has received comparatively less attention, perhaps because at glance sight it appears simpler than those large imaging datasets. We argue that behavioral data is in fact more complex than meets the eye and that defining clear standards for behavioral data may benefit all fields that rely on such data.

Standardizing how we define, name, format, organize, describe and store behavioral data can provide multiple benefits, including:

- efficiency (e.g., less work, reuse of code, automated software);
- robustness (e.g., less errors because of ambiguous idiosyncrasies);
- transparency (e.g., fewer hidden choices in the code and data);
- quality (e.g., via automated checks of data quality, consistency and completeness);
- usability (e.g., via clear documentation, ready-to-use data).

Note also that non-standardized data formats call for non-standardized data analyses which may obfuscate results at a time where more papers are published than anyone can read. By contributing and using data standards, we may accelerate scientific progress in psychological sciences, as seems to have been the case in other fields (for examples, see Teeters et al. 2015).

Here we present key ideas, concepts and principles that guided us in creating the Behaverse data model (v2020.12.1); the more detailed, somewhat opinionated and continuously updated specification of this data model is accessible at https://behaverse.github.io/data-model/. While there have been significant efforts to make behavioral data easier to share and find, our focus here is on structuring behavioral datasets to both reveal the essential structure common to behavioral data and make them easier to (re)use.

2 Challenges of behavioral data

There are key challenges to systematizing behavioral data.

First, behavioral data is highly diverse, as it includes body movement, gaze, key presses, mouse clicks, written output and speech to name just a few. We currently have no clear standards for each of these measurement types, no standards that would be consistent across measurement types and no standards on how to relate multiple measurement types (both conceptually and practically). Hence, while we are technically able to record rich, multivariate behavioral datasets, we lack the conceptual and software tools to effectively exploit that richness.

Second, to interpret behavioral data it is necessary not only to characterize the behavior itself but also the context in which that behavior occurred. Taking as an example the most basic of cognitive tests, a particular key press is interpreted as being a response to a particular stimulus within a particular task that evaluates to “correct” or “incorrect”—the key press on its own, however, is not very informative. Note that this is not necessarily the case for other types of measurements (e.g., functional connectivity between two brain areas). Hence, the accurate description and effective processing of behavioral data requires rich annotations of the task and its underlying theoretical constructs, the stimulus and the person’s state. Major efforts have been made in this direction (e.g., Poldrack et al. 2011); however, current solutions haven’t yet matured enough to be an integral and standard part of the behavioral data analysis process.

Third, and related to the previous point, the way we describe behavioral data is limited by our understanding of what a task is. Indeed, although “tasks” or “tests” are the cornerstones of experimental psychology and related fields, we do not have a theory of tasks (which could for instance characterize the structural relationships between any two tasks) or even a clear framework on how to name or think about fundamental concepts like “instructions”, “feedback” or “trial”, let alone how to convert them into usable data structures—this applies not only to concepts in psychology but also more general concepts like “raw data”. This lack of clarity on concepts that are pervasive in behavioral data have led to the discarding of what seems to us to be critical information (e.g., task instructions not being recorded anywhere) and is at least partially responsible for the large inconsistencies one may find today across publicly shared datasets (e.g., names, meanings and units of measurement). Hence, there is a clear need to better conceptualize tasks, clarify concepts and converge on standards.

Finally, the current practices and software tools used today for behavioral data analyses seem inadequate to handle the rich and complex data structures that seem necessary to accurately describe behavior. Without a clear understanding of those data structures we can’t create effective tools that exploit that richness; but without effective tools there is no incentive for researchers to invest effort in structuring their data accordingly. Hence, until we have clear standards,
Table 1: Data Consistency Levels. It is our understanding that current standards in behavioral sciences places us within levels 0 to 1.

| Level | Description |
|-------|-------------|
| 0     | The dataset is incomplete; critical information is missing (e.g., description of what the variables mean). |
| 1     | All datasets are formatted in a unique way and can’t be joined without reformatting. |
| 2     | Datasets can be joined when they originate from the same task "variant" (e.g., a 2-back task using digits) but not from distinct variants (e.g., a 2-back versus a 3-back task). |
| 3     | Datasets can be joined across all variants of a task (e.g., all N-back tasks). |
| 4     | Datasets can be joined within a family of tasks (e.g., all CPT-like tasks). |
| 5     | Datasets can be joined across several task families. |
| 6     | All datasets can be joined. |

well-structured rich datasets, effective data analysis software and a demonstration of added value, most researchers will understandably continue to work the way they’ve done in the past. Hence, while we should aim for better standards and tools, we still need to take into account current practices and tools and offer solutions that can be useful today.

The challenges we just described are considerable and overcoming them will require sustained efforts over many years. Our goal here is to contribute to overcoming these challenges and improve the way we describe and organize behavioral data. The solutions we propose here focus on three dimensions:

- **Clarity.** Below we describe various ways in which current datasets are inconsistent. We then present and define several key concepts for behavioral data, the most important of which being perhaps the notion of a “trial” which we define as an instance of a “task-pattern”. Rows in a “trial table” are then formed by extracting data from event data according to a task-pattern (using a query-like process) and each row in the “trial table” needs to contain all the information that is necessary to evaluate that trial (i.e., determine whether the response was correct or not). We also define different types of data tables (e.g., “L1” data) as well as canonical data tables (see [https://behaverse.github.io/data-model/](https://behaverse.github.io/data-model/)).

- **Consistency.** There are many choices to make when structuring data. These include, for instance, which naming conventions to adopt (e.g., “RT” versus “response_time”), which specific names to use for a particular concept (e.g., “subjects” versus “participants”) and in what units to express certain variables (e.g., “seconds” versus “milliseconds”). While many of these choices may be arbitrary, it is vital for achieving the overarching goal of consistency to actually make these choices and document them in a clear way (Martin 2009)—we have started this process and documented our choices publicly (see [https://behaverse.github.io/data-model/](https://behaverse.github.io/data-model/)).

- **Usability.** Our particular choices for structuring behavioral data is motivated by the desire to make this data model useful and compatible with the tools and processes most researchers already use today. More specifically, we focus on tabular data (rather than more complex data structures) and aim for a good balance between human readability and computer/data efficiency. As we describe below, behavioral data involves many different types of data which could be compactly stored in a wide range of related tables. Such tables would however be much harder to process for humans as the information about a particular trial would now be distributed over multiple tables. Instead, we define, a primary “trial table” that contains all of the high level information about a trial (in line with current practices), and whose primary key serves to connect additional, possibly subtrial data (e.g., the timestamp of each of the images presented during that trial).

To keep this paper short, we focus here only on what we believe to be central ideas; more content and specifics are available in the accompanying website ([https://behaverse.github.io/data-model/](https://behaverse.github.io/data-model/)).

3 Data consistency levels

In this section we describe how typical behavioral data currently available in public repositories look like and detail various issues that make it hard to reuse them. Behavioral data from experiments in psychology or related fields are currently scattered across multiple locations, including researchers’ personal webpages or various public repositories (e.g., [https://osf.io](https://osf.io))—which over the past decade have made it much easier to find relevant datasets. Exploring these datasets quickly reveals large differences in how behavioral datasets are formatted, named, organized, described and shared—sometimes even within the same lab. Unfortunately, finding a behavioral dataset today is no guarantee that it will be usable at all and it seems that in most cases substantial work would be necessary to understand and use them.
To qualify the current state and future progress in behavioral data standardization we devised a data consistency scale which describes 7 levels of consistency, defined by the type of table joints—or merging of different data tables—that a data model supports (see Table 1). Next, to get a rough sense of the data consistency level in cognitive psychology, we selected three popular cognitive tests—the digit-span task, the N-back task and the AX-CPT task. We then searched, downloaded and reviewed recent datasets from https://osf.io Our goal here is not to make claims about the quality of the specific data samples we chose or of the research conducted using that data (hence, we keep them anonymous). Our goal is also not to be exhaustive and have a definite characterization of the current state of affairs. Instead, we want to point out the diversity and inconsistencies that currently exist in such datasets and describe the various issues that one encounters right after discovering what seems to be a relevant dataset. Below we describe these issues in the order one would encounter them.

3.1 Inconsistent data formats

Most data sets seem to be in csv format. However, we also found several Excel files and proprietary formatted data which could not be read at all. Oftentimes, data is shared as a single data file (containing the data for all participants) or in multiple files that all have the same structure (e.g., one file per participant). These datasets rarely provide a codebook to explain the meaning and possible values in their datasets and it would therefore be necessary to manually go over other available materials (e.g., the corresponding research paper) to attempt to uncover that information.

3.2 Unknown or inconsistent data levels

Behavioral data come in various levels of granularity. Some data sets might contain each response given by every participant while others may only include aggregated data for each person (e.g., one row per participant versus one row per trial). It is typically impossible to know which level of data granularity the shared data offers before actually opening and inspecting the data files.

It is also very common that data tables mix data that are from different sources or levels of granularity. For example, a data table might include trial-level data for each participant (i.e., a row for each response the participant gave) but at the same time have a column that indicates the age and gender of the participants (e.g., the values “21” and “female” repeated across all rows within a given participant) or even summary statistics (e.g., d’prime), whereby it can sometimes be ambiguous as to whether those summary statistics were computed on the trial-level and then joined to the trial-level data or whether they were computed using other data.

3.3 Inconsistent variable naming conventions

Naming variables is notoriously hard and unsurprisingly, there are numerous inconsistencies in variable names (Martin 2009). We found inconsistencies in naming conventions across but also within datasets. Some data sets use lower-case “snake_case” (e.g., “n_correct”) others use upper-case snake-case (e.g., “N_Level”). Some use CamelCase (e.g., “TrialList”) or a mixture between CamelCase and snake_case (e.g., “V_FalseAlarm”) or still something else (e.g., “TrialList.Sample”). Some variables may be in all uppercase (e.g., “CUE_ACC”) or include information about the coding scheme (e.g., a column named “FEMALE=1”). While one may argue that such conventions are more or less arbitrary, it stands to reason that a given convention should be used consistently across a given dataset. This is not the case in the random sample of studies we’ve reviewed as within the same table we could find for example “Span_amount”, “CorrectAnswer” and “TrialList.Sample“.

We also note the variability with which the same construct is named and coded. For example, most if not all datasets have a variable to refer to individual participants in a study. Common variable names to refer to participants are “id”, “Subject” and “SubjectID”. The use of “id” may however be ambiguous (id could perhaps refer to trial index). Sometimes the values that this variable takes is an integer (e.g., 15), sometimes it’s a concatenation of something that seems to be a study or condition name and an integer (e.g., “A_15”). Coding schemes for the subject variable may be somewhat arbitrary but there might be an issue when there are multiple datasets. For example are “A_15” and “B_15” different people or are they the same person (participant 15) that completed two different tasks (“A” and “B”)?

Another variable that is common in behavioral data sets refers to individual trials within an experiment. Again we observed quite some variability. While it is common to use the name “trial” or “id”, we also found datasets where the trial index variable was missing and seemed thus to be implicit in the order of the rows of the table and other cases where the “trial” variable was not used to refer to the index of the trials but rather to describe a type of trial (e.g., “start”, “nontarget”, “v_target”).
3.4 Unknown values and units

Another common issue, which might be resolved by the use of codebooks, is the absence of information about the possible values a variable can take and what units a variable is expressed in. For example, it is very common for data sets in experimental psychology to include response time data. It is typically not possible to determine if they are expressed in milliseconds, seconds or minutes before inspecting the data and using domain knowledge to infer the units.

3.5 Conclusion

A quick review of publicly available datasets reveals substantial inconsistencies in the way individual researchers/research groups (including ourselves) structure their data. Such inconsistencies are inconsequential for researchers working on their own data but limit the reuse of data by other researchers and the aggregation across data sets, even for datasets collected using very similar tasks.

In what follows we first describe some key properties of behavioral data before introducing the behaverse data model we currently use.

4 Behavioral experiments require multiple types of data

Data from cognitive psychology experiments are often shared in the form of a single table where each row refers to an individual trial completed by a person. While it is convenient to only have one file for data-analysis, this “simplicity” is in fact illusory and valuable data is currently hidden within the associated paper, computer code (or still other documents), if not missing altogether.

Typical behavioral data collection scenarios involve collecting data that are semantically distinct but intrinsically linked by virtue of the data collection situation. Consider for instance a typical cognitive psychology experiment. A research group invites participants to their lab to complete a computerized version of the “digit-span” test twice. What type of information could one expect this study to collect? Below is a non-exhaustive list of the kinds of data that are or should be recorded:

1. information about the study (e.g., who conducted the study, when and where; what was the intentions; is the study approved by an ethics committee; what was the funding source); this information is typically idiosyncratically present in manuscripts but should be structured in a standard way, for example, in a “Study” table.

2. information about the participants. This can include variables like birth date, gender, or nationality. Part of this information may be in the manuscript (e.g., “we recruited participants from city X”) and part of it may be in the trial data (e.g., the “age” and “gender” variables that are in the trial-level data). It is important to note that some information about participants is fixed (e.g., birth date) while other information may be context dependent and linked to the actual moment of data collection (e.g., age). Static information about the participant should be stored in a “Subject” table, while dynamically changing information (e.g., age) might be stored in a “Session” table.

3. information about the activity participants engaged with. In cognitive tests, this would include for instance the name of the task, task parameters, the instructions given to participants. This information is typically buried in a research paper and often incomplete (e.g., the actual task instructions, although essential, are rarely listed in full). More and more often, the actual code that was used to run the activity is made available as well—but it may require significant work to uncover task parameters from code. Information about the task or activity should be organized in an “Activity” table.

4. Information about the hardware being used and of participants’ physical environments. For example, this could indicate particular brands and models of tablets or computers, versions of OS and software.

5. Information related to the interactions between the participant and the computer/environment, in particular information about what stimulus was shown, when and where and what inputs participants made.

6. Information about events that occurred while participants were engaged in the activity. For example, this could include information about the quality of the data collection process (e.g., average frame rate) or observations made during the experiment (e.g., experimenter notes that a participant seems to be falling asleep); this type of information might be stored in a lab or personal notebook.

7. Information about participants progress through the study (e.g., list of participants having completed one test but not the other, data and time of completion of tasks, order of task completion).
The list above is not exhaustive but includes the main types of data that could in principle be collected in all behavioral experiments. The point we want to make here is that a data collection campaign comprises in fact multiple data tables and each data table has its own type (i.e., specific requirements, formats).

Our goal in this document is not to go over each of these data types and review existing solutions (although such an enterprise would certainly be useful). Our primary focus in this document is on the data type (5) which we’ll refer to as the actual behavioral data. In our opinion, this is the data type that has received the least attention and presents the largest inconsistencies across studies. It is also the type of data that is most relevant for behavioral data analysis and which would most benefit from standardization.

5 Behavioral, interaction data

There is a lack of clarity on the meaning of terms that are commonly used in behavioral data (e.g., what constitutes “raw data”? what is a “trial”? what is a “task”). In http://behaverse.org/data_model/ we define several of those terms and other conventions we use in the behaverse data model. In what follows, we attempt to present the big picture view of behavioral data and clarify essential terms.

| Data collection | Data storage | Data extraction & preparation | Data analysis pipeline |
|-----------------|--------------|-------------------------------|------------------------|
| 1 | 2 | 3 | 4 |

Figure 1: From data collection to analysis. 1) Subjects interact with digital artefacts and produce data. 2) The resulting data (“source data”) is typically stored in idiosyncratic formats, possibly determined by technical constraints of the digital artefacts. Furthermore, this “source data” may contain data that is not of direct relevance to researchers (e.g., technical information about the software) and important information may come from other sources (e.g., information about the study that is present only in the corresponding research paper). 3) It is typically necessary to extract the relevant data from the source data. Here we distinguish “event” data and “trial” data. Event data describes the behavioral data as a sequence of time stamped events, which have specific types (e.g., a mouse click) and data (e.g., the screen coordinates of the click). Trial data organizes those events following a task-pattern into a tabular form, where each row describes one trial. Further data files are necessary for example to describe the study. Note that it is typical for the data collection artifacts to already embed some data processing code and keep as source data only the “trial” data. 4) The most important type of behavioral data appears to be the event data from which different trial datasets may be extracted—this is in our opinion what should be viewed as the raw data and it will be valuable in the future to standardize behavioral event data and develop effective tools to deal with such data and extract trial-based data from them. 5) We define as Level 1 data, the data tables which are organized by trial. These are the tables we believe are most useful given current practices. In particular, we define the L1-Trial table, where each row contains complete and standardized information describing a particular trial (as is already currently the case, albeit inconsistently) and where the trial identifier is used as a primary key to additional, more detailed or specific tables (e.g., a table describing each of the mouse clicks that occurred during a trial). 6) The L1 data serves as the standardized input to data processing pipelines, which will derive additional tables (e.g., L2, L3), for example by transforming and summarizing data or aggregating across subjects.

5.1 Source data, raw data and derived data

We consider as source data, all the data that is saved by the data collection artifact (e.g., computerized cognitive test) in its original structure and format (e.g., a single data file in a proprietary data format; multiple json files). Source data can contain all sorts of data. It includes the raw data but may also include metadata (e.g., information about the
artifact itself) as well as derived data (e.g., a performance score computed from the raw data). Source data is typically in idiosyncratic formats and not usable as is.

Not all source data is raw data; and raw data needs not be source data. There are certain operations that can be performed on the raw source data to extract and constitute a dataset that is more usable without that dataset losing the “raw data” status. For example, if a source file is saved as a csv (comma separated values) file, converting that csv file into a tsv (tab separated values) file, is a trivial operation that has no consequences on the outcome of the study. On the other hand, filtering out some data based on performance or rounding numeric values are operations that may impact the outcome of subsequent analyses; hence the data that results from applying those operations can no longer be considered “raw”.

Operations we consider to preserve “rawness” are selection by type (not by value), removal of duplicates, renaming of variable names for clarification, change of units, reordering of rows and columns and referencing/indexing (e.g., numbering rows of a certain type) and reversible file format conversion (e.g., csv to tsv). In short, as long as the information in the data is equivalent to the information in the raw source data, in our opinion, that data can be said to be raw.

5.2 Event data and trial data

Two common ways to structure behavioral data are by event or by trial (source data may contain either event data or trial data or both). Event data lists particular events that occurred during a study (e.g., a person pressed a key, a stimulus was displayed on the screen) with a timestamp (i.e., when did that event occur) and information describing the event (e.g., where on the screen did the click occur, how long did it last). The event data format is common in cases where behavior is related to other, time varying measures (e.g., in fMRI or EEG studies); it is much less common in behavioral sciences where information about when particular events occurred is often discarded. In those fields, it is much more common to structure the behavioral data by trial, meaning, as a table where each row corresponds to a “trial” and each column to a variable describing what happened during that trial (e.g., for trial_index = 3, correct = TRUE).

It is important to note that beyond the shape factor, trial data and event data are quite different. Event data may describe events as they occurred and are thus more objective (e.g. a click occurred at timestamp 6.824). Trial data, on the other hand, are fundamentally tainted by the experimenter who needs to define (typically implicitly) a “task-pattern” which defines which events to select from the flow of events that occurred during the study and how to aggregate and/or transform them in order to constitute a row in the Trial table.

Let’s take an example to make this point clearer. In a N-back task, participants are shown letters, one at a time, and asked to report whether the letter that is currently displayed is the same as the letter shown N steps earlier. Let’s further compare a 2-back and a 3-back test that use the exact same sequence of letters. The event data from these two tasks may look virtually identical (they have events describing the occurrence of letters and key presses). The trial data, on the other hand should look differently because for the 2-back test we use a different “task-pattern” than in the 3-back test. For example, in the first case we might describe the stimulus of the first two trials as “3-1-3” and “1-3-4”, while the same sequence of events in the 3-back task only forms one trial whose stimulus could be described as “3-1-3-4”.

Figure 1 shows various steps in the lifetime of a dataset, ranging from its collection to the aggregation of summary statistics across participants. The format and structure of the source data is subject to various engineering constraints and specific to particular data collection software systems; it is therefore unlikely that we’ll converge on standards for source data that would apply to all use-cases any time soon. However, we could aim to define standards for raw event and trial data which could be readily used as input for data analyses pipelines and shared on public data repositories.

Here we focus on describing the L1 data, leaving for later standardization efforts of event data. This choice is motivated by our belief that standardizing trial data will be of most practical value to the research community.

5.3 Key concepts for specifying trial data

The data format that seems most useful and characterizes many shared behavioral datasets displays one row per “trial”—we call this the “Trial table”. For example if an experiment tested 50 participants and each participant completed 200 trials, the Trial data table would contain 10’000 rows in total (assuming all the data was in a single table).

It is important to note at this stage that the term “trial” is not used in a consistent manner in the literature and the corresponding data files. The following section aims to highlight and clarify this issue.

5.3.1 The meaning of “trial”

Different meanings are associated with “trial”. Firstly, “trial” may be used to refer to iterations of a chunk of code that is executed repeatedly (or equivalently a sequence of stimulation and input recording events). For example, a trial
may consist of the presentation of an image on the screen and the recording of a keypress made by the user after the appearance of that visual stimulus. Secondly, “trial” may be used as an index to refer to individual rows in a data table. For example, each time the user presses a key we add a line to a data table that indicates which stimulus was shown and which button the user pressed. Thirdly, “trial” may refer to an instance or sample of a specific experiment in the statistical sense. For example, we want to determine if a particular coin is biased and repeatedly throw that coin and record the outcome; each throw represents a trial of that particular experiment. Finally, “trial” may be used to refer to a period of time or “episode” during the experiment (e.g., “the participant blinked during the second trial”, “there was a 5 minutes break between trials 50 and 51”). In the most basic cognitive tests, all three meanings are congruent and thus interchangeable. But as experimental designs increase in complexity, even slightly, those notions are no longer equivalent and it becomes necessary to use more precise terminology.

Let’s take a simple example to illustrate this point. Imagine a task where a letter is shown for 1 second and participants have to press one of two keys in response to that letter during the subsequent second—this code loop then repeats 100 times. In condition-1, participants are asked to press the right key each time they see the letter X and to press the left key otherwise (a “Sustained Attention to Response Task” like test Robertson et al. 1997). In condition-2, users are asked to press the right key each time they see the letter X but only if it was preceded by the letter A and to press the left key otherwise (the AX-CPT task; Braver et al. 2001). Finally, in condition-3, both tasks are to be completed at the same time: a single letter is successively shown on the screen, but there are now two sets of buttons, one per task.

While the same code can be used to run these three conditions, from the perspectives of the participant and researcher, they are different in important ways. In condition-1, we would expect the stimulus description to refer to a unique letter, while in condition-2, a stimulus would refer to pairs of letters (this information is necessary to determine in each case whether participants’ responses were correct or not). Furthermore, if condition-1 and condition-2 use the same sequence of letters, the resulting number of trials will be different across the two conditions. Consequently, in this example, a “trial” in the code-loop sense no longer maps directly to a “trial” in the table index sense as information from two different code-loop trials is now contained in a single table-index trial. Next, if we consider the second experimental condition, one might assume that an experimenter will be interested only in those instances where a letter X was shown and it was preceded by another letter. If those instances define “trials” in the statistical sense, then trials should count only these specific instances. For example, if we assume that there were 100 code-loop trials (i.e., presentations of letters) but only 5 of those presented the letter X then there could at most be 5 trials (in the statistical sense) in that experiment, and thus only 5 rows in the corresponding data table. Finally, if we focus on condition-3, we see that for a given letter, there are two “trials” (one per task) occurring at the same time. Trial in this (and other cases) can therefore no longer be used to refer to a time period—to refer to particular, temporally distinct and non-overlapping time periods in an experiment we recommend to use “episode” instead. In condition-3, we could then have the same episode index correspond both to the 5th trial of the first task and the first trial of the second task.

The example above illustrates that “trial” can be used in inconsistent ways and that it is necessary to clarify its meaning. Within the behaverse data model we use the statistical definition of trial and define a trial with a corresponding task-pattern (see below). For indexing rows in a table we use a more generic “id” variable and for indexing particular time periods in a study we use “episode”.

5.3.2 The task-pattern

Consider again the example experiment presented earlier where under two different conditions, letters were presented successively and participants were required to press one of two keys in response to those letters. The event data from both of these conditions could virtually be identical, with the same type of events being recorded each time a stimulus is shown or key is pressed. However, the corresponding trial data would look rather differently across both sets of conditions.

One can think of the trial data as something that is “created” from the event data (+ some other stuff). Indeed, one could write “extraction” code that would parse the event data looking for specific sequences of event types, extract the data corresponding to those event types and process and shape them into a row of the trial table—we call this code the “extractor” and save its parameters together with its trial data.

The specific sequence of event types, used by the extractor to query the event data, is what we call the task-pattern (in analogy to pattern in regular expressions). A task-pattern is typically of the form {stimulus-set; action-set}. In condition-1 of our example task, the stimulus-set might be all letters, while in condition-3 it might be all pairs of successively presented letters or all pairs of letters where the second letter is the letter “X” (depending on the experimenter’s intention). In both cases, the action-set is any of the two possible button clicks that occur within 1 second after the stimulus. Task-patterns can of course be more complex; the key idea here is that the definition of a trial of a particular type is determined by a task-pattern. In the behaverse data model, when we index a trial, we index trials for a given task-pattern.
There are two points we want to emphasize here. Firstly, while the event data can be seen as an objective description of what actually happened during a study (e.g., the letter “A” shown on the screen center at 10:42:01.621; the left arrow key was pressed at 10:42:02.246), the trial data necessarily reflects the experimenters view of what that data means (e.g., the key press is a response to the letter, the response time is computed as the difference of times stamps and equals 0.615 seconds, and the response is correct given the current task rule). In fact, a different trial dataset could be generated from the same event dataset. The take-home message then, is that a) we need to store the event data as this data is privileged and more objective/raw than the trial data, and b) for a given trial dataset we need to maintain information about its provenance (e.g., the name of the task-pattern or extractor-code used to go from event data to trial data). Secondly, we believe that the concept of task-pattern is important beyond the context of data extraction and might be useful to characterize tasks for computational modeling or to implement artificial agents capable of performing tasks.

5.3.3 Evaluation

The task-pattern defines what constitutes a valid trial within a given experiment; it defines a subset of all possible stimulus and input sequences. Each element in this set of valid trials is mapped to a value. For example, it is very common in cognitive psychology for the response on a given trial to evaluate to “correct” or “incorrect”. The value function or “evaluation” can be seen as a set of rules which are typically (implicitly) described in the task instructions (e.g., [to be correct:] “if you see the letter X press this key, otherwise press that key”); the value function may also be defined relative to an idealized policy—the particular way the experimenter believes participants should map stimuli (sequences) to action (sequences) within the context of the study.

5.3.4 Runtime extraction and evaluation

It is important to note that the software we use to present stimuli to participants and record their actions typically encodes information that reveals our intentions and may in fact distort the data. For instance, some researchers might not record event data and instead create the trial data directly as events unfold in time—their code instantiates an “extractor”. This will typically discard data (e.g., when did a trial start) which makes it impossible to later reconstruct the time course of events as they occurred. Furthermore, that same code also typically includes evaluation code, as this might be necessary within the experiment itself, for example to display participants a correct/incorrect feedback signal for a given response.

It can be convenient and sometimes necessary to have these data processing functions embedded in the data collection code and operate during runtime on the events as they occur. However, one should also be wary of the fact that this code may contain errors. If we record only the output of those processes, i.e., runtime generated trial data but no event data, it might be impossible to detect and ultimately correct those errors.

5.3.5 Trial data versus L1-data

When describing the data that is extracted from the event data we used both the terms L1-data and Trial data in the sections above. These two terms, however, are not synonymous. Rather, L1-data refers to the state of the data (typically multiple tables) within a stage of the data analysis pipeline (see Figure 1). Trial-data, on the other hand refers to a specific type of data table where each row contains data from a single trial as defined above. In the next section we’ll review the structure of the L1-data, and discuss what other tables besides the Trial table may exist within L1.

6 L1 data model

Behavioral data (e.g., from computerized cognitive tests) are typically shared in a tabular format (e.g., one csv file per task), where rows typically correspond to individual “trials” and columns refer to different types of variables that describe that trial (e.g., response time). This, however, is insufficient. Firstly, it is already the case that the single-table trial-data does not include all necessary information. For example, it is typically necessary to read the paper about that data to learn about task parameters that did not vary across trials (e.g., the duration of stimulus presentations). Extracting that data and putting them in a consistent format would facilitate subsequent data usage. Secondly, behavioral data contains information that can be grouped into different semantic categories. These subcategories may have nested structures which do not play well with a simple single-table format but may instead be properly organized into multiple sets of tidy tables. More specifically, we define the following semantic data categories for the L1 data:

1. **Context**: provides context information for a particular trial, such as, identifiers for a study, a session, a participant and task.

2. **Task Information**: describes the tasks participants were exposed to (e.g., instructions, task parameters).
3. **Extraction Information:** describes how event data was converted into trials.

4. **Stimulus Information:** describes what stimuli were presented to participants.

5. **Options Information:** describes the different options participants had for responding on a given trial.

6. **Input Information:** describes the actions participants made (e.g., a button click).

7. **Response Information:** describes the meaning of participants inputs within the context of the task (e.g., option “match”).

8. **Evaluation:** describes the value associated with participants’ responses (e.g., this response was correct); this value is not necessarily communicated back to the participants.

9. **Feedback Information:** describes if and how participants received explicit information about their response or performance (e.g., green check after a correct response); this data describes physical events shown to the participants. Note that one may have the case where a “green check” feedback is shown to participants after an incorrect response (i.e., evaluation and feedback are distinct constructs).

10. **Outcome Information:** describes the consequences of the participants’ action in the test. For example, in a serial ordered search task, participants are asked to open boxes to search for a token. Opening a box has the outcome of revealing its content and changing the state of the world (e.g., it reveals an empty box). While an outcome may implicitly contain feedback information, it is not necessarily the case. On the other hand feedback is solely meant to convey participants information about their performance. Outcome and feedback and evaluation are distinct constructs. In our box opening example, a participant may correctly click on an empty box (evaluation), see a green check (feedback), and see that the box is in fact empty (outcome).

11. **Reward Information:** participants sometimes get a reward in tests; this could for example take the form of points, money or even food.

12. **Experimental Design Information:** provides additional, optional data or features that the experimenter believes will be useful to interpret participant’s responses (e.g., tagging certain trials in the N-back task as being “pre-lure” or “post-lure” with the intention to contrast performance on these two types of trials).

13. **Hardware Information:** provides information about the hardware that was used to collect the data (e.g., this keypress was collected from keyboard #2).

14. **Technical Runtime Information:** provides information about how well the trial was executed from a technical point of view (e.g., were there unexpected lags?).

15. **Information about additional data:** provides information about additional measures that might have been collected during the study (e.g., brain imaging data).

Each of these categories could have its own table with additional tables associated to them because there are typically different subtypes of data for each of these (for example, there are different kinds of possible stimuli and each kind of possible stimulus could have its own table).

There are two points we want to make here. First, behavioral data, as we hope to have demonstrated, is more complex than typically assumed; it involves a myriad of interconnected data tables. Second, current practices and data analysis tools do not address this complexity and instead focus on an easier to handle subset of the data (i.e., only the data that is strictly necessary for a particular analysis).

In order to get a more comprehensive and consistent handle on all of the behavioral data while at the same time remaining compatible with current practices and tools we opted for a particular set of design principles to organize the multiple L1 tables (see Figure 2).

The first principle is to keep a trial table which is similar to what is already customary in the field. Each row in this table describes one trial and columns may contain summary information about particular aspects of that trial. For example, in a digit-span task where the stimulus is a sequence of digits presented at a certain rate one may summarise the stimulus for a given trial as “3;4;5;1”. We define standards and conventions for that trial table to achieve consistency across datasets (see https://behaverse.github.io/data-model/).

The second principle is to separate information depending on whether or not it is common or specific (e.g., to a task) and whether it describes the trial as a whole or particular events that occurred during the trial. For example, the example of the digit-span test, “3;4;5;1” describes the stimulus at the trial level and is thus present in the trial table. The timestamp of the digit 5 during that trial is specific to an event and is thus present in the stimulus table which describes all the stimuli that occurred within each trial.

The third principle is that the trial table serves as the master table with the id of each row in that table serving as the key to link all the tables within L1. For example, knowing from the Trial table that “3;4;5;1” was presented on trial_id 2378,
one can find within the Stimulus table the list of stimuli shown during that trial together with the properties of those stimuli (e.g., timestamp, location, duration).

Figure 2: L1 Trial data. 1) In source data, relevant information may be scattered across multiple data files in a way that is not practical for subsequent processing. There are various design options to reorganize the source data into data structures that can be standardized and are easier to use. 2) One solution is to factor the data into many compact tables within a relational database system. While this solution has many technical advantages, it doesn’t play well with current practices. 3) An alternative design solution—the one we chose for the current behaverse data model—defines a main ‘L1 Trial’ table which is similar to what researchers already use today. However, in addition to providing the trial data, the L1 dataset contains additional, related tables (as in 2). Tables in L1 are related to each other by various primary keys, the most important one being the trial identifier within the Trial table. We believe that this solution is both of practical use for researchers and offers the possibility to augment the Trial table in a principled way to capture more of the richness of behavioral data than is typically the case.

We believe that this design strikes a good balance between the somewhat contradictory requirements (e.g., the efficiency of a fully relational database versus human readability and ease of use); it is compatible with the way researchers are already structuring their trial data and offers a principled way to organize related data that is currently ignored but shouldn’t.

7 Discussion

The standardization of behavioral data structures may not be the most exciting endeavour for a researcher—after all, great scientific advances were made without such standards, researchers can analyse data without following standards and it may seem to many that time spent on such mundane issues is time diverted from doing actual research. While there certainly is some truth to those statements, we believe that developing good standards for structuring behavioral data holds the promise for significantly improving the quantity and quality of behavioral research and may lead to novel insights.

As have argued many before us (e.g., Gorgolewski et al. 2016), standardizing data structures may increase research quality by clarifying concepts that are understood or used differently by different people. When those standards are public, they contribute to make science more open, transparent and reproducible. Finally, the use of standards can guide the development of various software tools that are specifically designed to take advantage of those standards.

There are a few examples that demonstrate how sometimes even simple data organization principles can lead to the development of an elegant and efficient software ecosystem that greatly facilitates the analysis of data. In the R community, for example, the notion of “tidy” data (e.g., “tidy data”; Wickham 2014) has led and contributed to the development of the suite of tools known as the “tidyverse” (Wickham et al. 2019) which has had a massive impact on data science. Similarly, in the neuroimaging community, the BIDS’ way of organizing imaging data has had profound positive effects for the field as whole, facilitating the sharing and reuse of imaging data but also leading to the development of software tools to check for example the integrity of data but also efficient and standardized data analysis pipelines (e.g., https://fmriprep.org/; Esteban et al. 2019). What these examples show is that the development of standards for structuring data can lead to the development of tools and data analysis standards that greatly benefit the field. It is our hope that by contributing to standardizing behavioral data, equally impressive progress can be achieved in behavioral sciences.

In this document, we focused only on a few key concepts; other ideas are presented in greater detail in the projects’ website (https://behaverse.github.io/data-model/) which holds an updated version of the behaverse data model. Many questions remain unanswered, various aspects of behavioral data to be explored and numerous decisions
8 Conclusion

Behavioral data is fundamental in cognitive sciences and there is clearly a need for standards to organize such data so it can be efficiently analyzed, shared and reused. Here we emphasized several key issues and presented constructs we believe are essential for structuring behavioral data and which currently seem to be used inconsistently.

Much remains to be discussed. To keep this document short and decrease the likelihood of its content becoming obsolete as our standards evolve, we decided to focus here only on key points and refer the reader to the online documentation of the behaverse data model (see https://behaverse.github.io/data-model/).

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