SensePath: Understanding the Sensemaking Process through Analytic Provenance

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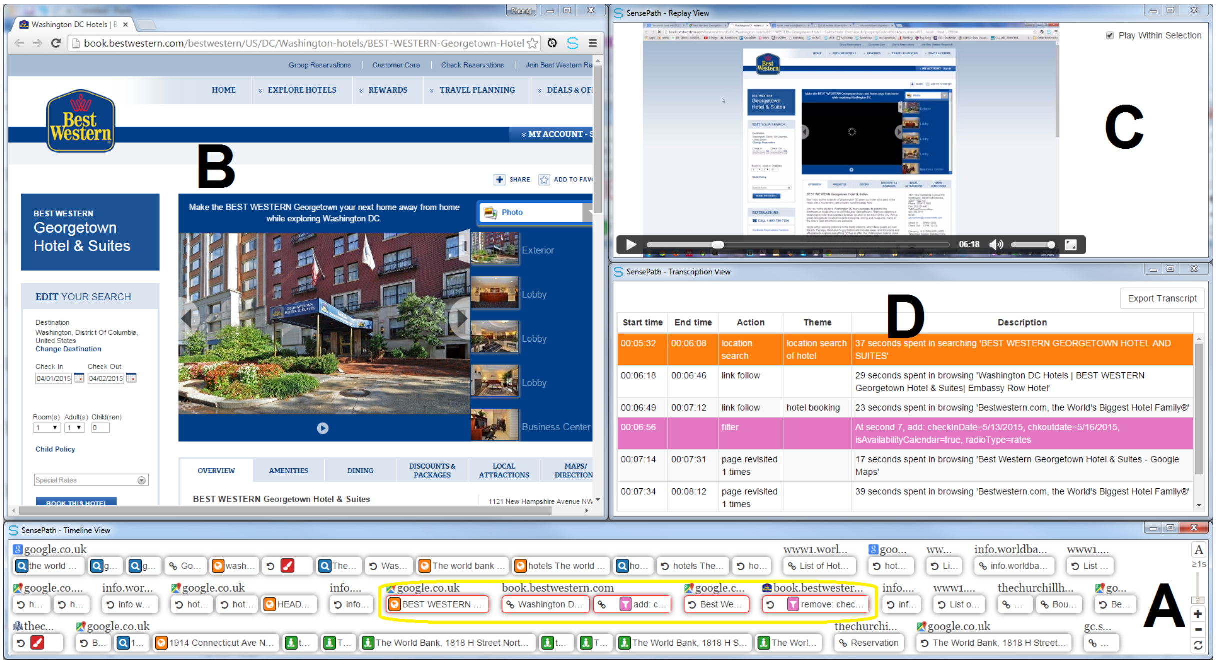

Fig. 1: Four linked views of SensePath. **A:** The *timeline* view shows all captured sensemaking *actions* in temporal order. **B:** The *browser* view displays the web page where an action was performed. **C:** The *replay* view shows the screen capture video and can automatically jump to the starting time of an action when it is selected in another view. **D:** The *transcription* view displays detailed information of selected actions (the highlighted ones in the timeline view).

Abstract— Sensemaking is described as the process of comprehension, finding meaning and gaining insight from information, producing new knowledge and informing further action. Understanding the sensemaking process allows building effective visual analytics tools to make sense of large and complex datasets. Currently, it is often a manual and time-consuming undertaking to comprehend this: researchers collect observation data, transcribe screen capture videos and think-aloud recordings, identify recurring patterns, and eventually abstract the sensemaking process into a general model. In this paper, we propose a general approach to facilitate such a qualitative analysis process, and introduce a prototype, *SensePath*, to demonstrate the application of this approach with a focus on *browser-based online sensemaking*. The approach is based on a study of a number of qualitative research sessions including observations of users performing sensemaking tasks and post hoc analyses to uncover their sensemaking processes. Based on the study results and a follow-up participatory design session with HCI researchers, we decided to focus on the *transcription* and *coding* stages of thematic analysis. SensePath automatically captures user's sensemaking actions, i.e., *analytic provenance*, and provides multi-linked views to support their further analysis. A number of other requirements elicited from the design session are also implemented in SensePath, such as easy integration with existing qualitative analysis workflow and non-intrusive for participants. The tool was used by an experienced HCI researcher to analyze two sensemaking sessions. The researcher found the tool intuitive and considerably reduced analysis time, allowing better understanding of the sensemaking process.

Index Terms—Sensemaking, analytic provenance, transcription, coding, qualitative research, timeline visualization.

1 Introduction

Sensemaking is described as the process of comprehension, finding meaning and gaining insight from information, producing new knowledge and informing action [32]. Given the rapid increase in data volume and complexity, more tools are needed to support sensemaking, which in many cases remains a slow and laborious process performed by human analysts. The design of such tools requires a deep understanding of the sensemaking process, which is a reoccurring goal of

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qualitative research conducted by many HCI researchers. Common methods for such qualitative analyses are grounded theory [9] and thematic analysis [19]. Typically, researchers need to design a study, collect observation data, transcribe the screen capture videos and think-aloud recordings, identify interesting patterns, group them into categories, and build a model or theory to explain those findings. Unfortunately, this process largely remains manual and thus very time consuming.

Meanwhile, there is a growing interest in the visual analytics community to capture and model the sensemaking process of using visual analytics systems to analyze data [42]. The information that describes such interactive data exploration and the human reasoning process that accompanies it is termed *analytic provenance* [28]. Gotz and Zhou [17] divide analytic provenance into four layers according to its semantic richness (in descending order):

Task: (highest) high-level analytic goals such as "analyze stock market to generate investment recommendations",

Sub-task: more concrete analytic goals in approaching the task such as "identify the performance trend of companies",

Action: analytic steps to implement a sub-task such as "sort companies by their changes in stock price", and

Events: (lowest) user interaction events to perform an action such as a "mouse click".

There is a connection between analytic provenance and sensemaking qualitative research: *events* and *actions* are at a semantic level similar to that of the observation data; *sub-tasks* and *tasks* describe the high level sensemaking information that qualitative analysis aims to uncover. Capturing lower level events and actions is relatively straightforward in a visual analytics system. However, higher level analytic provenance is usually part of users' thinking, which a visual analytics system does not have direct access to. Existing approaches can be broadly categorized into *manual* and *automatic* capture methods. The manual methods [27, 38] largely rely on users to record their analysis process through note taking, whereas the automatic methods so far can identify a group of actions that are likely to be part of the same sub-task without knowing what the sub-task actually is [17]. There is limited success of automated inference of sub-tasks and tasks from lower level events and actions [42].

In this paper, we propose a general approach to help HCI researchers recover user's thinking using analytic provenance information. To illustrate the approach, we developed *SensePath* to support thematic analysis of online sensemaking tasks (browser-based). We chose this domain because many of the everyday sensemaking tasks such as travel planning, are now performed online [34]. The design of SensePath is based on the observation of a number of sensemaking sessions and the post hoc analyses that researchers performed to recover the sensemaking process. This is followed by a participatory design session with HCI researchers that led to a number of design requirements such as supporting reasonably long sensemaking tasks (up to two hours), integration with existing qualitative analysis workflow, and non-intrusiveness for participants.

As a result, SensePath was designed to target the *transcription* and *coding* phases during which a researcher needs to transcribe the observation data, such as screen capture video and think-aloud recording (transcription), and then identify the common themes of the sensemaking actions within them and assign appropriate names (coding). SensePath consists of two components designed for different stages of thematic analysis: one runs in the background during the observation to automatically capture analytic provenance, which includes sensemaking actions; the other component is designed for post hoc analysis phase and it visualizes the recorded information in four linked views to help transcription, coding, and identify frequent patterns and high level sense-making process. While some features are tailored for sensemaking, the general approach of understanding user's thinking can be applied to a wider qualitative research. Also, SensePath can be extended to support the analysis of other online activities, not limited to sensemaking tasks.

The tool was used by an experienced HCI researcher to analyze two sensemaking sessions. The researcher found the tool intuitive and considerably reduces the analysis time, enabling the discovery of underlying sensemaking processes.

In summary, our main contributions are:

1. A general approach combining the strength of analytic provenance and visual analytics to understand user's sensemaking process. This approach can be potentially applied to other qualitative research in HCI beyond sensemaking.

2. A qualitative study and a participatory design session to understand characteristics of qualitative research on sensemaking.

3. A visual analytics tool SensePath to demonstrate the general approach. It supports the transcription and coding of the observation data of online sensemaking tasks.

4. A qualitative user evaluation that demonstrated the effectiveness of the general approach and the tool SensePath.

2 Related Work

2.1 Sensemaking and Qualitative Analysis

The notion of sensemaking relates to the way in which human process and interpret information about the world, leading to the creation of new knowledge or insight, which informs further action [32]. There are a number of different sensemaking theories, which draw attention from scholars in human-computer interaction, psychology and other areas that consider sensemaking in different contexts. Examples include Dervin [11], who considers how sensemaking is related to information seeking behaviors and needs, and Weick [40], who was concerned with how sensemaking takes place in organizational settings, from individual and social contexts. Pirolli and Card [32] offer a notional model of sensemaking, describing a cyclic process involving representations of information in *schemata* and the manipulation of *schemas* to gain insight forming some knowledge or understanding. Klein et al. [23] offer the *Data/Frame* theory describing the interaction of *data*, which are aspects of the world and *frames*, that are the sensemakers representations of the situation.

Qualitative research methodologies [1] are commonly used in study of sensemaking. They allow researchers to reveal often complex user experiences and understand issues that are experienced subjectively or collectively [1, 29]. Moreover, sensemaking research is often concerned not with testing an existing theory, but building a new one through the collection and analysis of relevant data, generating new knowledge about users and the usage of technology [33].

There are a number of inductive approaches to qualitative research popular in sensemaking studies, such as *grounded theory* [9], *content analysis* [37], and *thematic analysis* [19] that rely on the interpretation of rich textual and multimedia data. There is commonality in these approaches in that they all require a level of manual processing of data, coding and indexing it before describing it in the context of categories or themes. Furthermore, in the case of multimedia data, transcription of audio or video data is often also required. Though these approaches lead to important insights, they are labor intensive, time-consuming and costly in their application [41]. There are a number of widely used software packages which are designed for researches using an inductive approach, offering ways to code and index data in various formats [25]. These tools give qualitative researchers useful ways of managing data, however, a qualitative analysis is still a largely manual process which requires a substantial investment of time and resources in leading to insightful findings.

2.2 Analytic Provenance for Sensemaking

Analytic provenance describes the interactive data exploration using a visual analytics system and the human sensemaking during that process. Besides the four semantic layers [17] discussed earlier, it also includes the *7W information* [15] (Who, What, Where, Why, When, Which, and hoW), which were initially proposed for *data provenance* [3,14,36] that focuses on the data collection and computational analysis. This provides the context necessary for interpretation, such as authors, creation time, input data, and visualization parameters. Similar to other scientific workflows, an analytic provenance pipeline consists of capture, storage, analysis and visualization. Heer et al. [20] discussed design considerations for such pipeline, which covers underlying provenance's models, visual representations, and operations for analysis. The following discussions focus on the capture and visualization, in the context of recovering of user's sensemaking process from analytic provenance.

2.2.1 Capture

There is limited literature on capturing *events* because it is relatively easy and provides little semantics alone. Among these, Glass Box [10] can record a wide range of low-level *events* such as mouse clicks, key strokes, and window events. Its objective is to capture and archive intelligence analysis activities so they can be retrieved later. On a higher semantic level, *Actions*, such as changing the visualization settings and sorting a dataset, are usually performed through interactive widgets including menus and buttons. In theory, it is straightforward to capture them if a visualization system intends to do so. Some systems [35] maintain an action history to support undo and redo, which is an example of utilizing the actions' provenance.

Capturing *task* and *sub-task* is usually more challenging. As previously mentioned, such information is usually part of users' thinking that a visual analytics system does not have direct access to. Existing methods either take a manual or automatic approach. Manual approaches encourage users to record their thinking during sensemaking. However, this will not work if the method introduces considerable distraction or does not offer any benefits. Allowing user annotation is one of the most common forms [27,38]: the user creates *notes* or *annotations* that record comments, findings, or hypotheses. Those notes can be associated with the visualization, allowing users returning to the states when the notes were made [30,35] to re-examine the context or investigate further. The incentive to users is that such annotation digitizes a common sensemaking activity (i.e., note taking) and allows for features such as searching. This also integrates notes with their visualisation context, allow for better interpretation. However, annotations are unlikely to cover all the analytical thinking. For example, users are more likely to record the findings they made than the process or approach that led them there. To encourage user to write richer notes, a visual analytic system needs to provide additional benefits such as the ability to create visual narratives [38] that reveals the reasoning process and help users review and plan exploratory analysis for complex sensemaking task after recording the current progress [26].

One of the main disadvantages of manual capture is the requirement of direct input from users. Automatic approaches try to address this by inferring higher level analytic provenance from what can be automatically captured including event and action provenance. However, this turns out to be a difficult task. An experiment studied the effectiveness of manual recovering of reasoning process from a user's action provenance, and the results showed that about 60% to 70% of high level analytic provenance can be correctly recovered [12]. Given the difficulty, a few methods attempted to partially uncover the high level analytic provenance. One such example is *action chunking*, i.e., identify a group of actions that are likely to be part of the same sub-task, without knowing what the sub-task is [17]. Such approaches apply heuristics to infer patterns from action logs based on repeated occurrence and proximity in data/visualization space or analysis time. More recently, there has been advancement in developing an automated and real-time technique to learn about users [5]. Based on very low-level events, mouse clicks and movements, collected from a visual search task, the algorithms can detect whether a user would be fast or slow at completing the task with 62% to 83% accuracy. They can also infer some user traits including locus of control, extraversion and neuroticism with 61% to 67% accuracy.

Deriving user thinking from their interaction data can be of value beyond understanding sensemaking and is common in other domains. For example, many websites record user browsing interactions in hope to derive higher level information such as user goals and needs. Data mining approaches are commonly used to detect patterns within such data [8], which can then be used to provide better service such as recommendations [39]. Chi et al. [7] proposed an algorithm to infer user needs from user's surfing patterns based on the concept of *information scent*, which is the perception of the value and cost of information sources obtained from proximal cues with respect to the goal of the user [31].

2.2.2 Visualization

Analytic provenance visualization is commonly used to provide an overview of the sensemaking process or reveal any patterns during this process, both of which can help researchers to understand users' thinking. Node-link diagrams are a popular choice to show an overview of the sensemaking process [2, 13, 16, 22, 30, 35]. In most cases, nodes represent system states and edges are actions that transition the system from one state to another. Once an analytic provenance network is created, graph layout algorithms can be applied to improve the visualization. A sensemaking session can have hundreds of system states, and the analytic provenance network usually needs to share the display estate with other visualizations. As a result, it can be challenging to show the entire network within a limited space. It is possible to apply techniques for visualizing large networks such as clustering and aggregation. However, this needs to be done in a way that does not lose the information important for understanding the sensemaking process. To the best of our knowledge, we are not aware of any work addressing this challenge yet.

Besides the overall sensemaking process, the details of each system state and user actions are important for recovery of users' thinking. To provide more context, the common approach is *detail on demand*: when a sensemaking step is selected, the visual analytics system shows the corresponding visualization state and the action's information [22, 30, 35]. This works well if a visual analytics system allows user to go back to a previous state: showing the sensemaking context essentially restores all the visualization views to a previous state. However, to understand a sequence of sensemaking actions, researchers must go through one step at a time, sometimes back and forth. This can introduce extra cognitive work load on the user's memory, thus slow down the analysis. Methods such as GraphTrail [13] show the full details of multiple system states and the links between them at the same time. By zooming and panning, users can choose to see more sensemaking steps (with less detail) or more information about individual system state (but less states simultaneously). This method works well when the visualization state is simple, e.g., only has one view. When a system consists of multiple visualizations, it becomes difficult to see the details of each state when more than one states are shown.

Chronicle [18] utilizes a similar interface to SensePath, but with different design intentions. It captures the entire editing history of a graphical document to allow further study of how a complex image product is accomplished. In contrast, the goal of SensePath is to help analysts recover the high level sensemaking process. Following a similar approach, Delta [24] allows comparing different editing workflows to choose the most suitable one by visualizing the steps performed in those workflows.

3 Approach and Requirements

3.1 Approach

Two sets of observations were carried out to understand the characteristics of qualitative analysis of sensemaking activities. The purpose was twofold:

1. To check whether there is any unique characteristics of qualitative analysis in sensemaking studies, in comparison to general HCI research; and

2. To understand the process and tools used, identifying any potential issues that our visual analytic tool can address.

These are *meta observations* in the sense that we observed the process of qualitative analyses of sensemaking activities that themselves included user observation (i.e., observe how participants approach a sensemaking task) and the qualitative analysis afterwards. In other words, each set of observations includes both how a HCI researcher collected observation data when a participant was performing a sensemaking task, and the data analysis session afterwards, during which a HCI researcher used a qualitative method to analyze the observation and gained a deeper understanding of the participant's sensemaking process. From now on we call our observations *meta observation* to differentiate them from observations during the qualitative research.

The first meta observation used "selecting a smart watch" as the sensemaking task. The participants were asked to research online and select the smart watch that they would like to purchase. The observation was repeated six times with different participants. Each session stopped when the participant decided on the smart watch model, lasting between 30 to 45 minutes. These observations were performed by a junior HCI researcher with limited qualitative analysis experience and he recorded the sensemaking process by making notes on paper and screen recording. Interviews were conducted once the task was completed, and the HCI researcher again made paper notes on participants answers to semi-structured questions. Once all six observations were completed, the researcher conducted thematic analysis on the observation data and the results were summarized in a two-page report. As part of the meta observation, we interviewed the researcher after the report was finished to understand his qualitative research process, i.e., the way he collected observation data and the qualitative analysis performed afterwards.

To ensure that the qualitative analysis we observed was not biased, we conducted a second set of meta observations that used a different sensemaking task conducted by a more experienced HCI researcher. One participant was tasked to plan a holiday for a fictitious family with particular needs. Two further participants were given the task to select a smart watch as described above. This researcher also used thematic analysis to analyze the observation data. The process of meta observation is the same as the one described in the previous paragraph.

To identify any unique features of qualitative analysis in sensemaking research, we conducted our own thematic analysis on the meta observation data (which is different from the thematic analysis by HCI researchers on their observation data). Once completed, we confirmed our findings with the two HCI researchers. In summary, we did not discover any unique characteristics of qualitative analysis for sensemaking. This implies that the approach and tool we developed for sensemaking are likely to be applicable to qualitative analysis intended for different purposes. Our study did equip us with detailed knowledge about the actual qualitative analysis process, which help the design of our visual analytics tool SensePath. These are discussed in more depth in the next section.

After the (meta) thematic analysis, we ran a participatory design session with HCI researchers to discuss our findings and possible design of a visual analytics tool to support this process. One of the outcomes is a list of requirements, which are discussed below. The design ideas are described in the section after.

3.2 Requirements

Similar to existing literature, we describe a qualitative research process with the following steps:

1. **Study Design**: Decide the study setup, such as sensemaking task, dataset and data to capture, based on the targeted research question.
2. **Data Collection**: Recruit participants and capture their sensemaking process. The collected data could include screen capture videos, think-aloud recordings, video recordings and interview notes and recordings.
3. **Transcription**: Transcribe video and audio recordings verbatim.
4. **Coding**: Identify common themes in data and assign appropriate names.
5. **Categorization**: Group codes or themes into categories.
6. **Model**: Match the themes and categories with an existing sensemaking model or design a new one, depending on the research question.

Step 2 to 6 represent a progression on the semantics: each step takes the output from the previous step as input, and produces an outcome with richer semantics. This is similar to the four layers in the Gotz and Zhou model [17], but targeting different aspect: the former focuses on the sensemaking model and theory, whereas the latter is user activity centered.

We propose the following requirements based on the meta thematic analysis results:

1. **Thematic analysis support**: this is the qualitative research method used in both our meta observations and also shares many characteristics with other popular qualitative methods such as grounded theory.
2. ***Transcription* and *coding* efficiency**: each of the steps from 2 to 6 can be time consuming; however, these two steps are where a visual analytics tool can potentially make the most difference. Their length largely depends on the tool's efficiency rather than external factors. For example, *data collection* primarily depends on the task's completion time and the number of participants. Also, transcription and coding are not as abstract or semantically rich as *categorization* and *model*, which makes automated support easier.

The participatory design session with a number of HCI researchers led to several other requirements:

3. **Existing workflow integration**: the tool should not change the way researchers currently work and ideally works together with other softwares already used in the analysis workflow.
4. **Non-intrusiveness**: the tool should not distract participants or change their behaviors during the sensemaking task.
5. **Scalability**: the tool should support sensemaking sessions common in qualitative research with a duration up to an hour or two.
6. **Lightweight**: the tool should be lightweight and support multiple operating systems.

4 SensePath

4.1 Design

The design process started with a close examination of the steps we want to support. For *transcription*, we ruled out the possibility of automatic video or audio transcribing: these are research challenges of their own right and require expertise different from visual analytics. During the meta observation data analysis, we noticed that the large portion of time spent on transcribing the video was identifying the sensemaking actions the participant took, such as searching, opening a link, and their timings. These can potentially be captured within the browser, thus considerably reduce video transcribing time.

From the participatory design session mentioned earlier, we found that an important part of the *coding* process is to understand the sensemaking activities from the video transcription: when a participant spent several minutes on a page, he/she was likely reading through the information; when a participant switched between two pages back and forth, he/she might be comparing two smart watch models. Understanding the nature of such sensemaking activities, i.e., reading or comparison, is the prerequisite for identifying common themes and naming them. To a certain extent, this is the equivalent of inferring "sub-task" from "action" in the Gotz and Zhou's model [17]. However, this process is difficult to be completely automated [12]. After further discussion with the HCI researchers, we identified a few important factors to this process and they can be supported by visual analytics:

1. The actions before and after the current one. These provide useful contextual information because an "action" is usually a part of a "sub-task", which consists of a number of actions. For example, when a participant went through the web page of a number of hotels in succession, he or she might be comparing these hotels, especially if all these pages are opened from the same hotel booking website. Showing a number of actions together would help a researcher identify the connections between them and potentially find an interpretation for all the actions in the sequence as a whole.

2. Seeing what a participant was looking at. It may appear obvious, but it can give a researcher the needed context to understand the sensemaking action. For example, looking at the Google Maps indicates the participant was trying to locate certain place. This can be particularly useful if the researcher is not present during the observation.

3. Understanding what a participant was thinking. While this can be partly captured through think aloud or post hoc interview, another common technique is to allow note taking. Besides helping the participant carry out the sensemaking task, this also gives the researcher some insight about the participant's thinking.

4.2 Overview

SensePath is implemented as a Chrome extension consisting of two components. The first one is a background process running in the participant's browser to automatically capture all the required analytic provenance during the observation stage of the qualitative study. It also offers the additional function to add note and highlight text on a web page (Point 3 above). Otherwise, participants will not notice any difference from their normal sensemaking session (Requirement 4, non-intrusiveness for participants).

The second component is a set of four linked visualizations (Fig. 1) using the captured provenance to facilitate *transcription* and *coding*. These views are:

- A *timeline* view that displays captured sensemaking actions in their temporal order (Fig. 1A). This allows researchers to see an action in the context of other actions (Point 1 above).

- A *browser* view that shows the web page when the sensemaking action was performed (Fig. 1B). This provides the contextual information of sensemaking actions (Point 2 above).

- A *replay* for screen capture video that is coordinated with sensemaking action selection in other views. (Fig. 1C). This provides additional contextual information about browser interaction such as scrolling and mouse movement (Point 2 above).

- A *transcription* view that displays the detailed information of selected actions (Fig. 1D). The generated transcription can be exported and then used in popular qualitative data analysis software (Requirement 3).

4.3 Provenance Capture

4.3.1 Content

SensePath captures the analytic provenance of participants sensemaking actions, as described in the Gotz and Zhou model [17]. The HCI researchers we talked to preferred higher-level information, but this is not always technically feasible. For example, it is possible to detect that a web page was opened for a long time, but it is difficult to tell whether the participant was reading, thinking, or simply away based on the information available from the browser alone. Based on the feedback from the participatory design session, we decided to record four aspects of actions that were regarded useful for qualitative analysis by the HCI researchers we talked to.

Type: When the participant opens a web page, the default action is *browsing*, which lasts until they switch to another page. During that period, we focus on two common types of actions: *search* and *reading*. Search is further divided into *keyword search*, *filtering*, and *map search* that includes *location search* and *route search*. As discussed earlier, *highlighting* and *annotation* are provided for note taking and capture part of user thinking.

Timing: This is the start and end time of an action.

Context: The contextual information provides additional clue when looking at individual actions. It varies according to its action type such as the keyword for search and the selected text for highlighting. Also, title, URL, and a screen shot of the rendered web page are always recorded as part of the context.

Relationship: How a page was activated is recorded with three possibilities: *revisit* a previously opened page, directly *link* from an existing page, or manually *type* a new address.

Fig. 2 summarizes all the action types and relationships captured in SensePath.

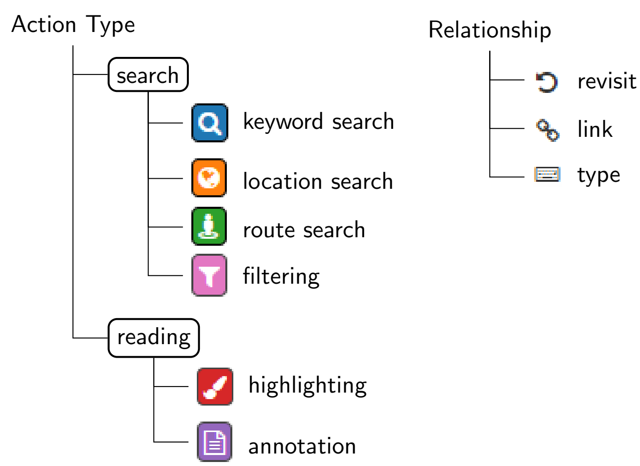

Fig. 2: All the *action types* and *relationships* that SensePath captures, together with their icons.

4.3.2 Mechanism

The detection of all the "search" actions are based on URL parsing. When a web page is loaded, its URL is parsed and compared against a set of query templates to check whether a search was performed and identify its type and parameters. In this prototype, we support automatic detection from the most popular web services: search engines (Google, Yahoo, Bing, Ask.com, and DuckDuckGo), map searches (Google Maps, OpenStreetMap, and Yahoo Maps), social networking sites (Facebook and Twitter), e-commerce sites (Amazon and ebay), and hotel booking websites (Booking.com and Expedia). All these Web services follow its own query template and expose all the parameters in the URL. This makes it possible to extract the required information from their URLs. Below are two examples:

- Google keyword search: `https://www.google.com/search?q=`{*keyword*}

- Yahoo Maps route search: `https://maps.yahoo.com/directions/?o=`{*source*}`&d=`{*destination*}

For the Google keyword search example above, SensePath uses a three-parameter template for its parsing: the host name (`www.google.`), the path name (`/search`), and the regular expression to extract the required information (`/\Wq=([\w%+]*)/i}`). Adding support for additional services only requires the knowledge of these three parameters.

Detecting "filtering" actions does not require prior knowledge about the search query template as in the "search" actions. We applied a heuristic that if two consecutive URLs share the same domain and pathname and the only difference is in the parameters, the second page is the result of filtering action on the first one. More specifically, the current URL is compared against the last one, and the parameters are parsed to a collection of key/value pairs if the domain and path are the same. There are three possible parameter changes: *addition*, *removal*, and *update*. For example, if the first and the second URLs can be:

1. `hotel.com/search?loc=chicago&numGuests=1`
2. `hotel.com/search?loc=chicago&numGuests=2&checkInDate=2015%2F10%2F24`,

The parameters of this filtering action can be captured as *add:* {*checkInDate=2015/10/24*}, *update:* {*numGuest=1*$\rightarrow$*2*}, and may be interpreted as "the participant sets a new check-in date and change the number of guests from 1 to 2".

All the "search" and "filtering" action heuristics only work if a web service exposes its parameters in URL. In other words, our method does not work if POST or AJAX requests are used. So far, we have not encountered such service yet. For example, Google Maps uses AJAX calls to load map tiles, but all the search information required by the tool is available in the URL. Also, most popular online services use GET instead of POST requests. It is possible to support Web services that encode the required information in POST or AJAX call by monitoring all the communications between the browser and the server, not just the changes in URL. This will require considerably more implementation efforts and is only possible with open source browsers such as Firefox and Chrome (with access to all client-server communications). The only service that SensePath cannot detect is Bing Maps, which encode query parameters as HEX strings; for example, `https://www.bing.com/maps/#Y3A9NTEuNTkwMTk5fi0wLjIyNTAwMCZsdmw9NiZzdH...` is the URL in searching for "london". It will require more information from the service provider to parse its queries.

Both "reading" actions are implemented using the content script [1] in Chrome extension API, thus all information needed can be saved. For example, when a sentence is highlighted, the relative location of the DOM element containing the text to the entire page structure is captured. The limitation is that once the web page is updated, e.g., text has been updated, the recorded position might not be correct anymore. The "timing", "context" and "relationship" actions are also captured through Chrome extension API in a similar way.

To guarantee the capability of restoring any visited view, the system needs to save a static copy of the web page at the time of action. This is similar to the P-Set model [21] for visualization exploration where the visual transforms, parameters, and results need to be stored to allow fully describing the process. However, for simplicity, we only capture the action type (such as "keyword search") and the parameters (i.e., the search keyword), but not the resulting web page (i.e., searching results). The browser snapshot and screen capture video can compensate this to a certain extent.

4.4 Timeline View

The timeline provides an overview of the entire sensemaking process and shows all the captured actions in their temporal order (Fig. 1A). An action is represented as either a bar or a tile, showing the four aspects of analytic provenance information discussed earlier. Fig. 3 shows an example of an *action bar*. The page URL (context) is shown atop the bar. The first icon shows that this action revisited a previously opened page (relationship). The lack of any icon at the beginning of the bar implies that this is a *browsing* action. Next is the page title, only part of which is shown because of the limited space. This is followed by an icon indicating the type of that action such as a *filtering*. Fig. 2 shows all icons representing action types and relationships in SensePath. Note that action type icons have colored background and a black border to easily distinguished from relationship icons. The last part is the contextual information specialized for each type of action, which is filtering parameters in this case. The width of the action bar corresponds to the length of its action, and the relative position of the action type icon marks when the action happens.

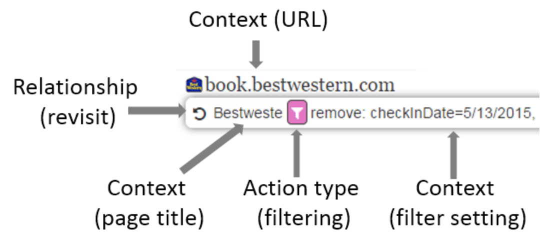

Fig. 3: An *action bar*.

An *action tile* contains similar analytic provenance information but with more details. Fig. 4 shows the same action as in Fig. 3 but as a tile. Because more height is given, a tile includes a screen shot, which can help remind the researcher about the web page. This can also be useful even when a researcher is not at the observation session because they can get a rough context of what the page is about. The rest of the analytic provenance information is the same as that in an action bar, except that more details (e.g., the page title) are displayed because of the extra space.

Fig. 4: An *action tile*.

The timeline can be shown with either action bar or tile; and the user can switch between the two through interaction. The former is more compact thus better for scalability, whereas the latter shows more details and good for close inspection. Fig. 5 shows part of a timeline with a number of action tiles.

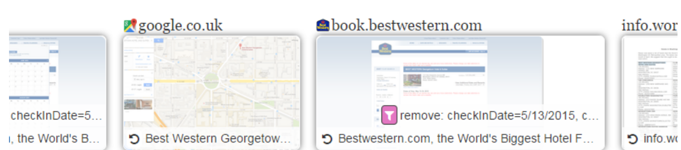

Fig. 5: Part of a timeline with action tiles.

4.4.1 Scalability

Both action bar and tile can reduce their size through zooming to accommodate more actions within the visible part of the timeline. Fig. 6 shows three zoom levels of a timeline. At the smallest level, only the action type is visible. More details become available after zooming in: the middle level shows that the last location search is about "Best Western" hotel, and the most detailed level (bottom row) reveals that the first location search is about some "headquarter" and the second action is revisiting the web page of World bank. When there are large number of actions or the timeline is fully zoomed out, only a few letters are shown for each action bar, thus is not very informative. In this

[1] `https://developer.chrome.com/extensions/content_scripts`

case, information richness is sacrificed for scalability. However, interactive features such as selective zooming are included to mitigate this issue, which will be discussed later. Action type icon is always visible (such as the top row in Fig. 6), which indicates what the action is.

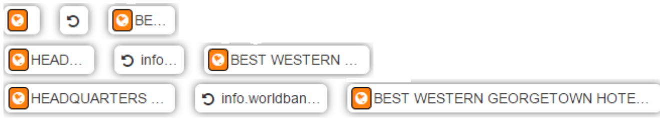

Fig. 6: Three zoom levels of a timeline with the least information on the top row and increasing in the below rows.

Adjacent actions that are similar can be merged to further improve scalability. Fig. 7 show such an aggregated action with eight highlights. Instead of showing individual actions, the merged action requires less space and also arguably easier to understand, i.e., those eight highlights were made on the same Google Plus page.

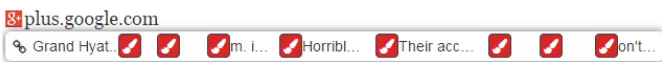

Fig. 7: A merged action bar combines eight adjacent highlights on the same web page.

Because of the small bar height, it is possible for a timeline to have multiple rows. This, in combination with aggregation and interaction (described below), allows SensePath to display a reasonably large sensemaking session within a limited space. Fig. 1A shows about 50 actions out of a total of 70 actions from a 30-minute long session. This addresses Requirement 5 on scalability.

4.4.2 Interaction

A number of interaction features were added to support the analysis of sensemaking process. Clicking on an action will show the associated web page in the browser view (Fig. 1B). This allows researchers to see what the participant was looking at, which is a prerequisite for understanding their thinking.

Mouse over an action bar highlights other actions for the same page with a red border (Fig. 8). The example in Fig. 8 shows that a page was revisited a number of times during a short sensemaking session. Mouse over an action brings up a tooltip with additional details (Fig. 8).

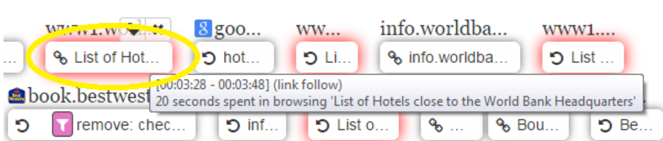

Fig. 8: Mouse over an action (the one with a yellow eclipse) highlights all other actions with the same URL (with red border). This also brings up a tooltip showing additional action information.

SensePath also supports focus+context through *selective zooming*. Fig. 9 shows an example: the top row is the status before selective zooming and the bottom row is the same set of actions with the zoom level of only the middle action adjusted. This can be applied to an arbitrary set of actions and allows analysts to concentrate on certain actions without losing their context. A potential problem is that analysts may forget the different zoom levels among actions, thus left with a wrong impression about action length (indicated by the bar width). SensePath provides a reseting button in the bottom-right corner that sets all the actions to their original zoom levels. Visual indication of different zoom levels is plan for the next version of SensePath.

Finally, a researcher can filter actions based on their time length. For example, if a researcher thinks that actions that last a few seconds are not important, they can be filtered out with the slider to the right side of the timeline (Fig. 10), which sets the minimal length that a visible action needs to have. When threshold changes, actions that will be removed fade out first before completely disappear. This allows the researcher to preview the effect of filtering.

Fig. 9: Selective zooming: only the middle action (with red border) has its zoom level changed.

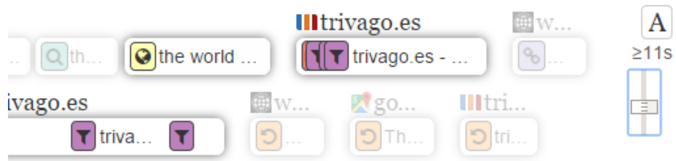

Fig. 10: The slider on the right controls the minimal length of an action to remain visible. Actions fall below the threshold fade out first before completely disappear, allowing users to preview the effect of filtering.

4.5 Browser View

As previously discussed, when an action is selected in the timeline, its associated web page is showed in the browser view (Fig. 1B). This allows researchers to examine the web page that a participant was looking at when performing a sensemaking action. If there is any annotation or highlighting, the browser view will automatically navigate to that part, informing researchers which part of the page the participant was interested in.

4.6 Replay View

SensePath can link the timeline to an externally captured screen video to provide additional information about participants behavior during the sensemaking session. When a researcher selects an action in the timeline, the replay view automatically jumps to the corresponding part of the screen video when the action is about to start. This avoids manual search within the action video, which can be time consuming. After selecting an action in the timeline, a researcher can first check the web page in the browser view and then start the video playback in the replay view if he/she wants to find out more. The playback automatically stops when it reaches the end of an action. Alternatively, the researcher can choose to let the video continue, then the corresponding action in the timeline will be highlighted as the video progresses.

4.7 Transcription View

While it is possible to see the full details of an action by mouse over, there is no easy way to do this for a set of actions. The transcription view addresses this issue by presenting all the details in a tabular format (Fig. 1D). For each action, this view shows its starting and ending time, action type, any assigned themes, and an automatically generated description such as "37 seconds spent in searching Best Western George Town Hotel and Suites". This description is based on a predefined template for each different action type with advise from the aforementioned participatory design session. Row backgrounds match the color of action type icons in the timeline view. The design of this view resembles the transcript interface of popular video transcribe softwares to reduce the learning efforts required.

All the information displayed in the transcription view can be exported as a timeline in the SMPTE [2] format. This can be imported by many popular qualitative data analysis softwares such as InqScribe [3] as a transcript. This allows researchers to continue using their existing workflows in such software (Requirement 3). Moreover, SMPTE

[2] http://en.wikipedia.org/wiki/SMPTE_timecode
[3] http://www.inqscribe.com/

transcript can be used as a subtitle file in popular video players such as VLC [4].

4.8 Implementation

SensePath is implemented as a Chrome extension using standard web technologies including HTML5, CSS3, and JavaScript, together with D3 library [4] for visualization. Thus, it satisfies Requirement 6 about lightweight and support multiple operating systems. However, because highlighting and annotation features require modifying the structure of a web page, they must be implemented as a browser plugin. We decided to target Chrome browser first due to its popularity.

SensePath consists of two components: the provenance capture and the provenance visualization. The capture component relies on content script injected into a loaded web page (to allow highlighting and annotation) and Chrome extension API (to allow automatic action extraction). Therefore, it always works as long as the Chrome extension is enabled. The captured data is exported as a JSON file, which can then be loaded by the visualization component.

The four linked visualizations communicate using the *messaging passing* mechanism provided by the Chrome extension API. When an interaction occurs in one view, it sends a message to notify all other views. Each view constantly listens and responds to such messages. For instance, when an *action* is selected in the timeline view, it broadcasts the selection interaction. The replay view listens and changes the current time frame in the video to the part when that action was performed. The replay view uses HTML5 video tag [5] to display the video capture, thus possible to programmatically set the current playback position to a specific point, or to start/pause the playback, and to respond to those events. The replay view also maintains a list of start/end time of all actions, thus when a video is playing, it finds the action that contains the current time frame and sends a message to the timeline view to make it highlighted.

5 EVALUATION

We conducted a user-centered evaluation of the SensePath tool in order to establish an understanding of its use by an experienced qualitative researcher and to identify opportunities for improvement. To do this we first conducted a number of user studies of participants carrying out an online sensemaking task, and we then recruited an analyst to carry out an analysis of the sensemaking process of the users using SensePath. The process is the same as previous meta observations, with the exception of only using SensePath for the qualitative analysis.

5.1 Online Sensemaking Task

In the first part of our study we conducted a number of studies of users performing online sensemaking tasks in order to establish a ground truth dataset for the analyst to use within SensePath. We recruited two participants to take part in this study; a post-doctoral researcher and a PhD student, both male. Participants were given the same task, which was to use Chrome browser to find appropriate accommodation for two academics attending a conference at the World Bank headquarters in Washington, D.C. We provided participants with information about the location and dates of the conference, but gave no further details in the scenario in order to maintain suitable complexity in the task, and to ensure it was as realistic as possible. Both users were given 30 minutes to do the sensemaking task, and asked to present us with their choice of hotel and rational behind it at the end. Throughout the study user's interactions and analytic provenance information was collected within SensePath, as well as a screen recording using commercial screen capture software. We also encouraged user's to give think-aloud responses throughout the study, and finally conducted a structured interview asking the user to reveal:

- The rationale behind their choice of hotel and information used to support it
- The process they went through in order to make their choice of accommodation
- Their strategy in approaching the task and the steps they took

5.2 Analysis with SensePath

For the second part of our evaluation we recruited an analyst to use SensePath to carry out an analysis of the online sensemaking activities collected in the user studies outlined above. We recruited an analyst with 7 years of experience in qualitative research, is the holder of a PhD in an HCI related topic, and has a good understanding of sensemaking. We gave the analyst a short tutorial in the use of the SensePath tool, explaining it's features and use, as well as briefing her on the purpose of the analysis she would carry out. She was provided with a laptop computer running the SensePath tool connected to an external monitor providing a multi-screen set-up as illustrated in Fig. 11. Both sets of data collected in the previous part of this evaluation were loaded into SensePath, and we asked the analyst to carry out an analysis of each separately. During the analysis, we encouraged the analyst to provide feedback through a think-aloud protocol. We recorded her responses and other observations using written notes. At the end of each analysis we asked the analyst to complete a discovery sheet reporting her findings. The discovery sheet included the following questions:

- Identify the steps the user took in choosing suitable accommodation
  - The beginning and end of each step in the data
  - Provide a name (code/theme) for each step
- Identify any interesting patterns in the data
- Identify the user's strategy in approaching the task, and characteristics which demonstrate this

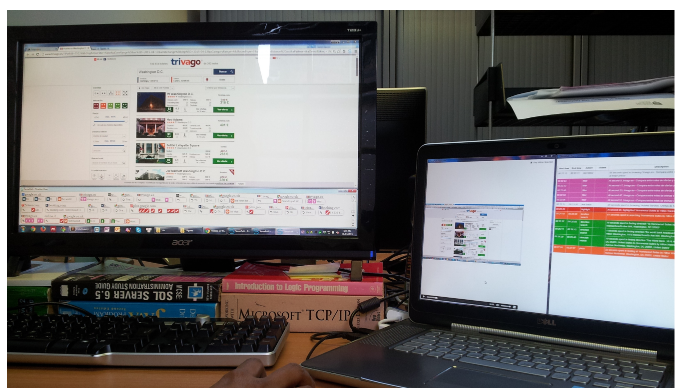

Fig. 11: The setup of the qualitative analysis during evaluation. The monitor on the left shows the timeline and browser view, and the laptop on the right shows the replay and transcription view.

5.3 Findings

Although the evaluation we have described was of a small scale, and involving the participation of only one analyst, we have yielded some interesting and insightful findings.

The analyst took approximately 1 hour to analyze 30 minutes of study data. This shows a reduction of half the time taken when analyzing study data using SensePath compared with traditional methods of video analysis, which would typically take around 4 hours of analysis for every hour of study data [6].

The analyst initially used the timeline visualization to see user interactions at a low resolution, before focusing on interesting parts of the data in more detail. As user actions are visualized in a single view,

[4] `http://www.videolan.org/vlc/index.en_GB.html`

[5] `https://developer.mozilla.org/en-US/docs/Web/Guide/HTML/Using_HTML5_audio_and_video`

at a high level, the analyst reported that she could quickly make an initial summary assessment of the user's overall performance of the task, before identifying potentially interesting user behaviors in the data which she wanted to look at in further detail. One such example of this is when she saw many highlighting actions on a Google Plus page, next to each other in the timeline, she said "it seems that the guy [the user performing the task] found interesting information on that [Google Plus] page because he highlighted a lot there". She then moved the mouse over the action icons to read the highlighted text in the tooltips. Interestingly, she quickly concluded that "he only focused on negative reviews". She clicked on some of those icons to open up the Google Plus page to gain more context. Unfortunately, that page is content-dynamic, thus some highlighted texts failed to be reselected. She watched the video in the replay view and heard that the participant was talking to us about his preference to negative reviews (we used think-aloud protocol), which confirmed her initial judgment. She also mentioned that offering highlighting feature to the user seemed useful because it allows the analyst to quickly identify the user's interests.

To understand the whole process, the analyst quickly went through all the actions shown in the timeline. The analyst was able to successfully describe the steps taken by the users in their approach to the task. Those steps are all correct according to our assessment when re-watching the screen capture video and think-aloud recording of the user's sensemaking session. Fig. 12 shows a reproduction of a written diagram created by the analyst illustrating those steps she identified. As an example of those steps, the analyst pointed to her diagram and explained "that guy searched for the address of the headquarters, then viewed it in Google Maps to get a sense of where it is".

start ⟶ Google to find address of HQ ⟶ G.Map to view it ⟶ look in travel website (trivago)

filter by stars ⟶ select hotel ⟶ look at pictures in hotel website ⟶ check its location in G.Map

look at reviews (negative ones) ⟶ compare cost of 3 hotels ⟶ check new hotel ⟶ find one

check address in G.Map ⟶ compare distance from HQ

Fig. 12: A reproduction of diagram produced by the analyst during the evaluation illustrating the steps taken by the user in the task.

The analyst reported that using the timeline view she could easily identify interesting recurring patterns in user behavior because all actions are shown together. One such pattern is that when the user finds a hotel in a booking website, he looks at its pictures first, then finds its location in Google Maps, and checks the distance from the headquarters. The analyst stated that the user repeated this pattern for several hotels he found.

The analyst managed to find the rough strategy that the user applied in approaching the task: the user targeted reasonably cheap hotels, evidenced by filtered out 5 stars, but also considered close distance to the headquarters, based on comparison of those hotels in Google Maps. This confirmed with what the user told us: as a professional academic, he did not want to spend too much money from the university.

The analyst commented that the video and audio recordings were intrinsic to carry out a fuller, more detailed analysis by providing additional information that was not available in the timeline and browser views such as the movement of the cursor or scrolling on a page. Therefore, the analyst mentioned that the replay view helped her gain further insight into user behavior. As the analyst did not have to watch the video entirely, she felt that she could save valuable time in the analysis. Furthermore, she stated that as clicking on an action in the timeline view skipped to the relevant place in the screen capture, further time was saved in scrubbing through the video, which often happened in her experience of analyzing video data. One such example of using the replay view is when she saw a long action bar with location search icon. She knew that the user spent a lot of time in a Google Maps page, looking at a specific location; however, what exactly he was doing is neither available in the timeline nor the browser view. Thus, she needed to watch the video to get more information.

5.3.1 Opportunities for further development

Overall our tool proved to be useful in enabling an analyst to gain insights into a user's online sensemaking process quickly and much less costly than a traditional qualitative analysis. In our analysis however we were able to identify opportunities for further design and development of SensePath. Foremost, though the analyst was able to quickly become familiar with the tool, she found it difficult to find the start time and end time of user actions in the timeline view in the absence of a visible scale. Also, although the tool is able to capture and visualize actions such as filtering, the analyst felt that she needed to refer to the video and audio recordings to find what filters or sorting the user performed, as this was not apparent in SensePath. This meant she needed to refer to video and audio data to try and find this.

6 Conclusion and Future Work

In this paper, we propose a general approach to support the deep understanding of sensemaking through analytic provenance and visual analytics. As an example, we developed SensePath to facilitate thematic analysis for online sensemaking tasks, targeting the transcription and coding phases. A meta thematic study was conducted to understand the characteristics of such analysis and a participatory design session was held to gather design requirements.

SensePath automatically captures a number of analytic provenance information that was identified important for understanding sensemaking process. This was then presented in four linked views: timeline, browser, replay, and transcription. The timeline provides an overview of the sensemaking process and can support a reasonably long sensemaking session common in qualitative research observations. The browser view shows the web page the participant was looking at when performing a sensemaking action, and is complemented by the replay view with the screen capture video of the action. The transcription view provides all the details for a set of actions and can export the information in a format compatible with popular qualitative analysis softwares such as InqScribe, so that analysts can continue working in their existing workflow.

An evaluation was conducted with an experienced qualitative researcher, who found many features of SensePath helpful for her work, and the data collected from the observation showed that SensePath met most of the requirements it set out to achieve. A more rigorous evaluation will be conducted to understand how SensePath is used in a real setting. The evaluation showed a reduction of half the time in analyzing video data from a single researcher; and a larger scale controlled experiment is planned to more accurately measure how much time SensePath can save in the transcription and coding phases.

SensePath at its current state is in the middle of an iterative development process. The next step is to address the issues identified in the evaluation and extend the approach to other domains beyond online sensemaking tasks. The visualization component can be reused straightforwardly. However, the capture component of SensePath is currently tightly associated with extracting sensemaking actions in a web page, thus needs to be updated. Of course, a discussion with targeted users is required to understand what actions and information are important to capture. Also, to make this more accessible for nontechnical users (such as the analysts) in adding automatic detection of "search actions" from new web services, we plan to build a simple GUI, in which they can specify the search templates, thus save the effort of manually modifying the code.

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