Boundary Value Exploration for Software Analysis

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Abstract—For software to be reliable and resilient, it is widely accepted that tests must be created and maintained alongside the software itself. One safeguard from vulnerabilities and failures in code is to ensure correct behavior on the boundaries between sub-domains of the input space. So-called boundary value analysis (BVA) and boundary value testing (BVT) techniques aim to exercise those boundaries and increase test effectiveness. However, the concepts of BVA and BVT themselves are not clearly defined and it is not clear how to identify relevant sub-domains, and thus the boundaries delineating them, given a specification. This has limited adoption and hindered automation. We clarify BVA and BVT and introduce Boundary Value Exploration (BVE) to describe techniques that support them by helping to detect and identify boundary inputs. Additionally, we propose two concrete BVE techniques based on information-theoretic distance functions: (i) an algorithm for boundary detection and (ii) the usage of software visualization to explore the behavior of the software under test and identify its boundary behavior. As an initial evaluation, we apply these techniques on a much used and well-tested date handling library. Our results reveal questionable behavior at boundaries highlighted by our techniques. In conclusion, we argue that the boundary value exploration that our techniques enable is a step towards automated boundary value analysis and testing which can foster their wider use and improve test effectiveness and efficiency.

Index Terms—boundary value analysis, boundary value testing, test diversity

I. INTRODUCTION

Even though boundary value analysis/testing [1]–[4] is a core technique in software testing, it has been acknowledged in the literature that establishing and maintaining correct/meaningful behavior at boundaries requires creativity and is hard to realize [3]. In practice, many faults can be found near boundaries that delimit different sets of inputs which should or are handled differently by the software, i.e. where the behavior of the software changes or should change considerably.

The traditional way to proceed is for testers to start from a specification and then use partition analysis (PA) to partition the input space into partitions or sub-domains in which the behavior of the software should be the same (so called equivalence partitions) or similar. Then, boundary value analysis (BVA) techniques instructs testers to sample from the boundaries between the sub-domains to obtain and execute tests (BVT) that can ensure correct behaviour at the boundaries [4].

A downside of the techniques used for BVA/BVT of today is that they do not give concrete methods for identifying sub-domains; often it is assumed that the specification explicitly states them and directly helps in identifying boundaries. However, this might depend on the way that the specification is written and since most non-trivial software specifications are not complete, are implicit, or are specified only in natural language and thus vague, it is not clear how to proceed. In particular this is a problem for complex software with large input spaces, for heavily or non-linearly dependant inputs, and when inputs are of complex and highly structured types. Overall, this limits the wider use of BVA and BVT for software testing and quality assurance. Furthermore, since this process typically depends on human analysis it is not clear, in general, how to automate it, which limits efficiency.

In this paper, we introduce the concept of boundary value exploration (BVE) to support BVA and BVT in situations where the specification might not be complete, consistent, explicit, or even exist. We also propose two concrete techniques for BVE that are based in information-theoretic distance functions previously proposed for measuring test diversity [6]–[8]. For illustration and evaluation, we then apply these techniques on a much used and well-tested component for the handling of dates in the high-level programming language Julia. Our results reveal questionable behavior at some of the identified boundaries. In particular, our boundary detection algorithm revealed boundaries of the SUT by measuring and visualising values of the program derivative [8]. In short, our contributions are that we:

- propose a clarification of BVA and BVT and their relation, and
- introduce the novel concept of Boundary Value Exploration (BVE) to support BVA and BVT by identifying candidate boundary values, and
- describe two concrete techniques for BVE, respectively, a boundary detection algorithm using distance functions as a means for detection, and software visualization to enhance the understanding of boundaries and to select additional boundary inputs.

The rest of this paper is structured as follows. Section [II] presents an overview of the most relevant existing literature on BVA and BVT. In Section [III] we clarify and distinguish BVA and BVT, introduce BVE and describe their relation, followed by a motivating example that highlights the prospects using BVE in Section [IV] In Section [V] we then further
describe and apply the BVE techniques for boundary detection and visualization to our case and reveal boundary candidates. Section VII briefly discusses the findings and their implications for software testing while Section VIII concludes.

II. BACKGROUND AND RELATED WORK

In equivalence (or category/domain) partitioning and testing, similar test inputs are grouped together in equivalence classes that cover contiguous regions of the input space/domain. The assumption is that similar inputs would be handled in a similar way. However, this may not always be the case as the program would go through the same path by the software under test and be more likely to be affected by the same faults. Thus, testing one of the inputs in a partition should be enough to catch such faults.

There are many partition strategies, but sampling test inputs for each partition is typically still challenging and can be costly. Strategies based on search algorithms or combinatorial testing can help, but there is a fundamental trade-off between the cost of sampling tests/inputs and the cost of running and evaluating the results. For instance, Adaptive Random Testing (ART) techniques use distance measures to sample test inputs further apart from each other with the aim to cover different partitions and increase test effectiveness. However, the high cost repeatedly calculating distances often hinder applicability in realistic systems, such that simple random exploration of the input space can be more effective. Even though random testing techniques can generate many test inputs, the effective coverage of partitions remains prohibitive if execution of sampled tests is slow or an automated oracle is unavailable. An alternative approach would be to sample at or around the boundaries between partitions since it is critical to ensure that inputs on either side of a boundary is correctly handled, so called boundary value analysis or testing (BVT).

Traditionally, BVA (or BVT the terms have often been used interchangeably) is based on a human developer analysing a specification to identify partitions and the boundary values they imply and then write down test cases that ensure correct behavior at the boundaries. While early results questioned the value of partitioning and BVA in comparison to random testing, later results showed that BVA could have higher fault-detection ability than both random testing and equivalence partitioning (EP). However, neither EP nor BVA have been clearly defined, since they rely on a non-formal understanding of what constitutes a partition, and alternative ways of coming up with boundary values have been used, e.g., based on experience from previously problematic inputs, previously known issues, or “natural” boundaries of the data types involved. Analysis of source code, or based on distance/diversity metrics. However, regardless of the method and agent used (e.g., a human tester or automation via an algorithm such as search) to identify boundary values, few techniques actively seek and, once found, explore the boundary.

In the original formulations, similarity referred solely to the program taking the same execution path for all inputs in the same partition/domain, but over time the terms have been used in a more general way.
In connection to testing, most SV proposed tools and techniques focus on maintenance, fault detection or change impact analysis [19]. Authors in [23] propose similarity maps as a visualization technique that uses dimensionality reduction to visualize the diversity between tests in a test suite. In their industrial evaluation, the similarity maps brought awareness to relevant issues related to maintenance of the tests where unnecessary redundancy was being added and kept to test repositories introducing waste [23]. Similarly, authors in [24] developed a tool that mines test execution logs in search for details about failing tests (e.g., error messages, exceptions thrown, time stamps). This information is then aggregated into distinct classes of failures and then displayed in dashboards in Continuous Integration monitoring systems. In their evaluation with industry partners reveal that their dashboards provides a holistic view of the failures and aids testers in identifying the faults behind the failures [24].

Feldt et al. [25] apply software visualization to test history data in order to support more effective analysis, planning and execution of quality assurance. Particularly, test information is visualized in a heatmap and monitored through meetings with stakeholders. Their results show practitioners can use the heatmaps to make decisions about prioritising test effort, resource allocation or awareness of problematic areas of the SUT. Moreover, authors analyse the correlation between the heatmap and the different souces of development data (e.g., code churn or number of failures) to highlight attention areas to stakeholders. Nonetheless, these and other visualization tools must work in combination with stakeholders to support data driven decision making in software development [25]. Enström et al. [26], investigate further the usage of heatmaps from test history to support decision making. Their evaluation reveals that practitioners find the visualization useful to support test planning, however the type of visualization required is dependent on the task, and participants reported on the importance interacting with the visualization.

Furthermore, Borg et al. [27] combine the test results from project with the file structure of the design under test into an interactive 3D city visualization (i.e., a cityscape). Their tool shows a landscape of the various files committed into a project as a building, where the building’s height is the number of times the file was committed and a color gradient indicates how often the committed file, respectively, failed or passed. The resulting visualization reveals insights about regression testing activities such as error prone areas and tests that should be changed to increase coverage.

As these SV studies show visualisation can help developers and tester get an overview, trigger reflection, and spot important patterns in the testing and quality of the software being studied. Similarly, we also use software visualization to trigger insights and reflection on boundary behavior by showing candidate boundary values. This can then help test generation, planning, and, generally, decision making. In particular, our use of visualisation with interaction to allow exploration of boundary areas, via 3D plots of the input space, is novel.

### III. Boundary Value Analysis, Testing, and Exploration

Boundary value analysis (BVA) and boundary value testing (BVT) are umbrella terms to describe different techniques that identify and ensure correct software behavior at boundaries. While the former is typically presented as a black-box technique focused on identifying partitions and, thus, boundaries given a specification, the latter is seen as a white-box technique to actually ensure that the boundary is actually where it should be. However, the two terms are often used interchangeably without clarity in how they differ or overlap [8]. In the following, we define these concepts more clearly, relate them to each other, and propose a new concept, Boundary Value Exploration (BVE), as a set of techniques that can support them both.

A useful characterisation was given by Hierons in [13] which defined boundaries more formally through their elements, namely pairs of input \((x_1, x_2)\) for adjacent sub-domains \(S_1\) and \(S_2\) with \(x_1 \in S_1\), \(x_2 \in S_2\), and \(x_1 \neq x_2\) being close together. The latter criterion requires that an ordering or ideally a metric has been identified [13]. Recently, Feldt and Dobslaw noted [8] that generally applicable compression distances from information theory can be used in this context and by considering also the distance between the outputs, i.e. \(d_{output}(o_1, o_2)\) where \(o_1 = P(x_1)\) and \(o_2 = P(x_2)\) and where \(P(x_i)\) denotes running the program \(P\) on the input \(x_i\), they proposed that boundaries can be defined as pairs that lead to high values of the program derivative \(d_{output}(o_1, o_2)/d_{input}(x_1, x_2)\).

A problem with previous proposals for BVA has been that they assume sub-domains to exist but they do not describe how to identify sub-domains given a specification. Even when a complete, formal specification is available it might not be clear how to identify its sub-domains. The problem is further exacerbated since, in practice, specifications are often implicit (undocumented) or, even when explicit (documented), they are frequently incomplete, hard to understand, or even incorrect. The proposal of program derivative [8] allows a clear alternative: define boundaries to be subsets of pairs of inputs with high derivative values for relevant distance functions on inputs and their outputs. By selecting relevant input pairs and running an implementation on them and then calculating distance and derivative values we can explore actual boundaries in an implementation.

Figure [1] shows an overview of our approach by outlining the main artefacts (on top, straight rectangles), their activities (lower half, rounded rectangles), and their main relations (arrows). Central in our approach are the boundaries of which we highlight to main types: expected boundaries that are either clear from a specification or which a boundary value analysis identifies, and actual boundaries arising from the

\[\text{Here, } d_{output} \text{ and } d_{input} \text{ are two distance functions, one for outputs and one for inputs. While they can be the same, and compressions-based distances like the normalized compression distance can be good default choices, do not need to be and a tester can select specific and multiple distance functions depending on their needs and their knowledge of the specification and or the implementation.}\]
IV. Motivating Example

To demonstrate the mechanics and impact of BVE in practice and motivate its use, we here present and apply two concrete BVE techniques, namely boundary detection and boundary value visualization, on a concrete case. We’ve chosen the `Date` library of the Julia programming language as our object of investigation since it is relatively simple while still showing interesting behavior.

Julia offers a useful feature for the in-code retrieval of type minimum and maximum values for numeric types as well as composite types based on numeric types using the `typemin` and `typemax` functions. `Date` is one such type as it is typically constructed from three integers, the year, month, and day. For instance, in Julia version 1.1.1, we can apply `typemax` to the `Date` type:

```
 typemax(Date) → 252522163911149-12-31
```

This result’s validity can be verified through the instantiation of a date from its three constituting integers. Table I contains a variety of such date instantiations that was identified during our boundary value exploration and which we will refer to in the following. The above example can be found in row 1, for example.

Since `typemax(Date)` should by construction be an extreme value of type `Date`, we would expect later dates to be invalid. However, when testing this it turns out it is valid and seemingly correct, as shown in row 2 of Table I. However, if we continue and increment the year parameter beyond the `typemax` value, while keeping month and day unchanged, this results in a seemingly invalid, but nevertheless non-exceptional, result (see row 3). The function `Dates.day` for that date returns 28 whereas 31 was entered. Our exploration has helped demonstrates that `Date` in Julia 1.1.1 is not isomorphic in its API, since

```
 d == Date(Dates.year(d),Dates.month(d),Dates.day(d))
```

does not hold true for all its instances. Still, and inconsistent with the above, overstepping the month or day parameters through the `Date` instantiating function does trigger exceptions, as can be seen in rows 10 and 11 of Table I.

Such acceptance of overflow values can cause runtime errors in the software. Even proper error handling in the calling code does not help due to the acceptance of invalid state. In practice, possible triggers for resulting runtime errors are invalid user input, e.g. by adversaries, or the reading of erroneous files.

Consequentially, the `Date` implementation seems to deviate from the `typemax` specification. In the Julia type `Date` example, and others, there may be practical reasons for the deviation of boundaries, e.g. those of performance. Either way, the boundaries of `typemin` and `typemax` are ill-defined, to say the least, and cannot be relied upon in code.

The question at hand is what the `actual` boundaries of type `Date` in Julia are, and how they can be detected? It turns out that with the help of diversity measures in support

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3Worse still, for the month field, a clearly invalid value is assigned.
of information theory, we can identify the actual boundaries without the need of an oracle, domain knowledge, or access to the code. This is demonstrated for type Date below.

Nearby input/output pairs that deviate strongly suggest boundaries. We would expect pairs nearby the specified typemin and typemax boundaries to peak in neighbor diversity, relative to other valid/non-extreme neighborhood pairs. Figures 2 and 3 exemplify how diversity information may be used to learn about the actual boundaries, here on Julia Date. Figure 2 illustrates the diversity for neighboring pairs starting from the extremes typemin (backward in time) and typemax (forward in time). What can be observed is that, not aligned with expectation, the derivatives around both extremes are not outstanding, whereas for both cases, outlier peaks in diversity can be observed further out in the supposedly invalid space. Intuitively, these peaks represent uncommonly diverse neighbors, which suggests boundaries for further exploration. We call those outliers here boundary candidates.

Figure 3 shows how a boundary can be extracted for visual analysis in a, here, two-dimensional space. For a fixed non-leap year, we visualize all diversity-measurements nearby those of very high diversity with input parameters day and month. The color intensity/opaqueness of lines signifies the magnitude of the diversity. Even without access to an oracle, we are able to clearly see the connected boundary. These visuals can be created on demand and help the tester to understand areas of input-space with relevant properties. This can further be extended to the visualization in 3d, which is conceptually explained in support of Figure 4. There, opacity in a wall highlight the boundariness in-between neighboring inputs/output pairs, here suggesting a straight boundary along one axis. The overall space is usually exhaustively large, but with the help of BVE and exploratory techniques that highlight interesting candidate pairs or candidate pair neighborhoods, sub-spaces can be entered and explored by free navigation with the calculation of diversity being done on-demand.

V. EXPLORING THE BOUNDARY

With the visualization of neighborhoods and regions in input search space, and the support of information theoretical diversity measures, we still don’t know where to start to

### Table I

| Nr. | Command | Output | Explanation |
|-----|---------|--------|-------------|
| 1   | Date(25252163911149,12,31) | 252522163911149-12-31 | typemax(Date) |
| 2   | Date(25252163911150,1,1)  | 252522163911150-01-01 | typemax(Date) |
| 3   | Date(25252163911150,12,31) | -252522163911150-6028347736506387-28 | typemax(Date) |
| 4   | Date(25252163911151,10,7) | -252522163911151-10-07 | typemax(Date) |
| 5   | Date(25252163911151,10,8) | -252522163911150-6028347736506385-06 | typemax(Date) |
| 6   | Date(25252163911150,1,1)  | -252522163911150-01-01 | typemin(Date) |
| 7   | Date(25252163911151,12,31) | -252522163911151-12-31 | typemin(Date) |
| 8   | Date(25252163911151,7,25) | -252522163911151-07-25 | typemin(Date) |
| 9   | Date(25252163911151,7,24) | -25252216391150-6028347736506379-07 | typemin(Date) |
| 10  | Date(2020,12,32)           | ERROR: ArgumentError: Month: 0 out of range (1:12) | month out of range |
| 11  | Date(2020,31)              | ERROR: ArgumentError: Day: 32 out of range (1:31) | month out of range |
| 12  | Date(typemax(Int),1,1)     | 63131837319416-12056695473012772--7378697629483820630 | year is typemax(Int) |

Fig. 2. The calculated diversity of consecutive days for Julia Date instantiation starting at typemin (dotted line) and typemax (solid line). Both progress beyond the specified boundaries, meaning for typemin back in time, and for typemax forward. For a specified extreme value, a large diversity is expected at the on-set, but not observed for either case. However, extreme values that are potential boundary candidates and of interest for further investigation (for typemin at 162 and for typemax at 281). The BD-algorithm introduced in [V] extracts these outliers for that purpose.

Fig. 3. Without an oracle, we can extract a boundary of the software. Here we see a boundary of the Date API for a non-leap year, with input dimensions day and month.
search for potentially wrong boundaries due to the huge size of the uninteresting regions within the search space. From somewhere, the exploration needs to get information about interesting areas. The typemin and typemax can play such role. We can use them as starting points for investigation, and to validate their correctness. In other contexts, this information can come from developers or testers. We call this entry point an entrance to the search. An entrance is a pair of nearby input values that land on the opposite sides of a boundary, e.g. for Date, the pairs (typemin,typemin) and (typemax,typemax+1) are examples of entrances.

For data types that contain a next function $\nu$, we can detect boundary candidates by iteratively leveraging $\nu$ with a diversity measure to compare the difference between the consecutive values. Outliers are then recommended as boundary candidates for further investigation. In the case of Julia Date, $\nu$ would be the next day function, which in Julia can be obtained adding Dates.Day(1) as in

$$\nu_{\text{Date}}(d) = d + \text{Dates.Day}(1)$$

We can create a simple algorithm to automatically detect the outliers by iterating through pairs $p = [p_1, \nu(p_1)]$ given an entrance by the user. The general description of that schema is presented in Algorithm 1. Its mechanics can be illustrated, revisiting Figure 2. Starting with the entrance typemax for $\nu$ provided by the Julia language, the algorithm processes forward until it detects a potential boundary candidate, and terminates. As a stop criterion, here, an outlier was declared as being 3 standard deviations larger than the mean, which is an outlier criterion commonly applied in statistics.

This search is effective, however not efficient, as it potentially requires passing through the entire search space. It can be used as to direct BVE into interesting areas, e.g. for visual exploration. This is exemplified below. Algorithm 1 can be adjusted to detect the lower boundary which can, for Julia Date, be reached through the previous function $\phi_{\text{Date}}(d) = d - \text{Dates.Day}(1)$. The BD-algorithm terminates for the clearly visible outlier pairs $b_\phi$ and $b_\nu$ for both extremes respectively.

Algorithm 1 Boundary detection algorithm.

| Input: | next function $\nu$, distance metric $d$, boundary entrance $e = [e_1, e_2]$ |
| Output: | boundary candidate $b'$ |
| Pairs = $\emptyset$ | $p = e$ |
| while $d(p_1, p_2)$ not outlier in $\{d(p_1', p_2') | \forall p' \in \text{Pairs} \}$ do | $\text{Pairs} = \text{Pairs} \cup \{p\}$ |
| $p = [p_2, \nu(p_2)]$ | end while |
| return $p$ |

We can further manually validate the correctness of the boundary candidates detected by the algorithm, both visually, and through trying them out in code. The from the BD-algorithm returned pairs $b_\phi$ and $b_\nu$ can be found in Table 1 for $\phi$ as the pair of rows $[8, 9]$, and for $\nu$ as pair $[4, 5]$. The difference taken up by the diversity measure becomes apparent when directly comparing the neighboring outputs in the table. The results for $b_\phi^2$ and $b_\nu^2$ are clearly valid, whereas for $b_\phi^1$ and $b_\nu^1$ they are clearly invalid.

The BD-algorithm is single-dimensional, and thus not that helpful for further exploration. However, leveraging the derivative information above, we can graphically investigate the neighborhood of the detected boundary pairs, and zoom into or out of interesting regions. Figure 3 shows the near neighborhood of $b_\nu$; this is where a manual visual investigation may start. The blue plateau in the center depicts the detected boundary pair between October 7 and October 8. Since October 8 has a strongly diverse output that year, a opaque boundary pair is even formed with September 8, which can be seen as a solid green wall. The same applies to the pair that splits October 7 on year ...50 and ...51 (strong yellow). The transparent walls along the different axes are explained by neighbors of high similarity (low boundariness). Within the valid ranges, we expect boundariness to be very low and the space therefore largely be hollow.

The space can be looked at from different angles. Figure 4 zooms out and gives a different perspective, looking at day and month primarily in a seemingly two dimensional view. The boundary candidate with the plateau $b'$ from Figure 3 is highlighted for orientation purposes. The outer boundary from Figure 3 can be re-identified in here, whereas the line crossing September/October with a bump in $b_\nu$ may raise curiosity.

In Figure 5 the view is zoomed out to investigate the larger space around the boundaries considering all three dimensions. An investigation in 3d can give clues that search may not capture otherwise. The plateau with the boundary can still be seen in the lower right corner (Figure 7 left). We further see the entire shape of the date API in that region, and how almost the entire year after typemax (row in front) is filled with similar days outputs (hollow space) that signal validity up until the 7th of October. The rotation (Figure 7 right) shows the large hollow space behind the boundary that leads up to the
boundary, signalling the relative similarity of the neighboring input/output pairs. This space extends far beyond the visible region, up until the boundary in the vicinity of \( \text{typemax} \).

With all information gathered, detected through the BD-algorithm, and validated visually, in summary, the BVE techniques applied suggest that better candidates for \( \text{typemin} \) and \( \text{typemax} \) of the \textit{Date} type in Julia are:

### Boundary Candidates

- \( \text{typemin} \text{Date} = 2021-07-24 \)
- \( \text{typemax} \text{Date} = 2021-10-07 \).

However, the current implementation accepts values beyond these boundaries which might be considered bad design or a bug.

### VI. DISCUSSION

In this paper we argued that the current adoption of boundary value analysis (BVA) and testing (BVT) is limited and then proposed concrete techniques for boundary value exploration (BVE). By building on general ideas for quantifying the distance and diversity between program inputs and outputs, and detecting areas of large changes, we then proposed automated techniques to detect, visualise and, thus, explore boundaries of a Date handling library. Taken together, the application of these techniques allowed us to identify previously unknown inputs to the library where its behavior is questionable.

We have yet to confirm with the developers of the library of these constitute expected or only actual boundaries and thus if they indicate bugs or that the specification needs to be updated. However, since the behavior of the tested library for these boundaries have recently changed (we performed our tests on
Julia version 1.1 and then saw different behavior on Julia 1.1.1) there is an indication that the identified inputs were important to consider.

Important future work is, of course, to assess the value of the proposed techniques on more cases and in empirical studies with developers and testers. In particular, such evaluation should include cases where the input and output spaces are complex and structured data types such as XML documents, trees, graphs etc. since, for them, it is less clear how to visualise changes. For example, if a boundary of the implementation of a graph-traversing algorithm is heavily tied to the specific structure of the graph it might not be trivial how to map differences between the graphs to values (for plotting) or to dimensions (for more complex visualisations). While functions that map complex data structures to numbers, e.g. the depth or number of nodes of a tree, might help to visualise and then identify boundaries, more non-linear mapping approaches might be needed. Future work should investigate if for example methods for dimensionality-reduction can help [28].

Extending our methods will also have to investigate how to select distance functions given the involved data types, specification, and or implementation. Even if domain knowledge is likely to be critical in this, future work should explore if some general rules can be found or if libraries of (data-type specific) distance functions can be useful and thus reduce the burden on developers and testers to add more specific ones.

VII. Conclusions

We proposed Boundary Value Exploration as a general concept to help identify boundary values for analysis and testing of software. By utilising general distance functions we could detect candidate boundaries and then visualise interesting areas around them, in the case of Date handling library. Overall, our results points to a more automated, agile and interactive way of analysing and testing boundary behavior of software that can lead to both increased effectiveness and efficiency.

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