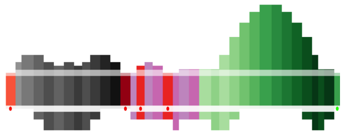

Alpscarf: Augmenting Scarf Plots for Exploring Temporal Gaze Patterns

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Abstract
Scarf plots visualize gaze transitions among areas of interest (AOIs) on timelines. Nevertheless, scarf plots are ineffective when there are many AOIs. To help analysts explore long temporal patterns, we present Alpscarf, an extension of scarf plots with mountains and valleys to visualize order-conformity and revisits. Alpscarfs are rendered in two complementary modes in aid of insight discovery. An R package of Alpscarf is available at github.com/chia-kaiyang/alpscarf.

Author Keywords
Visualization; eye movement; scarf plot; transitions

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

Introduction
Eye movement recording is advocated as "*the best way to study cognitive processes during silent reading*" [16], yet most eye tracking studies of scientific reading used either short text (~1000 words) [9, 10, 11, 14], or text accompanied by 1–2 charts [7, 13, 18]. In reality, scientific articles are longer with many references across sections. Thus, to understand the article, readers need to jump between paragraphs and sections and integrate the information thereof.

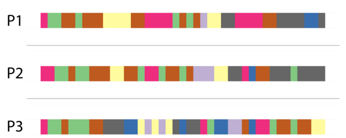

Figure 1. Scarf plots show similar pattern between P1 and P2 but not P3.

Figure 2. A sequence chart for P3.

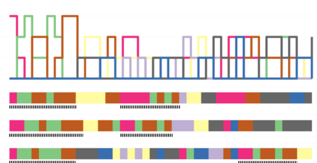

Figure 3. Scarf plot with momentous proportion over time. The visit pattern (pink-green-brown-green-brown, underlined) at the beginning is aligned and identifiable in the momentous plot. But unaligned occurrences afterwards are not identifiable.

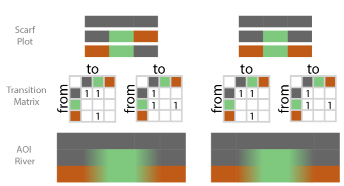

Figure 4. Two different scarfs result in identical transition matrices and AOI Rivers.

Using eye tracking to study reading strategies in scientific articles requires defining a hierarchy of *areas of interest* (AOIs); e.g., many paragraph AOIs in section AOIs in page AOIs. Because of the length of scientific articles, a number of AOIs (>10) may be investigated simultaneously. Nevertheless, common visualization techniques, such as scarf plots and transition matrices, are ineffective in helping analysts to discover patterns of AOI visits, especially for sequences longer than two transitions.

To facilitate exploratory analysis of temporal patterns with a large number of hierarchical AOIs, we introduce Alpscarf, an extension to scarf plots that visualize the conformity to a visit order (e.g., top-to-bottom reading) and the re-reading behavior as mountains and valleys (over and under scarfs). We also discuss a heuristic to select color palette for a large number of AOIs.

Related Work

Timeline-based visualization

Figure 1 – 4 shows four visualizations for eye movement data. A *scarf plot* [17] (Figure 1) represents each dwell as a rectangle, with the width proportional to the duration and color-coded by AOI. This encoding allows the AOIs that are fixated on longer to be more visually prominent [4]. Multiple scarfs can be juxtaposed to allow spotting similar patterns.

Using scarf plots to determine patterns of AOI visits is effective only when less than 10 AOIs are shown [2], because it is difficult to differentiate more than 12 colors [19]. Showing one AOI per row as *sequence charts* [8] (Figure 2) aids in distinguishing AOIs. However, patterns across participants would be difficult to identify because the charts are visually scattered.

Whereas the scarf plot is effective for visualizing AOI behavior individually, it is less apt for identifying the AOI pattern that is scattered in participants. Adding a line chart to show *momentous proportions* of AOI visits across participants (Figure 3) can help identifying *aligned* visit patterns, but not the *unaligned* visit patterns that occur at faraway timestamps [8].

AOI Rivers [6] (Figure 4) show proportion of AOI visits (aggregated across participants) as thickness of rivers, colored by AOI. The lane-changing in AOI Rivers shows the transition from one AOI to another. However, transition sequences longer than two AOIs can be visually ambiguous in AOI Rivers.

Transition-based visualization

All transitions of an AOI sequence of length n can be represented in an n-dimensional matrix. When $n > 2$, however, the resulting matrix would become sparse and its usefulness is disputed [8, 15]. Consequently, most research uses transition matrices to investigate the transitions only in pairs of AOIs. Blascheck et al. [5] proposed a few visualizations that are coupled with the hierarchy information (Figure 5). Nevertheless, it is still difficult to identify temporal patterns (e.g., circulation, repetitiveness) in the sequences longer than two AOI transitions.

To address the limitations above, we extend scarf plots with a visualization that assists in identifying
(1) patterns of longer than two AOI transitions,
(2) patterns across participants that occur at distant timestamps. Both properties should be achieved in a
(3) visually compact manner. We also propose a novel algorithm that is used to generate the extended visual components of Alpscarf.

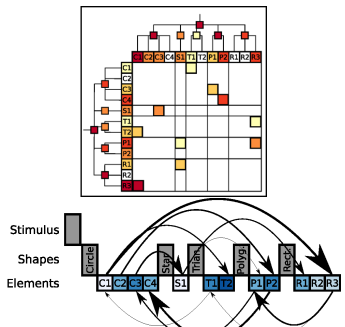

Figure 5. AOI Matrix (top) and AOI Tree (bottom) are effective for showing transitions between pairs of AOIs. Sequences of more than two transitions are still visually ambiguous. (courtesy of authors of [5])

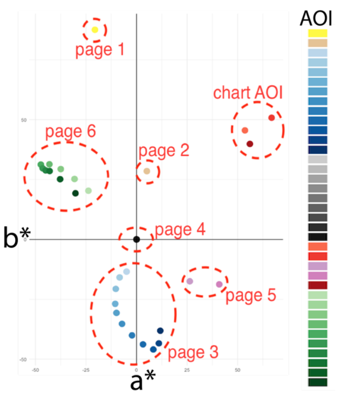

Figure 6. Adjacent groups of AOIs are represented with regions far from each other on the CIE a*b* plane (left). AOIs within each group (e.g., page) use colors in an order of luminance (right) and uniformly stepped in the CIE a*b* plane.

Visual Encoding

Alpscarf extends scarf plots by (1) color palette heuristics, (2) three additional visual components (mountains, valleys, creeks), and (3) two modes of scarf width (transition-focus, duration-focus).

Color palette

To assist in comprehending the order and the hierarchy of AOIs, we select colors with the following heuristics (based on the guidelines by Bianco et al. [3]):

1. Assign each AOI group (e.g., a page of the text) to a color hue, and minimize perceptual similarity of adjacent groups (e.g., page 1 vs. 2). This can be done by selecting regions that are far from each other on the CIE a*b* plane. An example of such assignment is shown in Figure 6. The group that is of special interest (e.g., chart AOI) can be assigned to a salient color such as red.
2. Assign each AOI within group to the colors ordered by luminance. The distance of the colors should step uniformly in the small region of the CIE a*b* plane.

These heuristics facilitate spotting transitions *across* AOI groups (e.g., finishing reading one section and starting another) by an abrupt change of both hue and luminance. However, transitions *within* an AOI group would still be difficult to discern due to color similarity.

Three visual components & two modes of scarf width

To assist in spotting transition patterns within each AOI group, three visual components are added around each scarf: (1) mountains, (2) valleys, and (3) creeks as shown in Figure 7. The *mountain height* indicates AOI visits conforming to an expected order (specifiable by the analyst). For example, reading paragraphs sequentially from top to bottom would result in a high mountain over the corresponding range on the scarf plot. The *valley depth* indicates occurences of revisiting. For example, frequent revisits in reading would show as wide valleys. Both mountains and valleys use the position channel to encode transition patterns (mentioned above), making them easy to spot when multiple Alpscarfs are juxtaposed. The algorithms for the heights and the depths are in the next section.

To allow short mountains and shallow valleys to be visually distinguishable, they are separated from the scarf by gaps, called *creeks*. The creeks can be used to add dot annotations for external events; e.g., highlighting text while reading.

Suppose we have a slow reader and a fast reader; they both read from top to bottom. Although both of their resulting Alpscarfs would show a mountain in the same height, the former one would be wider because of a longer duration. A perceptual bias may cause wider rectangles to be perceived as shorter, and narrower as taller [1]. Encoding the dwell time as the width of each rectangle, which is originally used in scarf plots, would be misleading. Therefore, Alpscarfs are shown in two modes: *Duration-focus* (bar width is proportional to the duration, log-transformed to ensure readability in case of outliers with very long durations) and *Transition-focus* (all bars are of equal width). For the slow- vs. fast-reader example, the transition-focus mode would result in the mountain of the same width and height. Finally, the view can be *normalized* across datasets, resulting in all Alpscarfs with the same width regardless of the number of transitions or total dwell time. Toggling normalization can aid in pattern discovery for tasks that have well-defined start and end event [6].

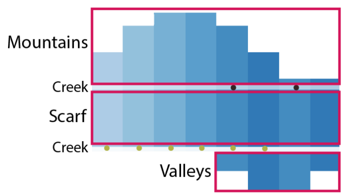

Figure 7. Mountains represent transitions conforming to an expected order (e.g., reading from top to bottom). Valleys represent revisits (e.g., re-reading previously read paragraphs). Creeks (with visual annotations) separate mountains and valleys from the scarf, to allow spotting short mountains and shallow valleys.

Mountain Heights

Algorithm 1 calculates a *conformity score,* which reflects how each region on the timeline conforms to an *expected order* of AOI visits. The expected order is a sequence of unique AOIs (e.g., the order of the appearance of sections in an article). The height of the mountains are proportional to the conformity score.

Consecutive bars form a mountain. Mountains are symmetrical, and the peak of the mountain indicates the middle of such sequence-conformity behavior. A long stretch of conforming region would result in a tall and wide mountain, which is visually prominent.

Valley Depths

The depth of the valleys are proportional to the *revisiting score* (Algorithm 2). Revisit window size can be adjusted; e.g., $w = 3$ for the direct revisits (1 → 2 → 1), $w = 4$ for the two-step revisits (1 → 2 → 3 → 1).

Algorithm 1 Conformity score calculation

Let $A = \langle 1, 2, ..., k \rangle$ a sequence of non-overlapping AOIs, each is coded as an unique integer
Input $O = \langle o_1, o_2, ..., o_k \rangle$, $1 \leq o_i \leq k$, each integer o_i is the expected visit order of AOI i
$D = \langle d_1, d_2, ..., d_m \rangle$ a sequence of gaze dwells, $\forall d_i \in A$
$s_{\min} = 2$ the shortest length of sequence to consider
Output $C = \langle c_1, c_2, ..., c_m \rangle$ conformity score, each element c_i is initialized to 0

function CONFORM($D, O, s_{\min}$)
  for all $i \in \{1, 2, ..., \|D\| - s_{\min} + 1\}$ **do** ▷ Go through the sequence of dwells
    for all $s \in \{s_{\min}, s_{\min} + 1, ..., \text{MIN}(\|O\|, \|D\| - i + 1)\}$ **do** ▷ Check each window size
      if $O_{d_{i+s-1}} - O_{d_{i+s-2}} = 1$ **then** ▷ Check if the order is still being followed
        for all $j \in \{i, i+1, ..., i+s-1\}$ **do** ▷ Increment the score within the window
          $c_j \leftarrow c_j + 1$
        end for
      else
        break ▷ Stop when the order is not followed
      end if
    end for
  end for
  return C
end function

Algorithm 2 Revisiting score calculation

Input w : sequence length of the revisit type to consider, $w \in \mathbb{N}, w \geq 3$
$D = \langle d_1, d_2, ..., d_m \rangle$ a sequence of gaze dwells
Output $R = \langle r_1, r_2, ..., r_m \rangle$ revisiting score, initialized to 0

function REVISIT(w, D)
  for all $i \in \{1, 2, ..., \|D\| - w + 1\}$ **do**
    if $d_i = d_{i+w-1}$ **then**
      for all $j \in \{i, i+1, ..., i+w-1\}$ **do**
        $r_j \leftarrow r_j + 1$
      end for
    end if
  end for
  return R
end function

Visual Analysis Tasks Supported by Alpscarf

Alpscarf simultaneously represents two temporal behaviors (whether AOI visits conform to an expected order, and whether AOIs were revisited) as mountains and valleys. This representation allows analysts to explore temporal characteristics (e.g., when did the behavior emerge? which AOIs were involved?) and their relationships (e.g., did they emerge together or exclusively?). The normalized view further assists analysts in comparing multiple Alpscarfs and spotting overall patterns in a set of Alpscarfs. Analysts can detect the commonality or deviations from temporal patterns by comparing size, location, and colors of mountains and valleys. Table 1 summarizes the analysis tasks effectively supported by Alpscarf (based on the taxonomy proposed by Kurzhals et al. [12]).

Below, we give examples of visual tasks in analyzing data from an experiment in reading a 6-page scientific article (n = 18, average duration: 32.5 mins, SD: 3.3).

Alpscarf vs. Scarf plot: beyond color palette heuristics

Figure 8 visualizes the reading data from three participants in scarf plots (using the color scheme in

	Example of questions
Where	• Which AOIs were revisited? • Which AOI order did a participant engage?
When	• When did sequential reading occur? • Did participants engage in certain viewing order repeatedly? • When did a specific viewing behavior (e.g., AOI revisiting) emerge? • When did the viewing behavior change?
Who	• Who showed a certain viewing order? • Who had a different or similar viewing behavior?

Table 1. Visual analysis tasks supported by Alpscarf.

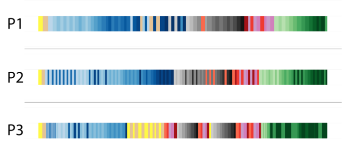

Figure 8. P1 and P2 are visibly similar, but not P3.

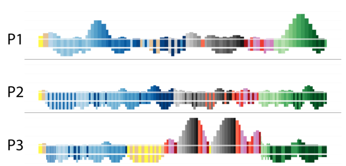

Figure 9. Duration-focus Alpscarfs show how P1 differs from P2.

Figure 6). At a glance, long stretches of blue and green regions are visible across all three. P1 and P2 seem to be similar in their yellow → blue → black/red → green pattern, while P3 exhibits a different pattern. Looking closer at the green region[1] of P1 and P2, scarf plots show that P2 frequently deviated from the top-to-bottom text order. However, identifying the precise locations of deviation and conformity is visually difficult.

In contrast, with Alpscarfs[2] shown in Figure 9, the tall green mountain in P1 indicates the participant mostly followed the text order, with a short re-reading at the beginning and at the end. P2, however, exhibits more valleys, indicating more jumps between two paragraphs in the section, possibly to integrate the information among them. These differences are easier to discern with Alpscarfs than with scarf plots.

In the middle of the reading, around black/red spans, both P1 and P2 frequently re-read (many valleys), but P3 mostly read sequentially (two tall mountains and some small ones). Besides, such sequential reading behavior continues from the black to the red page. This pattern would be difficult to identify in scarf plots.

Transition-focus complements Duration-focus
Scarf plots visualize data in duration-focus mode (bar width is proportional to the dwell duration). When this mode is adopted in Alpscarfs (Figure 10), the green region in P2 and P3 looks unalike. However, as the transition-focus mode (every AOI dwells has the same bar width) shown in Figure 11, the similarity of the green mountains in P2 and P3 indicates that they read this page in the same order at different speed.

While the transition-focus mode helps in pattern discovery, analysts should still switch back-and-forth between two modes to interpret the identified patterns. In Figure 11, the alternating blue/turquoise stripes at the beginning of P2 and P3 data look similar in valleys. There are two possible explanations: either they re-read two paragraphs to make deep inferences, or they were shallowly skimming the two. Switching back to the duration-focus mode (Figure 10) reveals the differences. Analysts could further investigate the cause of this difference; e.g., whether P3 faced a difficulty in understanding these paragraphs.

Conclusion & Future Work

We proposed Alpscarf, an extension of scarf plots in aid of identifying temporal patterns in long AOI sequences across participants. Mountains and valleys simultaneously show two patterns of interest (expected visit order and revisiting) for analysts to inspect their relationships. The duration-focus and the transition-focus mode complement each other, allow analysts to generate and test hypotheses about transition patterns.

As future work, we plan to extend choices of mountain-heights and valley-depths functions that are suitable to other eye-tracking domains. We also plan to evaluate Alpscarf empirically.

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[1] corresponds to the "Discussion" section.

[2] in duration-focus mode; height represents the conformity of the text order from top to bottom; normalized view.

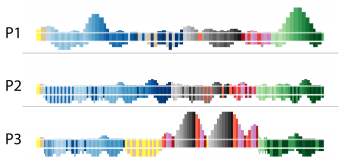

Figure 10. Duration-focus Alpscarfs show how P2 differs from P3 in the green region.

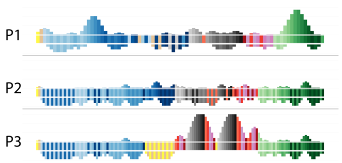

Figure 11. Transition-focus mode. Similar transitions (the alternation in blue region) in this mode may look different in duration-focus mode.

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