

Reducing Visual Complexity in Software Maps using Importance-based Aggregation of Nodes

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Abstract: Depicting massive software system data using treemaps can result in visual clutter and increased cognitive load. This paper introduces an adaptive level-of-detail (LoD) technique that uses scoring for interactive aggregation on a per-node basis. The scoring approximates importance by degree-of-interest measures as well as screen and user-interaction scores. The technique adheres to established aggregation guidelines and was evaluated by means of two user studies. The first investigates task completion time in visual search. The second evaluates the readability of the presented nesting level contouring for aggregates. With the adaptive LoD technique software maps allow for multi-resolution depictions of software system information while facilitating annotation and efficient identification of important nodes.

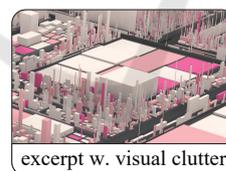
1 INTRODUCTION

Software maps are 2.5D treemaps that visualize software system information. They were introduced to make code quality of software systems visible to “stakeholders in the development process, particularly, to the management” by means of visualization of automated software analysis, metrics, and activity data (Bohnet and Döllner, 2011). Depending on their configuration, they facilitate exploring structures, monitoring development processes and software quality over time, and identifying areas that require attention in the ongoing development process. For a given task, a *map theme* configures a software map by specifying the mapping of attributes to the visual variables (adequate color scheme, layout, etc.).

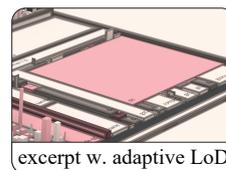
Treemaps represent well-known tree-structured data by means of space-constrained, recursively nested sets of rectangles that express *data elements* (nodes). Their sizes are proportional to per-node weights (Johnson and Shneiderman, 1991). Data associated with nodes, *the attributes*, can be mapped by the visual variables (Bertin, 1967) such as rectangle size, color, texture, and shading. Variants of treemaps are applied in a large number of applications and systems to interactively display, explore, and analyze multi-variate, hierarchical data of, e.g., file systems (Shneiderman, 1992), software system information (Wettel and Lanza, 2008), business data (Vliegen et al., 2006), stock markets (Wattenberg, 1999), or

controller performance data (Mitchell et al., 2004).

2.5D treemaps extend treemaps by using the third dimension: rectangles are extruded to cuboids, keeping the regular treemap’s two-dimensional reference space and layout (Bladh et al., 2004). 2.5D treemaps provide additional information display, that is, we can also map attributes to the cuboids’ height and to visually relate more attributes in a single view.



When depicting large structures, however, the common 1:1 mapping of nodes to cuboids can lead to visual clutter (Rosenholtz et al., 2005) and increase their visual complexity, an implicit measure of cognitive load and perceived interaction complexity (Harper et al., 2009). Cognitive load thereby describes the effort being used in working memory to accomplish the given task. At worst, multiple nodes are depicted within sub pixel space, which corrupts the visual display (visual clutter) and prevents any meaningful interpretation of the underlying data.



This article addresses these limitations by introducing an aggregation technique that reduces the visual complexity by means of an importance-based level-of-detail (*LoD*).

The LoD is implemented by means of adaptive ag-

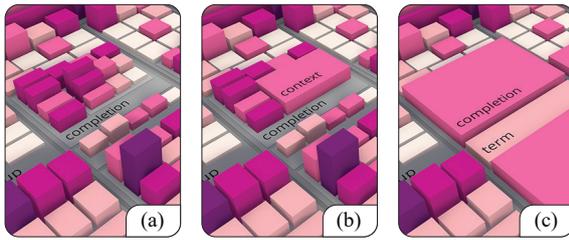


Figure 1: f.l.t.r.: stepwise bottom-up aggregation with consistent mapping and avg. accumulation of underlying data.

gregation on a per-node basis. For it, we introduce an importance measure that scores each node, e.g., based on its attribute values, resulting area on screen, or user interaction. This scoring is basically a “*Degree of Interest* [DoI] function which assigns to each point in the structure, a number telling how interested the user is in seeing that point, given the current task” (Furnas, 1986). The use of map themes narrows the importance of every node down to the attributes, mapping, and user interaction, and thus, enabling approximate scoring. A subsequent aggregation evaluates scores on a per-node basis, resulting in drawing a node either with or without its children. In the latter case a node is denoted as *aggregate* and depicts the accumulated underlying data using the same or a similar visual mapping (Figure 1).

With this adaptive LoD technique, we introduce software maps of minimum aggregation of areas considered interesting while maintaining valuable context information summarized at lower resolutions (Figure 2). We further describe the scoring and aggregation steps and introduce enhancements to the visual display of aggregates in the context of aggregation design guidelines. Finally, we discuss best practices and evaluate several implications to user interaction.

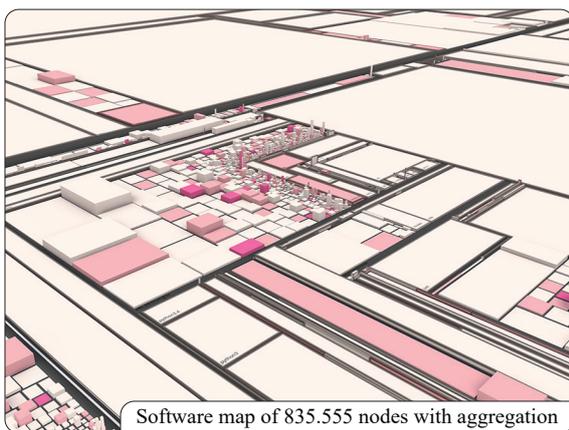


Figure 2: Importance-based LoD reduces the software maps visual complexity while preserving important information.

2 RELATED WORK

With respect to our approach, related work comprises the fields of interactive treemaps, level-of-detail techniques as well as hierarchical aggregation guidelines.

Interactive Treemaps. Since the original presentation of 2D treemaps (Johnson and Shneiderman, 1991) a number of treemap layout variations have been published, improving readability, stability, and the graphical elements’ aspect ratio (Bruls et al., 1999; Bederson et al., 2002; Tak and Cockburn, 2013). With the extension of 2D treemaps to 2.5D treemaps (Bladh et al., 2004), several challenges emerged, such as increased rendering costs, occlusion of graphical elements, supplementing padding (to enable the distinction of parents and auxiliary for reducing occlusion), as well as the need for additional, effective navigation techniques. Extruded 2D treemap shapes allow for a 3D attribute space mapping to 3D substitutes within a treemap’s two-dimensional reference space, hence, 2.5D. In contrast, various visualization techniques such as treecube or 3D polar treemap (Johnson, 1993) are classified as 3D treemap that lay out hierarchy elements within a three-dimensional reference space (Schulz et al., 2011). However, it should be noted that the term 3D treemap is often used to denote 2.5D treemap as well.

Similarly, we prefer the term software maps over *code cities* (Wettel and Lanza, 2008), since (1) the maps do not focus solely on source code, (2) the maps lack any analogues for parks, streets, rivers, traffic, etc, and (3) spatialization approaches usually do not originate from city planning processes.

Implementing software maps in industry applications necessitates meaningful labeling. To this end, our software maps utilize a concept first applied to cascaded treemaps (Lü and Fogarty, 2008), except that the cascaded representation does not naturally transfer to 2.5D. Instead, nested representation with additional padding at one lateral surface of a parent cuboid is used to provide sufficient space for labeling.

Level-of-Detail Techniques. The visualization of massive amounts of items using 2D treemaps (Fekete and Plaisant, 2002) causes visual clutter which drastically increases the cognitive load and is even worse for 2.5D treemaps. “Clutter is the state in which excess items, or their representation or organization, lead to a degradation of performance at some task” (Rosenholtz et al., 2005). This is resolvable via abstracted depiction of cluttering nodes by means of either temporal, spatial, or appearance distortion (Ellis and Dix, 2007). Map themes applied to software

maps typically use a lines of code measure as weight for spatialization in order to maintain a stable, recognizable layout and consistent footprint mapping (e.g., when exploring different datasets of a single software revision). In addition, even non-interactive depictions should convey maximum information (e.g., for reports on paper and other static provisioning), thus, we rely on appearance distortion which constitutes the abstraction through aggregation by means of strategies changing the gestalt of node representation.

For aggregation of 2D and 3D graph clusters the clusters' bounding box can be used for the aggregates' shape (Balzer and Deussen, 2007). Aggregation strategies for tree visualizations (Munzner et al., 2003) as well as for polar treemaps (Chuah, 1998) were described, though, limited to planar representations and using no or basic LoD control. For 2D treemaps, a progressive refinement strategy (Rosenbaum and Hamann, 2009) as well as an aggregation approach using subdivided shapes were described (Elmqvist and Fekete, 2010). Both approaches, however, focus on scarceness of rendering resource and limited screen size only. For identification and exploration of areas of interest through user navigation, the hierarchical structure can be used as basis for zooming stages (Blanch and Lecolinet, 2007; Liu et al., 2008). Our technique supports this implicitly through navigation (e.g., zoom) and explicitly through user interaction (e.g., fold/unfold) both by means of scores. However, our approach aims to reduce the need for user navigation in the first place and rely on automated DoI approximation instead. A multi-resolution technique by means of data-dependent level-of-detail with per-node aggregation was introduced (Hao et al., 2007) for pattern detection in time series. Though, pursuing the similar goal—utilize lower resolutions for less important areas and higher resolutions for important ones—the technique uses adaptive layouting and does not directly consider visibility constraints.

Aggregation Guidelines. Elmqvist and Fekete introduced guidelines for hierarchical aggregation describing the characteristics of the resulting display of aggregates from an observer's perspective (Elmqvist and Fekete, 2010):

- G1 Entity Budget** states that a maximum of displayed entities should be maintained.
- G2 Visual Summary** advises that aggregates should convey information about their underlying data.
- G3 Visual Simplicity** requires aggregates to be clean and simple in their presentation.
- G4 Discriminability** demands a distinguishable presentation of aggregates and data items.

G5 Fidelity indicates that abstractions and thus, their resulting aggregates may lie about their underlying data.

G6 Interpretability suggests aggregates to remain always correctly interpretable within the visual mapping.

These guidelines cannot be used as binary checklist, but require interpretation within the visualization and domain. Though not specifically designed for 2.5D treemaps, we apply all of the above guidelines for the design and evaluation of our LoD technique.

Generalization. The scoring and visual depictions of aggregates described herein, though focusing on rectangular-based software maps, can be generalized for treemaps that are based on inclusion. We note that there might be other scores for rectangular and non-rectangular treemaps or 3D treemaps that are not discussed herein but can be accounted for by the generalized scoring approach. The comprehensive work of Schulz et al. 2011 enlists various 2D and 3D hierarchy visualizations and can be used for easy identification of suitable visualization concepts.

3 AGGREGATION OF NODES

Rectangular software maps use cuboids to depict leaf nodes and inner nodes. The map themes configuration induces a *leaf cuboid's* appearance with respect to its visual variables—usually footprint, color, and height. The tree-structure of the depicted data induces a nesting of *inner cuboids*—nested representation with padding (Lü and Fogarty, 2008)—and communicates module affiliation and hierarchy level information. We prefer to add labels on the top faces of inner cuboids, sufficient space provided (additional padding at one lateral surface), designating the relative path of depicted software module and choose to use their luminance to encode the nesting level.

For the aggregation of an inner node, we replace the associated inner cuboid and all subjacent leaf and inner cuboids by a single *aggregate cuboid*. From the perspective of visualization, the inner node then becomes, essentially, a leaf node and could be represented as such: the aggregate cuboid's visual variables, i.e., color and height, are now used to summarize the mapped attribute values of underlying nodes appropriately. Due to the recursive weight mapping, the footprint of all underlying nodes is inherently aggregated by the aggregate cuboid (padding included).

Using aggregation, topological overviews of large datasets can be created, that help users to recognize

and remember patterns and correlations of a dataset in its entirety—the mental map (Misue et al., 1995). The aggregation, as a consequence of scoring, has to ensure that obvious, coarse features of a dataset are not disguising less prominent but significant details conveyed by *nodes with high DoI* (nodes-of-interest). Therefore we present a multi-resolution scoring that enables aggregation control on a global as well as local, per-node basis. Globally, aggregation might be omitted for nodes of certain hierarchy levels, e.g., the first two hierarchy levels to prevent unnecessary aggregation. Locally, the virtual camera’s viewport and its distance to graphical elements can be used to provide adaptive LoD. A user may also like to explore the treemap with locally adapting information density, e.g., by means of elaborated focus+context concepts such as lenses (Trapp et al., 2008).

A node n is scored by score functions s_c that map to the closed interval $[-1, +1]$, striving either for or against aggregation with $s_c > 0$ or $s_c < 0$, respectively. $c \in C$ thereby denotes one of various DoI criteria, based on attribute, view, and user interaction metrics. The total score of a node $\bar{\gamma}$ can be accumulated using a weighted mean of the set of scores:

$$\bar{\gamma} = \frac{\sum_c \omega_c s_c}{\sum_c \omega_c}, \quad (1)$$

with ω_c allowing for non-negative, domain or use-case specific emphasis on specific scores. The adaptive level-of-detail process by means of scoring and aggregation is illustrated in algorithm 1: it processes a given tree-structured dataset with respect to a map theme by accumulating attributes, scoring nodes, deriving total scores, and, finally, rendering and thereby aggregating the nodes. The functions `accumulate` and `score` denote fold operations, which recursively aggregate attribute values and scores, respectively. Various attribute aggregation operators are described in section 4. For scoring and score weights ω_c (used in `weighted_mean`) use-case specific strategies might be applied, accounting for the given task and domain. In this article, however, we focus on attribute, view, and user-interaction based scoring described in the following subsections.

3.1 Attribute-based Scoring

Attribute-based scoring analyzes and assesses data attributes mapped to the nodes’ visual variables and their characteristics. For any given map theme, attribute-based scoring provides principal scores for automated DoI approximation and appropriate initial aggregation. The usefulness of such scores strongly depend on the map theme. We, therefore, briefly describe only a few scores typically used in our software

Algorithm 1: Scoring and aggregation of nodes.

```

1 Function process(tree, map theme)
2   nodes ← nodes of tree
3   attributes ← attributes in map theme
   // attribute accumulation
4   foreach attribute in attributes do
5     accumulate(post_order(nodes),
   // attribute, aggregation operator)
   // calc scores for criteria ( $s_c$ )
6   functions ← score functions in map theme
7   foreach function in functions do
8     score(post_order(nodes), function)
   // derive each node’s score ( $\bar{\gamma}$ )
9   foreach node in nodes do
10    scores ← list of the node’s scores
11    node.score ← weighted_mean(scores)
   // render tree
12  root ← root node of tree
13  threshold ← aggr. threshold of map theme
14  draw(root, threshold)
15 Function draw(node, threshold)
16  if node is leaf then
17    render_leaf_cuboid(node)
18    return
   // aggregation
19  if node.score ≥ threshold then
20    render_aggregate_cuboid(node)
21    return
22  render_inner_cuboid(node)
23  foreach child in node’s children do
24    draw(child, threshold)

```

maps. A variance score s_{var} that calculates the variance or value range of an attribute, for example, can be used to indicate inhomogeneous distribution of attribute values among child nodes. It can be an importance measure configured to score against aggregation and thereby encourage additional exploration.

Likewise, a child count score s_{cc} either quantifying the number of immediate children or absolute number of all contained leaf nodes can be used to lessen the chance of aggregation of structural complex nodes (which not necessarily correlates to the nodes’ footprint). Alternatively, the computation of local outliers measuring a nodes isolation with respect to its surrounding neighborhood can be implemented using a *local outlier factor* (Breunig et al., 2000).

3.2 View-based Scoring

View-based scoring is common to most LoD techniques and scores the visibility of graphical elements on screen based on their screen space area. We use a screen-space area score s_{ssa} that approximates the number of pixels eventually used for the visual display of a single cuboid. For it, the axis-aligned bounding box of each cuboid is projected into screen space in order to obtain its screen-space area. If a cuboid obtains insufficient screen space for the visual display of its children or resides in sub-pixel space itself, at least for one major axis, it can be scored for aggregation. This reduces visual clutter resulting from (1) leaf nodes depicted smaller than single screen pixels and (2) Moiré and other aliasing artifacts due to under-sampling of both the axis-aligned cuboids and their spacing due to the inner nodes' nested representation with padding. Furthermore, we use a screen-space threshold to invoke aggregation much earlier in less important areas, which results in bigger cuboids and facilitates meaningful labeling of context areas.

Aside from that, we experimented with an occlusion score s_{occ} that uses occlusion queries to score irrelevant nodes for aggregation, if they themselves or their children cause lots of occlusion. However, a map theme should typically configure the height mapping to not cause extensive occlusion in the first place.

Since view-based scoring depends on the virtual camera's configuration and state, it is implicitly controlled, e.g., by user navigation. We suggest to perform scoring immediately after a user has completed a navigation operation and is presumably continuing to explore the data. Continuous scoring during ongoing navigation operations might cause distraction.

3.3 Interaction-based Scoring

Interaction-based scoring is used to score nodes within areas that are in the user's focus-of-attention based on user interaction. It is essential to software maps as it complements user navigation with direct node interaction capabilities required to support the visual information-seeking mantra: "Overview first, zoom and filter, then details-on-demand" (Shneiderman, 1996). To this end, we use a quasi-binary picking score s_{agg} to provide explicit user control over the aggregation state of inner nodes by means of toggling (e.g., mouse click or touch on a node). The score, being initialized with 0, toggles to either +1 or -1 depending on the scored node's aggregation state. Per-node interactions often occur in alternation with user navigation (such as zoom, pan, and rotate) and need to be processed immediately.

We further experimented with the following scores indentified as focus-of-attention measures:

- look-at direction of the camera (spot score s_{cam});
- cursor position (mouse-over score s_{mov});
- gaze data (gaze score s_{eye}) using eye-tracking.

We found these measures, however, to appear unstable and distractive due to frequent incomprehensible aggregation state changes, and postponed any further investigation at the time of writing.

Furthermore, we implemented a *temporal focus-density map* that enabled to capture various attention metrics per node over time (locus-of-attention score s_{loa}). The idea is to increase or decrease the nodes focus density over time, if the minimal distance between a cuboid and the users locus of attention resides below or above a certain threshold. We intended to use the score to hinder nodes of recent user interaction to aggregate and thus providing coherent, recognizable areas-of-interest and interaction. Instead, it resulted in mostly in-comprehensive and unexpected, distracting aggregation state changes: thus, we rejected this approach for actual use at the time of writing.

4 DISPLAY OF AGGREGATES

Observing the use of software maps in industry applications provided us insights on how map themes are typically designed and applied: a lines of code measure is almost always mapped to the nodes weight for spatialization in order to maintain a stable, recognizable layout and consistent footprint. To utilize preattentive processing the most relevant attribute for a given task is usually mapped to color. Finally, the height mapping is used for attributes that, when locally correlating to the color attribute, provides valuable insights. Two examples of software map themes:

Technical dept maps logic lines of code to footprint, a nesting level metric to color, and McCabe complexity (McCabe, 1976). It is used to reveal and monitor the 'technical debts' inherent to a software system's implementation.

Risk of knowledge drain maps logic lines of code to footprint, the number of active developers (per-node) to color, and a composite, nesting-level or McCabe based complexity measure indicating difficult-to-comprehend code to height. It is used to identify complex code units known only by few developers and reveal knowledge distribution.

In addition, non-linear attribute mapping modifiers are sometimes used such as logarithmic scaling in order to emphasize or account for certain aspects of

the depicted data. For simplicity, we assume any mapping modifier to be the identity function. Even though, software maps can be used to depict qualitative data, we focus on sequential and diverging data. With respect to our working prototype three presumptions were confirmed. First, maintaining the same color mapping for aggregates can hide important data. Second, aggregate cuboids are indiscernible from leaf cuboids. And third, abrupt aggregation state changes might attracted the users focus of attention. In the following subsections we discuss steps to at least partially resolve these issues.

4.1 Extended Aggregation Operators

In order to diminish the loss of information caused by aggregation (e.g., loss of underlying data distribution and structure) we introduce additional accumulation strategies for the attribute mapping applied to aggregates. For example, instead of averaging all underlying attribute values and use this average for the aggregates color mapping, we might use the minimum or maximum attribute value. To this end, we formalize the aggregation in attribute space and introduce *extended aggregation operators* that allow to account for specific data characteristics, e.g., outliers, variance, weighted average, minimum, maximum, etc. For a given inner node i we can apply a fold (higher-order function) $\Xi(i, v, o)$. This fold traverses the recursive structure of i and builds up a single, aggregated attribute value using an aggregation operation o on the map theme's attribute v .

A fold using an arithmetic mean operator for aggregation can now be denoted as $\Xi(i, v, \bar{n})$ with \bar{n} as operator that calculates the mean within a set of attribute values. This mean attribute-aggregation operator, however, might be insufficient for a given task: interesting attributes might cancel out each other or remain unnoticed because of their marginal share (e.g., due to a high number of children). Instead, attribute aggregation operators might favor attributes that deviate from the mean. For this purpose, we use $\Xi(i, v, \bar{n}_A)$ and $\Xi(i, v, \sigma^e)$. The operator \bar{n}_A derives the weighted mean, i.e., each attribute value is weighted by the attribute mapped to the node's footprint. This accounts for the node's spatial layout favoring large node footprints over small ones. For large treemaps, however, we observed that, e.g., outliers of height or color attribute primarily reside in nodes of medium to small footprints. σ^e is a deviation attribute-aggregation operators that weights each attribute by its deviation to the mean: $|a - \bar{n}_i|^e$ with a as attribute value and e as exponential deviation amplifier. Figure 3 illustrates the effect of these operators on the aggregates color.

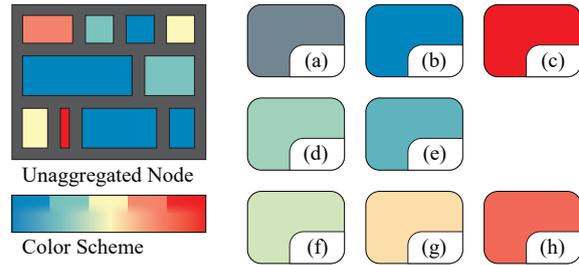


Figure 3: For an unaggregated inner node and a color scheme (left) and color mappings as the result of different attribute-aggregation strategies (right): (a) visual average (as reference), (b) minimum, (c) maximum, aggregate operators (d) \bar{n} , (e) \bar{n}_A , (f) σ^1 , (g) σ^2 , and (h) σ^8 .

4.2 Nesting Level Contouring

The visual display of aggregates is, without further specialization, indiscernible to the display of leaves. This can be resolved, by either truncating the aggregate cuboids or adding a contour (by means of a luminance offset) causing resemblance to padding. Truncation, however, is not applicable in 2D, increases the visual complexity of the cuboids, and is sometimes difficult to recognize, which makes contouring our preferable choice. The contouring alone is already sufficient to satisfy discriminability of aggregates to non-aggregates.

The contouring can be used to convey additional information about the underlying structure. More specifically, multiple contours can hint the degree of aggregation, i.e., the number of an aggregate's subadjacent hierarchy levels (nesting level). We denote this approach as *nesting level contouring* and use consecutive luminance offsets for the nested contours (Figure 4). To avoid cluttering due to too many nested contours for aggregates with high nesting levels, we apply line-stippling to the inner-most contour if the aggregate's nesting level exceeds the level of the inner-most contour. During exploration of datasets of various sizes, we empirically determined that up to three nested contours are quite useful.

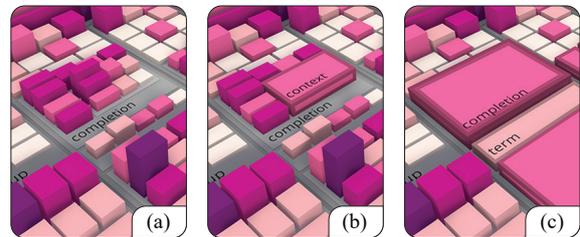


Figure 4: f.l.t.r.: stepwise aggregation of nodes in (a). For the aggregates in (b) and (c) nesting level contouring indicates the number of underlying hierarchy levels.

4.3 Animated State Transitions

Due to the preattentive nature of motion, aggregation state changes both instantaneous or by temporary transition have to be applied with care. To support the user during the exploration, we apply brief, animated transitions to aggregation state changes. It allows to smoothly transform a node state from not aggregated to aggregated and vice versa. For it, a node-local transition timing linked to the cause of aggregation was implemented. This dynamic timing enables transitions ranging from explicit, noticeable/fast to less distracting, unobtrusive/slow and can be setup by the map theme. Transitions directly caused by user interaction can be fast or even instant to not hinder the user in his task; Transitions caused due to data changes, or view-based scoring, on the other hand, can be slower and more unobtrusive. For the animation itself we used the following animation. When a node transitions into an aggregate, the aggregate fades out and reveals the inner cuboid as well as all its child nodes with their height limited to the aggregate's height. After the aggregate resolved, child nodes previously limited in height grow to their actual height. We found this to be helpful when changing the aggregation threshold or enabling view-based scoring.

5 EVALUATION

The presented LoD technique was evaluated in three steps. We (1) measured the reduction of visual clutter induced by aggregation, (2) performed a user study, to investigate the impact of aggregation to visual search, and (3) performed a user study to investigate the readability of nesting level contouring.

5.1 Evaluation of Visual Clutter

To confirm the actual reduction of visual clutter, we used the feature congestion method for visual clutter (Rosenholtz et al., 2005). Since it is a measure of difficulty in searching through a complex display it can be used as usability indicator of importance-based aggregation. The feature congestion was computed for each of the image pairs used in the following user study. In average our LoD technique caused a reduction of about 50% over these image pairs (Figure 5).

5.2 Evaluation of Visual Search

User Study Design. A qualitative and quantitative user study was performed with 18 participants (age: 18-35, 15 males, 3 females). The participants were

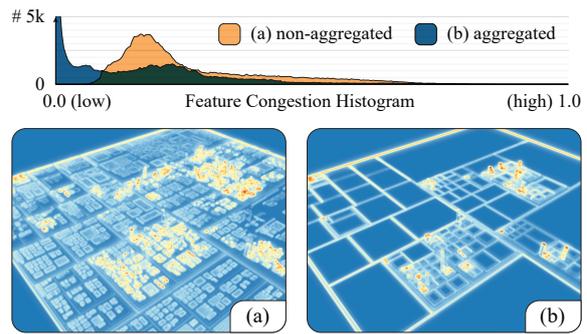


Figure 5: As a measure for visual clutter, color-mapped feature congestions for a software map is shown. The histograms indicates reduced visual clutter for (b).

asked to find 10 nodes of interest in different software maps with respect to height and color mapping. For it, we created a set of six pairs of images, containing an non-aggregated view and a view using automated attribute-based scoring, using different camera perspectives, and datasets. After an introduction to software maps (especially the color and height mapping), the participant could complete the visual search by selecting the nodes of interest in the static images. We ensured that a set of images shown to a participant did not contain a pair with the same view and dataset. The top nodes of interest (forming the ground truth for the error rates) for each dataset were selected by values of a normalized average function of values mapped to height and color and a threshold of 95%.

For the quantitative analysis we measured the *task-completion time* and *error rate* for each participant and each task. After completing the tasks, each participant was asked to answer questions about the user itself and to rate (from (1) strongly disagree to (5) strongly agree) the following eight statements with respect to the study and tasks:

$S_{\#}$	Statements with T denoting our LoD technique
S_1	I noticed the use of T .
S_2	The task was hard to complete without T .
S_3	The task was hard to complete using T .
S_4	I had problems identifying NoI* without T .
S_5	I had problems identifying NoI* using T .
S_6	I could easily identify aggregated nodes.
S_7	T was useful in the decision making process.
S_8	I think the use of T hides important information.

* node of interest

The error rate and task-completion time serves as an indicator for the usability of the presented technique. Therefore, we state the following hypotheses for the user study:

H_1 The use of our LoD technique (attribute-based scoring) reduces the error rate.

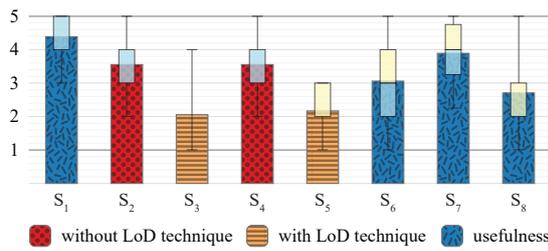


Figure 6: Results of the user study statements S_1 to S_8 rated by the participants. The value domain is: (1) strongly disagree, (2) disagree, (3) neutral, (4) agree, (5) strongly agree.

H_2 The use of our LoD technique (attribute-based scoring) reduces the task-completion time.

User Study Results. Most users (11 of 18) stated that they were familiar with the concept of 2D and 2.5D treemaps while only a few of them (3 of 18) stated that they were frequently working with treemaps. The results of the statement ratings (Figure 6) show that almost every participant recognized the use of the LoD (S_1 , $\mu = 4.39$) and rated the technique as useful for the given task (S_7 , $\mu = 3.89$). The statement ratings of S_2 ($\mu = 3.56$) and S_3 ($\mu = 2.06$), as well as S_4 ($\mu = 3.56$) and S_5 ($\mu = 2.17$), comparing the difficulty estimation for the given tasks with respect to the LoD technique, show that the technique improves the usability of software maps for the given task significantly (S_2 vs. S_3 $p = 3e-4$; S_4 vs. S_5 $p = 2e-4$). Besides that, the visual separation of aggregated and non-aggregated nodes needs some improvements (S_6 , $\mu = 3.06$). Additionally, the study shows that both, error rates and task completion time, are reduced significantly by using our technique. The lower error rate (without LoD: $\mu = 2.52$; with LoD: $\mu = 0.85$; $p < 0.01$) for the non-aggregated software map underline the participants opinion with respect to the statements S_2 to S_5 . Finally, the average task completion time was reduced in our experiment from about 38.5 seconds (without LoD) to 31.1 seconds (with LoD), but failed closely to show a significant effect ($p = 0.057$) within an independent t-test.

5.3 Evaluation of Contouring

A second user study was performed to determine if users are able to correctly identify (readability) aggregated datasets using nesting level contours. For it, an aggregated version of a treemap was shown together with a set of 4 valid or invalid depictions (multiple correct answers possible). The study was performed as an online survey with 12 participants.

User Study Design. Every participant had to answer 15 questions with four different depictions shown. This results in a number of 720 answers (= 15 questions \times 12 participants \times 4 possible answers).

User Study Results. The majority of answers were correct with 504 correct answers (208 true positives, 296 true negatives). The *precision* of the participants classification was about 62 % with a *recall* of 70% and a small effect size ($\phi = -0,165$). A chi-square test with Yates' continuity correction showed a significant difference between the number of correct and incorrect answers and the participants recognition of the correct aggregates ($p < 0.001$).

6 DISCUSSION

The aggregation of nodes was specifically designed to satisfy the aggregation guidelines suggested by Elmqvist et al. (Elmqvist and Fekete, 2010).

G1 Entity Budget. A simple entity budget is introduced with the viewport size; the view-based scoring and the used minimal screen-space area threshold implicitly limit the number of cuboids. In addition, the number of depicted nodes can be restricted for certain hierarchy levels. Technically, our scoring could just accumulate the number of children of the inner node that is scored (provided a persistent node traversal) and score for aggregation when the budget exceeded.

G2 Visual Summary. Aggregates use the same or at least a similar attribute mapping, depending on the used aggregation operators, thus, they always represent the underlying data. The presented nesting level contouring further allows for assumptions about the node's nesting depth. However, the aggregate does not capture the underlying data structure in terms of data localization, quantity of nodes, or value or distribution patterns of the mapped attributes.

G3 Visual Simplicity. We decided not to introduce an additional shape nor to modify the cuboid's geometry, but instead rely on the basic cuboid for an aggregation inherent to the 2.5D treemap.

G4 Discriminability. The contouring of aggregates as well as the option to label their top faces (which more likely provide the required additional space for a meaningful annotation) makes our aggregate cuboids easily discernible from inner and leaf cuboids.

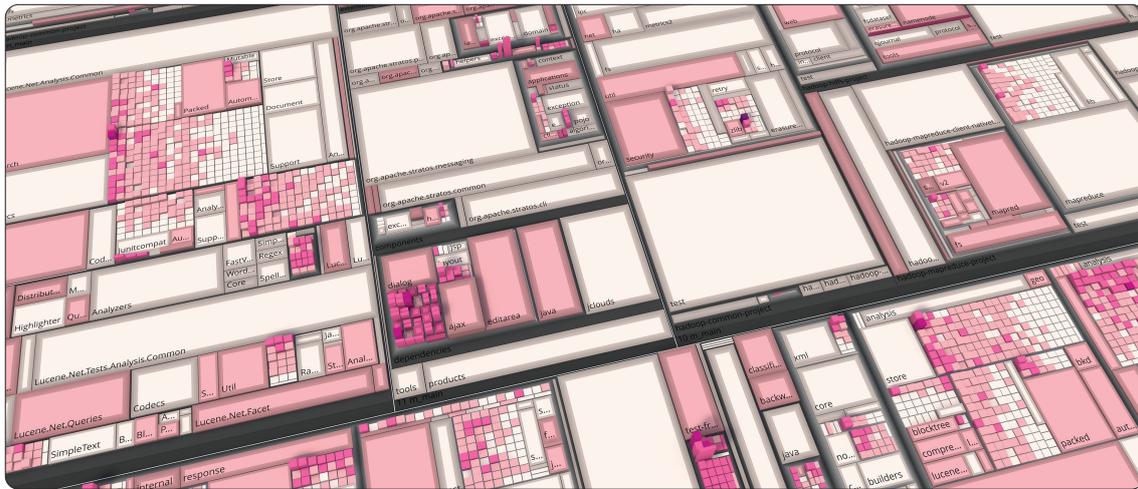


Figure 7: Software map of 50.363 nodes with importance based filtering and outlier-aware aggregation operator.

G5 Fidelity. With the presented aggregation operators the aggregates visual display and thus its conveyed information can be configured accordingly to the given task and importance measure.

G6 Interpretability. For the depiction of aggregated nodes the same visualization approach used for the depiction of inner nodes and leaf nodes is used. Except for the nesting level margin, which is orthogonal to the color mapping, the user is not confronted with any inconsistencies and, as our evaluations indicate, has no problems in interpreting the software map using our LoD technique. However, even though a user easily understands a thematic mapping, the selection of aggregation operators used for aggregates might impact the users performance and is currently not directly communicated.

7 CONCLUSIONS

We have presented a technique for importance-based aggregation of nodes for the visual display of multi-dimensional, hierarchical data using 2.5D treemaps. The technique was shown to be capable of “reducing a large dataset into one of moderate size, while maintaining dominant characteristics of the original dataset” (Cui et al., 2006) while satisfying common guidelines for aggregation (Figure 7). It (1) requires no layout re-computation, (2) allows for (mostly) unambiguous and self-consistent aggregates, (3) implements well-known interaction concepts, and (4) allows for additional annotation. Finally, the technique enables multi-resolution depictions of complex information, facilitates efficient identification of important

nodes, and thereby supports the *Visual Information Seeking Mantra* (Shneiderman, 1996).

Future Work. Experimenting with various, large datasets, we identified areas for further improvement. First, sometimes, a software system consists of very few inner nodes with massive number of children, either resulting in visual clutter or useless aggregates. For such cases, we plan to investigate in partial aggregation strategies, e.g., using procedural texturing for aggregate masking. Second, the aggregates as visual summary can be further improved by supporting the aggregation of qualitative data as well as conveying the underlying data distribution using, e.g., color weaving (Hagh-Shenas et al., 2006) or small diagrams rendered to the aggregate cuboids top faces. Last, we want to explore how aggregation can be used in communication and locus of attention guiding.

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