

# Sensecape: Enabling Multilevel Exploration and Sensemaking with Large Language Models

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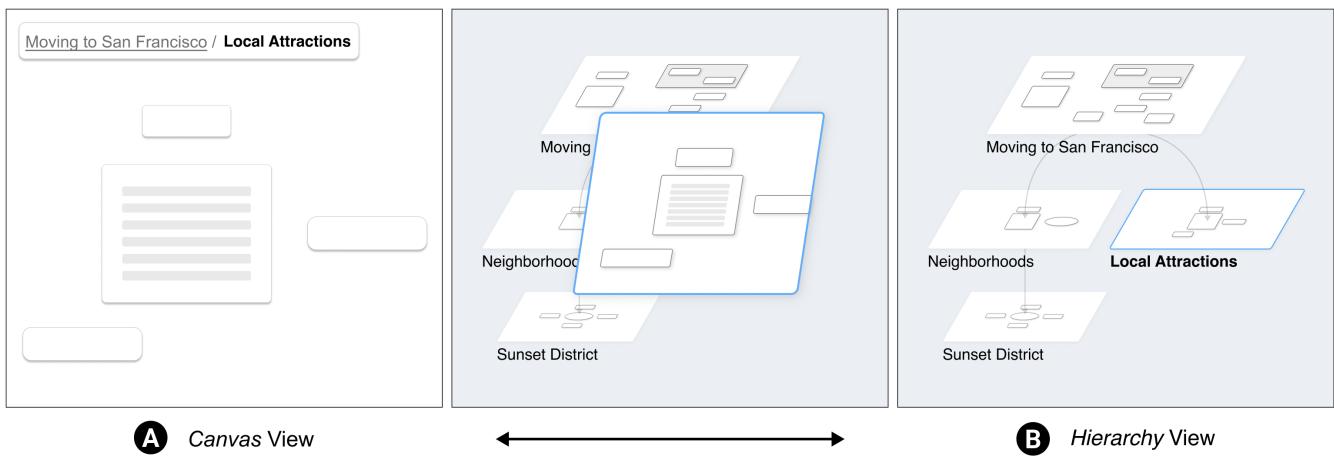
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**Figure 1: Sensecape allows users to seamlessly switch between (A) canvas view and (B) hierarchy view for multilevel exploration and sensemaking. Hierarchy view externalizes the notion of abstraction levels to help users oversee the information space and organize the collection of information for sensemaking.**

## ABSTRACT

People are increasingly turning to large language models (LLMs) for complex information tasks like academic research or planning a move to another city. However, while they often require working in a nonlinear manner – e.g., to arrange information spatially to organize and make sense of it, current interfaces for interacting with LLMs are generally linear to support conversational interaction. To address this limitation and explore how we can support LLM-powered exploration and sensemaking, we developed Sensecape, an interactive system designed to support complex information tasks with an LLM by enabling users to (1) manage the complexity of information through multilevel abstraction and (2) seamlessly switch between foraging and sensemaking. Our within-subject user study reveals that Sensecape empowers users to explore more topics and structure their knowledge hierarchically. We contribute implications for LLM-based workflows and interfaces for information tasks.

## CCS CONCEPTS

- Human-centered computing → Interactive systems and tools; Interaction techniques; Empirical studies in HCI.

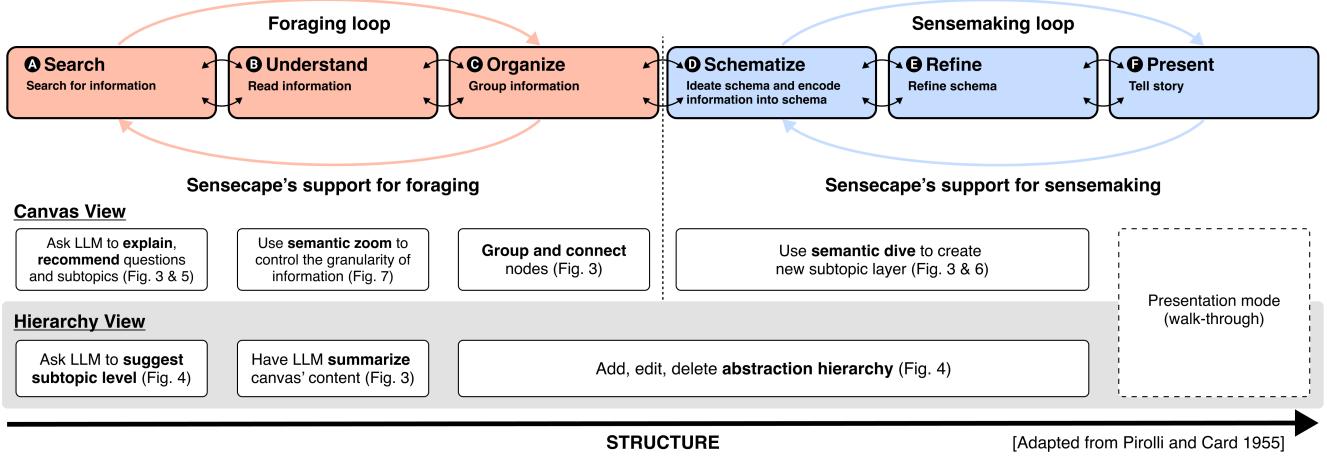
## KEYWORDS

information seeking; sensemaking; levels of abstraction; large language models; human-AI interaction

## 1 INTRODUCTION

Large language models (LLMs) are revolutionizing the way we engage in information-related tasks. Millions of users are now turning to LLMs (e.g., ChatGPT) to find explanations, write essays, and summarize content, among many tasks, thanks to their ability to instantly generate high-quality responses to flexible natural language queries. The application of perhaps the broadest impact might be how it can change the way people obtain and make sense of information. Instead of searching and browsing using search engines, people can converse with LLMs to acquire the desired information.

Although conversation is the most natural communication format, its inherent linear structure poses significant limitations for



**Figure 2: Information-seeking activities (top) alternate between foraging and sensemaking loops [45] and require encoding information into a structure as one moves from foraging to the sensemaking stage. How Sensecape supports each step (e.g., Search) in canvas and hierarchy views are listed, with the dotted line indicating the support not yet implemented.**

complex information tasks [33]. Linear conversational interfaces can be sufficient in supporting short question-answering tasks, such as responding ‘1 to 2 hours’ to the prompt “*how long does it take to drive to San Francisco from San Jose?*” But, they are ineffective in assisting in complex information tasks that require gathering, organizing, and synthesizing information in a nonlinear manner. Take a trip planning task as an example. When presented with a list of places from ChatGPT in response to the prompt, “*I am considering moving to San Francisco. What neighborhoods should I visit?*”, a user may want to get more recommendations, learn about a few locations in detail, revisit a previous list of recommendations for San Jose, or compare places between the two cities. However, with the linear organization of the conversation history, to perform these tasks, the user has to navigate back and forth, which can lead to users quickly losing track of the overall information activity [44].

The challenges mentioned above arise from the fundamental mismatch between the sequential nature of a linear conversation and the highly flexible workflow and organizational approaches that one utilizes when engaging in complex information tasks. Russell et al. [50] suggests that “*to answer task-specific questions, [we] search for a representation and encode data in that representation.*” As further highlighted in Fig. 2, information work requires alternating between two main loops – foraging loop and sensemaking loop. After exploring the information, people must find a good representation to encode it. Without support for flexible organization of the gathered information, making sense of the information can be severely challenging. In light of recent advances in LLMs and their growing presence in information-related tasks, these challenges can be exacerbated as LLMs become increasingly faster in generating large amounts of information. Therefore, the goal of this research is to reconcile this mismatch and enable fluid exploration and sensemaking workflow with LLMs by exploring how they should be integrated with the diverse structures often employed in information tasks.

We demonstrate a way to address these challenges with Sensecape, an interactive system that enables users to engage in exploratory search tasks with LLMs by enabling multilevel exploration and sensemaking. Specifically, as shown in Fig. 1, Sensecape allows users to switch between the canvas and hierarchy views to help them explore and reason at different levels of abstraction by externalizing the abstraction hierarchy and enabling flexible navigation across these levels.

In summary, our work contributes to the development of new interfaces for LLMs that enable users to engage in information-seeking tasks in a more structured and systematic manner, providing a more comprehensive representation of the information space for sensemaking through multilevel abstraction. We contribute:

- Sensecape, an interactive system that leverages the flexibility of a nonlinear interface suitable for exploratory tasks and the ability to flexibly navigate between the levels of abstraction in the information space;
- Externalization of multilevel abstraction for a more comprehensive and effective exploration of the information space for sensemaking;
- A user study demonstrating that enabling seamless exploration of semantic levels motivates and enables users to explore information space in an efficient and comprehensive manner.

## 2 RELATED WORK

This research is inspired by user studies of information exploration and sensemaking and builds on the tools designed to support them.

### 2.1 Information Exploration and Sensemaking

Complex information activities are often the interleave of two major tasks: exploratory search and sensemaking. When researching a complex and multifaceted subject matter, individuals tend to issue a series of iterative queries, scan and evaluate various information sources, and synthesize information from disparate sources to gain a better understanding of the topic, before incorporating it into

their own personal or professional knowledge bases [34, 61]. This has been referred to as *exploratory search* in prior literature [61]. This open-ended exploration and discovery of information is the opposite of searching for a specific answer or piece of information. It is commonly used in situations when the searcher has limited prior knowledge or experience with the subject matter and needs a deeper understanding before proceeding with a more focused search.

To help make sense of and work in complex, multifaceted information spaces, people take notes, curate relevant information, and create representations (e.g., tables, graphs, Cartesian plane) to organize information. This process of encoding information into external representations to answer complex questions is known as *sensemaking* [43]. This can free their mind from having to recall everything, help mentally process and synthesize all the information, and better reflect on the myriad ways the multiple facets are interconnected at different levels of abstraction [15, 16].

The complex and uncertain nature of this work makes it a non-linear and dynamic process. Specifically, it involves switching back and forth between deduction and induction [8], balancing divergent and convergent thinking [21], and reflection along different levels of abstraction [22]. Externalizing and reflecting on how the multiple levels and facets of information are interconnected or interdependent can be cognitively overwhelming and time-consuming. Furthermore, since the tools in which users take notes and work with this information are separate from the tools we use to explore information, it can be distracting to switch attention back and forth between the search and sensemaking tools [9, 35]. For example, an academic literature review can take anywhere from a few hours to several months and include finding, reading, and making sense of anywhere between 30-50 sources, depending on the complexity of the topic and the depth of the review [18, 31].

## 2.2 Tools To Help Explore and Make Sense

To help with finding relevant information, prior research has explored query suggestions that suggest relevant topics, terms, or questions (e.g., "Related Searches" and "People also ask for" suggestions in modern general-purpose search engines [2, 48]). To help triage the relevance of search results, previous work has explored dynamically updating the presentation of search results in real-time during the session [10, 51]. To help navigate relevant information returned by search engines, faceted search interfaces [25] employ categorization or clustering of search suggestions and results. To support the efficient collection of relevant information, previous work has explored highlighting and note-taking [49], quickly capturing information using clipping or bookmarking [32], clustering clipped information [13, 17, 45] and refinding information [19, 38].

Recent work has started to integrate exploratory search and sensemaking. For example, InkSeine [27], Google Docs, and Microsoft Word allow people to issue words and annotations in their notes as queries. Recently, Microsoft and Google announced tools like CoPilot that allow users to ask questions in a chat sidebar next to the work application [7]. However, these methods still rely on users to identify and articulate their information needs as queries and do not guide the searcher to further explore their knowledge gaps or how to integrate the relevant information into their current

knowledge. Research systems like CoNotate build on this and offer query suggestions based on the analysis of the searcher's notes and previous searches for patterns and gaps in any multifaceted information space [41]. Similarly, ForSense suggests parts of web pages to be clipped and clustered based on information the user has previously clipped and gathered [45]. InterWeave builds on these systems by not only leveraging the content of the user's sensemaking but also embedding contextual suggestions into the user's evolving schema and sensemaking knowledge structures [42].

Instead of employing a search engine to manually explore, curate and make sense of information across different information sources, large language models (e.g., GPT-4, LaMDA, LLaMa) have the unique ability to synthesize and generate information from large amounts of training data. They can instantly and directly deliver the designed information to users and help with more complex information goals. Sensecape leverages these advances in LLMs and an understanding of cognitive strategies to build an intelligent 3D digital whiteboard that can help information workers explore and make sense of any topic.

## 2.3 Visuo-Spatial Organization of Information

When working with complex information, people tend to organize information in their mind or externally, on notes or in their physical space [26, 30] (e.g., sticky notes, piles of paper). This visuo-spatial organization can help not only reduce the cognitive overload of storing everything in memory, share memory and mental context across information work sessions and collaborators [15, 39], but also mentally manipulate complex information, and solve problems using this information. It enables us to abstract complex and rich information and represent it in more manageable forms of representation so that we can apply spatial reasoning, such as rotation and transformation [28, 53], understand spatial relationships between information [57], identify patterns and symmetries, and solve problems creatively [40, 57].

Organizing information in a 3D space additionally enables us to think across different levels of abstraction and encode a more accurate and intuitive relationship between different pieces of information [57]. Especially when it comes to complex, multifaceted information or information related to physical or real-world objects. Creating and interacting with 3D representations of information can help store and process information better than 2D representations [14, 29, 36].

SemNet [20], the Information Visualizer project at Xerox PARC [11], Workscape [3], and Data Mountain [47] were early systems that introduced the 3D spatial layout of documents. The Web Forager [12] built on this work introduced a 3D spatial layout for web pages. The automatic spatial layouts of information in these systems leverage the user's ability to recognize and understand spatial relationships (both in 2D and 3D). The 3D interface makes it possible to display more information without incurring an additional cognitive load [47, 57].

Sensecape supports the nonlinear, iterative, and dynamic nature of complex information work by externalizing information at different levels of granularity and hierarchy, and highlighting inter-dependencies across these levels.

## 2.4 Managing Complexity of Information Space

HCI research developed and studied the effects of various interaction techniques for managing the complexity of information space:

- *Semantic zoom* allows users to zoom in and out of a visual representation of the information space, enabling them to focus on specific details or get an overview of the entire space. Zooming can enhance users' sense of control and help them better understand the spatial relationships between objects [5, 60].
- *Filtering* allows users to selectively display information based on certain criteria or parameters, making it easier to focus on relevant information. It has been found to be an effective technique for reducing information overload and improving task performance [24]. Similarly, *clustering and categorization* group similar items to reduce the complexity of a dataset. For example, a user might group similar products on an e-commerce website or cluster similar documents in a search engine.
- *Navigation* allows users to move around the information space, enabling them to explore different parts of the space and access relevant information. Effective navigation can improve users' comprehension of complex information spaces and reduce their cognitive load [6, 46].
- *Linking and brushing* technique involves linking multiple views of the same data, allowing users to see how changes in one view affect others. For example, a user might brush a region of a scatterplot to highlight the corresponding data points in other views. Research has shown that linking and brushing can improve users' ability to find patterns and relationships in data [4].
- *Flexible representations* combine some of the above interaction techniques to support information exploration and processing. For example, WritLarge [63] integrates pinch-to-zoom and selection in a single gesture for fluidly selecting and acting on content; and addresses the combined issues of navigating, selecting, and manipulating content by allowing the transformation of information across semantic, structural, and temporal axes.

Sensecape implements these interaction techniques to support exploration, reasoning around and management of complex information spaces.

## 3 SENSECAPE

To give a clear picture of the motivations underlying the design and features in Sensecape, we first present a motivating scenario, elucidating the challenges (Cs) that users encounter when performing complex information tasks with a conversational interface.

### 3.1 Motivating Scenario

Paul is a student considering moving to San Francisco after graduating. Since he has never lived there and does not know much about the city, he plans to do some research and visit in a few weeks. He decides to use ChatGPT for his research and trip planning.

**EXPLORATION.** Since he does not know much about the city, he is unsure where to begin and what to ask (C1). After thinking, he decides to directly ask, "*I plan to move to San Francisco. What should I look for?*" ChatGPT lists several things to consider: 'Location', 'Cost

of living', 'Climate', 'Culture', 'Commute', 'Housing options', and 'Activities and entertainment'. He finds all these topics relevant and worth investigating. However, since he can research only one topic at a time, he decides to explore 'Location' which, in full, reads: 'Location: Some neighborhoods are more walkable than others. Consider the proximity of your potential new home to public transportation, grocery stores, restaurants, and other amenities you may need.' This reminds him that he wants to live in a quiet neighborhood. So he asks, "*What are some quiet neighborhoods?*" ChatGPT returns several neighborhoods: 'Forest Hill', 'Outer Sunset', 'Sea Cliff', and so on. He asks a few follow-up questions about 'Sea Cliff' — realizing soon, however, that the list of underexplored neighborhoods (e.g., 'Forest Hill', 'Outer Sunset') is no longer visible due to the linear nature of the conversational interface (C2). Although he knows that he still needs to check other neighborhoods, he decides to instead explore another subtopic (e.g., 'Cost of living') because he does not want to exert effort to look for the list.

**SENSEMAKING.** After exploring the 'cost of living' using ChatGPT, he realizes that he should document and synthesize the explored topics and gathered information. He also realizes that ChatGPT's responses at different points of the conversation are relevant and useful for different topics (e.g., cost of living for residents in Sea Cliff). He wants to group these related information but cannot do this (C3) in the ChatGPT environment. He decides to use Miro, a digital whiteboard tool. He copies and pastes generated responses from the ChatGPT interface to the canvas. He zooms out to arrange them into groups, but too much text overwhelms him, making it difficult to identify key ideas in each response (C4). He breaks down responses into several nodes containing just keywords (e.g., 'Location', 'Cost of living'), relevant information in summary (e.g., 'Consider the proximity to public transportation, grocery stores, and restaurants'), and questions he wants answered (e.g., "*Which neighborhood is the best for a young single adult?*").

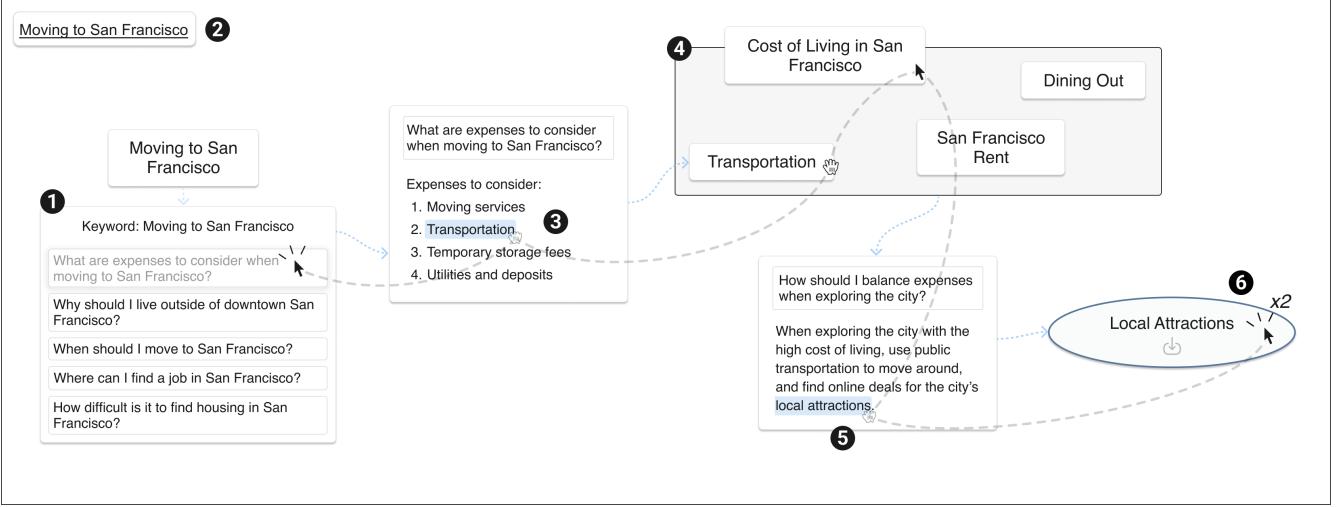
He zooms out again, checks keywords or summaries of the text, identifies the relevance of each node to another, and places them together. Moreover, he notices that the collected information can form a hierarchy, with the main topic 'Moving to San Francisco' at the top of the hierarchy and its subtopics from the first interchange (i.e., 'Location', 'Cost of living', 'Climate', and others) in the sub-level. He moves nodes accordingly to form a hierarchical layout. After returning to ChatGPT, he becomes curious about nearby cities such as 'San Jose'. He decides to consider them as possible destinations as well. Back in Miro, since this is not a subtopic under 'San Francisco' (now edited from 'Moving to San Francisco'), he adds 'My Future Home' above 'San Francisco' and then places 'San Jose' next to it at the same level. Unfortunately, the Miro workspace quickly gets cluttered as he expands his hierarchy with new subtopics and information (C5). The context-switching between two systems and transferring the generated responses to the workspace also becomes time-consuming and laborious. (C6).

In summary, the user challenges are as follows:

**C1. Slow Start:** Users with little knowledge of the topic struggle to know where to begin and what questions to ask.

**C2. Hard to Revisit:** Information organized in a linear sequence makes it challenging for users to track and revisit previous topics.

**C3. Lack of Structure:** The inability to group and specify connections across information makes sensemaking difficult.



**Figure 3:** An example workflow on canvas view. A user asks Sensecape to (1) generate a list of questions by selecting the node ‘Moving to San Francisco’ and the QUESTIONS button in expand bar (Fig. 4); Sensecape (2) updates the canvas topic to ‘Moving to San Francisco’ based on the new information on the canvas; the user explores ‘Expenses to consider’ when moving to San Francisco; the user (3) highlights ‘Transportation’ to create a node and (4) groups it with other relevant topics (e.g., ‘San Francisco Rent’, ‘Dining Out’), under their high-level topic ‘Cost of Living in San Francisco’. As LLM explains how to balance expenses when exploring the city, the word ‘local attractions’ catches the user’s eye. The user (5) drags the highlighted text out from the node to create its node and (6) double clicks it to *dive* into it (cf. Semantic Dive in Section 3.2) to explore the topic in a separate canvas.

**C4. Information Overload:** The large amount of information generated by LLMs can pose cognitive overload.

**C5. Visual Clutter:** When exploring multiple topics, the canvas can quickly get cluttered, making it challenging to understand the relationship between topics at a high level.

**C6. Cost of Context-Switching:** The disconnect between information exploration and sensemaking forces users to frequently switch contexts, which results in inefficient workflows.

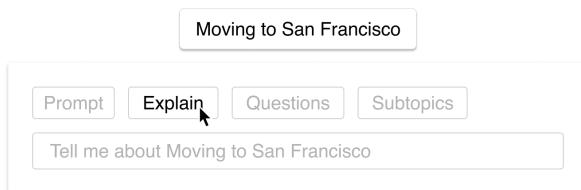
### 3.2 User Interface & Features

Sensecape consists of two main views: *canvas* view (Fig. 3) and *hierarchy* view (Fig. 5). The main difference is the semantic level at which users perform exploratory and sensemaking tasks. The canvas view allows users to search, gather, and organize information on any topic. The hierarchy view helps users reason at a higher level: users see each canvas, its topic, and where they are in relation

to other topics in the 3-dimensional space and at which level of abstraction. Below, we describe each view, its features, and how they help address the challenges (C1-C6).

**3.2.1 Canvas View [C6].** The canvas view is an infinite whiteboard where users can perform basic diagramming functionalities, such as adding, grouping, and connecting nodes with edges. They can also search and organize the generated response directly on the canvas (C6). The canvas view follows the *node-first approach*. The first step in any interaction begins with adding a node, which can be performed by double clicking anywhere on the canvas. After creating a node, the user can input text – e.g., topic (e.g., ‘San Francisco Culture’), statement (e.g., ‘San Francisco has a mild Mediterranean climate, but the weather can vary depending on the neighborhood.’), or question (e.g., “Why should I live outside of downtown San Francisco?”). As shown in Fig. 3 (2), as new information is added to the canvas, Sensecape uses LLM to summarize the content on the canvas into a single topic and updates the topic on display at the top left corner.

**Expand Bar [C1].** Once a node is added, the user can click it and have the expand bar appear below the node. Expand bar offers several functionalities to help users’ exploration and sensemaking. As shown in Fig. 4, expand bar allows users to use the node’s text as a PROMPT or as a basis for EXPLAIN, QUESTIONS, and SUBTOPICS features. Concretely, if the node’s text reads, “*What are the top San Francisco attractions?*” and the user clicks PROMPT, this question will be fed to an LLM. The LLM-generated response is then streamed to a node created below this node. QUESTIONS is designed to address the situation in which the user struggles to find out where to start



**Figure 4:** Expand bar: the cursor hovering over EXPLAIN previews the prompt in the input box as a placeholder. Clicking it sends this prompt to LLM and adds the response below.



**Figure 5: Hierarchy view:** Users can add (A) a canvas above (e.g., ‘Relocating to a new city’ above ‘Moving to San Francisco’) or (B) another hierarchy on the side (e.g., ‘Moving to San Jose’ next to ‘Moving to San Francisco’). To add a subtopic canvas, users can click (C) *Custom Subtopic* and specify the topic (e.g., ‘Sunset District’) or (D) *Generated Subtopic* to have LLM suggest a subtopic (e.g., ‘Marina District’).

and what questions to ask (C1). When the user clicks QUESTIONS, a node containing 25 questions – generated by LLM and begin with *What, Why, Where, When, and How* – is added, as shown in Fig. 3 (1). EXPLAIN helps expedite the exploration process by allowing users to quickly retrieve an explanation of a topic. Compared to PROMPT, which uses the node’s text directly as a prompt, EXPLAIN adds ‘Tell me about’ in front of the prompt, as shown in Fig. 4. Finally, SUBTOPICS generates subtopics around the node, facilitating the exploration process when the user is out of ideas on topics to explore (C1).

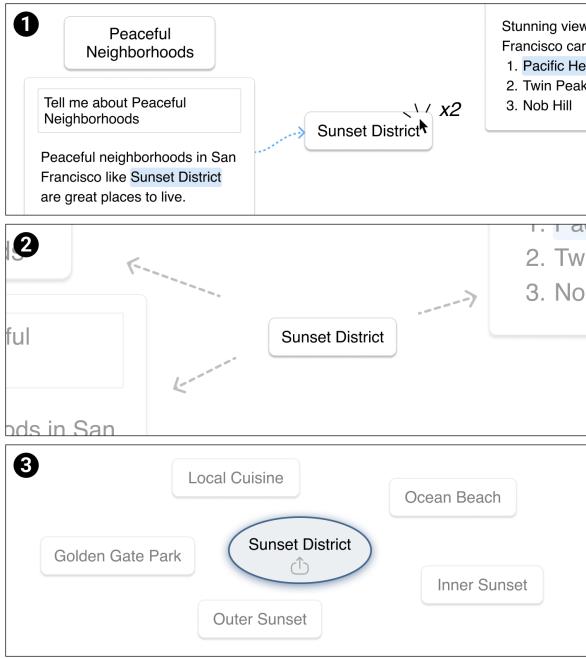
*Text Extraction [C2, C3].* To help users break down the generated response, users can highlight parts of the generated response and then either click or drag the highlighted text to the canvas to create a new node containing the highlighted text, as illustrated in Fig. 3 (3). This allows users to extract a topic or information they find worth exploring further at a later time (C2) and position it at the desired location for organization (C3).

*Semantic Zoom [C4].* While LLMs enable us to retrieve answers instantly, the amount of text generated can be overwhelming. In Sensecape, users can use semantic zoom to manage this information overload. By default, users will see the generated response as is. Then, as the user’s zoom level changes (i.e., the user zooms in or out), the response will dynamically update, as shown in Fig. 7, to show keywords, for example, when users zoom out. This can be useful if many nodes are on the canvas and a user needs to identify connections among the nodes. If they want to manually set it to any semantic zoom level regardless of the zoom level, they also have the option. For example, they can select SUMMARY or KEYWORDS to see the summary version of the response or its keywords, respectively. This can be useful, for example, if they ask multiple questions to

LLM and several responses are generated and are too long for the user to process. After Sensecape fetches the response from LLM, it feeds the response back to LLM and prompts it to return the response at different levels of detail – (1) LINES: response with multiple paragraphs/lines summarized into summaries of each; (2) SUMMARY: response with the entire response summarized into one paragraph; (3) KEYWORDS: response with the entire response abridged into keywords. By default, the semantic zoom – set at AUTO – changes the level of detail depending on the zoom level. For example, as the user zooms out, the semantic level progresses to the less detailed (e.g., ALL → SUMMARY → KEYWORDS) and reverts to the more detailed semantic level as the user zooms in to node (e.g., KEYWORDS → SUMMARY → ALL).

*Semantic Dive [C5].* When users find the current working canvas too cluttered or a node they would like to explore further in a separate canvas, they can quickly *dive* into that canvas by double clicking the node. When users double click the node, it transforms into an ellipse-shaped *portal* node and takes them to a canvas layer below the canvas they were in. In other words, Sensecape creates an empty canvas layer for exploring that topic and pulls the user into that layer. Thus in addition to being able to manually add the canvas layer in the hierarchy view, they can also do so in canvas view by performing *semantic dive* on any node.

**3.2.2 Hierarchy View [C5].** The hierarchy view (Fig. 5) offers a holistic view for users to identify where they are and what they are exploring in the context of the overall information space. It provides an overview of the information space and allows users to reflect on the relation between the canvases and navigate to them. At the same time, it is a way for users to address the visual clutter on their canvases, as zooming out from the canvas view into the

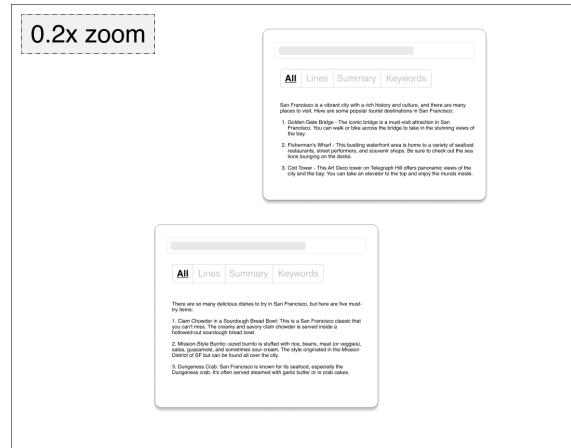


**Figure 6: Semantic dive:** Users can (1) dive deeper into the topic by double clicking on the node. (2) Surrounding elements are pushed away as the selected node is carried into a lower level canvas. In this new canvas, users are (3) automatically recommended subtopics of the topic dove into. Semantic dive also updates the hierarchy view, creating a lower level canvas matching the action in Figure 5 (C).

hierarchy view allows users to abstract and transform the content in each canvas into a more manageable form of representation (C5).

*Adding & Deleting Higher and Lower Level Canvas [C5, C6].* Users can construct their hierarchy by adding and deleting canvases. Users can add a higher-level topic canvas by clicking the BROAD TOPIC button shown in Fig. 5 (A), and users can add lower-level subtopic canvases by clicking the shadow underneath the canvases. On hover, the subtopic button reveals two options for users to add either a custom subtopic or a subtopic generated by LLM, as shown in Fig. 5 (C) and (D) respectively. Users can remove canvases and entire canvas branches to prune their exploration space. By allowing users to add and edit canvases in the hierarchy view, users can (C5) assign relations between canvases and (C6) simultaneously build their exploration and sensemaking space.

*Creating New Hierarchy [C6].* In addition to expanding upon the current hierarchy, users can form new hierarchies as shown in Fig. 5 (B). This new hierarchy can be expanded with the same construction methods shown in the same figure. Users can also create connections between hierarchies by adding a higher-level topic canvas. Once a higher-level topic canvas is added, Sensecape adds arrows from the higher-level canvas to each hierarchy to form a single hierarchy.

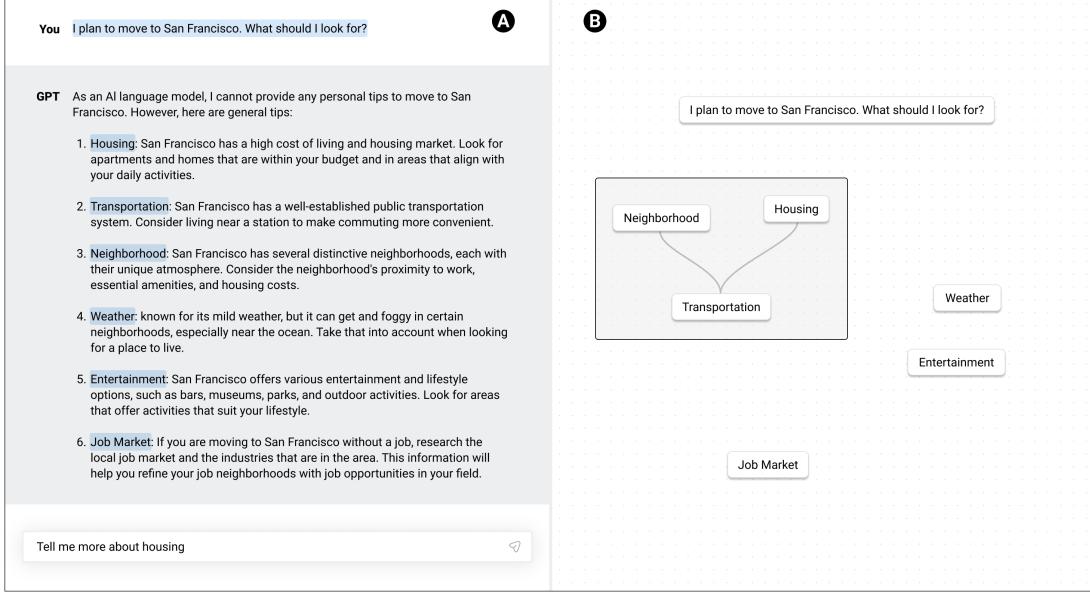


**Figure 7: Semantic zoom** allows users to control the granularity of the information. When they zoom out (e.g., 0.2x) to see multiple nodes on canvas, the text in each node can be overwhelming and difficult to read, as shown in (a). In Sensecape, users can set the semantic level to, e.g., keywords level, to manage information overload and help users identify and connect key topics within nodes, as shown in (b).

### 3.3 Implementation Details

Sensecape is a web application developed with React. The canvas was implemented using Reactflow, an open-source library for building diagramming applications.

Sensecape's generative chat feature used OpenAI's 'gpt-3.5-turbo' model, while all other LLM-based features used 'gpt-4'. The 'gpt-3.5-turbo' model was specifically used for chat responses as it generated content faster than 'gpt-4'. All other LLM-based features prioritized accurate interpretation of our prompts (e.g., to generate the most relevant subtopics of a topic). Thus we used the 'gpt-4' model. The prompts used to generate the responses are shown in Table 1 in Appendix.



**Figure 8: Baseline interface:** (A) conversational interface resembling OpenAI’s ChatGPT interface allowed participants to ask questions and issue prompts; (B) canvas view allowed participants to create, group, and connect nodes with edges. Participants could highlight any text in the conversational interface and click or drag the text to add them to the canvas.

## 4 USER EVALUATION

To evaluate whether Sensecape supports exploration and sensemaking, we conducted a within-subject study. Specifically, we aimed to answer the following questions:

- RQ1. Does Sensecape support exploration?
- RQ2. Does Sensecape support sensemaking?
- RQ3. What is the perceived utility of Sensecape’s features?
- RQ4. How do people see Sensecape being useful in their everyday knowledge work?

### 4.1 Conditions

To evaluate the usefulness of the features and interactions that we introduce, we set our Baseline interface to be an integrated environment with a conversational interface and canvas. As shown in Fig. 8, it had a conversational interface resembling ChatGPT in the left half of the interface and a canvas with diagramming features on the right. Users could interact with the conversational interface in the same way as they would with ChatGPT’s interface. The canvas on the right side served as a note-taking area. They could easily add parts of the text generated by LLM in the conversational interface region by highlighting text (including their prompt), clicking the highlighted text, or dragging it out to add the node containing highlighted text to the canvas on the right. Baseline lacked the hierarchy view and had only basic diagramming functionalities such as adding, grouping, and connecting nodes. Sensecape users could use these basic diagramming functionalities in addition to the hierarchy view and features (e.g., semantic zoom) described in Section 3.

*Design Rationale for Baseline.* Our initial Baseline had ChatGPT and Miro side by side – the setup described in Section 3.1 – instead

of the *integrated* environment described above. We made the change because our pilot study made it clear that it was a significantly weak setup to compare against. Since participants had to transfer all the text from ChatGPT to Miro, whereas Sensecape users did not have to, it was difficult to evaluate the effectiveness of the features introduced in Sensecape. Thus, we developed the Baseline interface so that the difference we test is the new features and environment.

### 4.2 Tasks

Participants were asked to use Sensecape and Baseline to explore two topics: (A) IMPACT OF AI ON THE FUTURE OF WORK and (B) IMPACT OF GLOBAL WARMING ON ECONOMY. The order of the system and topics was counterbalanced – hence 4 (= 2 x 2) conditions – to minimize the order bias. They were instructed to imagine that they have to give a talk on the topic in two weeks and are using the system to explore the topic and document what they find. To encourage them to organize the collected information, they were told that they would meet with colleagues in the coming week to plan the talk and share the canvas and hierarchy they populated on Sensecape. (Full instruction in Supplementary Material.)

### 4.3 Procedure

After completing the consent form, participants answered demographic questions on a pre-study survey. Then they engaged in two tasks. Depending on which condition they were assigned to for each task, they used Sensecape or Baseline to explore one of the aforementioned topics. Each task required participants to complete a pre-task survey, pre-task exercise, task interface tutorial, task, and post-task survey. The pre-task exercise had two purposes: (1) to assess their prior knowledge of the topic and (2) to help them become

familiar with basic diagramming functionalities. Participants were asked to use Sensecape's canvas view with only basic diagramming functionalities – add, edit, group, and connect nodes with edges – to list any related topics they know or questions they are interested in exploring. After this exercise, they watched the system (Sensecape or Baseline) tutorial and engaged in practice tasks to learn how to use the assigned system. Then they engaged in the task (Section 4.2) with the assigned system for 20 minutes and then answered a post-task survey to assess its usefulness. After participants completed the two tasks, they completed the post-study survey, where they were asked to specify which system they prefer and rate the usefulness of features in Sensecape. Lastly, they engaged in an interview to elaborate on their experience and the reasons for their responses. Throughout the study, participants were asked to think aloud. The study was screen recorded for accurate transcription and analysis of their exploration and sensemaking processes. They received a \$30 gift card for participating in this 1.5-hour study.

#### 4.4 Participants

We recruited 12 participants (age:  $M = 26.9$ ,  $SD = 4$ ; gender: 4F, 7M, 1 Prefer Not to Say) from a local R1 university and via mailing list. They had various backgrounds, including computer science, industrial design, neuroscience, and engineering. Most participants (9 A Lot, 3 Some) had much experience researching complex topics (“searching and making sense of lots of information”). They varied in their experience using online whiteboarding tools (3 A Lot, 6 Some, 3 None) and interacting with / prompting generative AI models such as ChatGPT, new Bing, and DALL-E (4 A Lot, 6 Some, 2 None). Most participants (2 A Lot, 9 Some, 2 None) had experience drawing concept maps, mind maps, or knowledge diagrams.

#### 4.5 Measures

To observe and analyze the differences in exploration and sensemaking behavior, and perceived utility of suggestions, between Sensecape and Baseline systems, we used the following measures.

**4.5.1 Exploration Measures.** The search-as-learning and information retrieval communities have consistently used the number of domain-specific terms and the number of nodes in a mind map or knowledge structure as measures for information exploration [58, 64]. Following these practices, we used three measures for exploration: (1) *number of prompts issued*; (2) *number of nodes* created in the knowledge structure; (3) *number of concepts* – the number of unique, relevant, domain-specific concepts on the canvas.

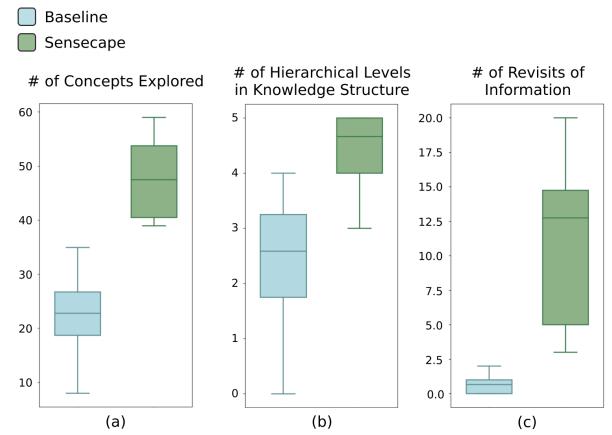
**4.5.2 Sensemaking Measures.** Prior literature [58] and the Sensemaking Model by Pirolli and Card [43] agree that organizing information into schema is an essential step in the sensemaking process. From a cognitive process perspective, this process of structuring information into knowledge hierarchy requires comparing, contrasting, and differentiating new and existing information – all of which involves revisiting information previously interacted with. Consequently, we used two measures to assess sensemaking. The first is the *number of hierarchical levels* in the knowledge structures. In the Sensecape condition, this included levels of hierarchy on both the canvas and hierarchy views, which allowed us to understand not only the number of concepts explored, but also how participants

conceptualized the relationships between concepts. In the Baseline condition, this was the number of levels in their concept maps. The second measure was the *number of revisits* to previous topics. In the Baseline condition, this included scrolling up to read previous chats or clicking and editing parts of the concept map that they had created with previous interactions. In the Sensecape condition, the same interactions were considered.

**4.5.3 Perceived Utility Measures.** To understand the perceived utility of Sensecape's features, we used responses to the post-study survey and interview as measures. For example, this included responses to questions asking for their agreement (1: Strongly Disagree; 5: Strongly Agree) with statements, such as “The hierarchy view is useful for making sense of complex information.”

### 5 RESULTS

In this section, we report the findings from analyzing participants' survey responses, think-aloud, and system usage logs to: understand how Sensecape might support exploration and sensemaking and how participants perceive the utility of its features and Sensecape for their everyday knowledge work.



**Figure 9: When using Sensecape, participants (a) explored more concepts, (b) structured their knowledge representations more hierarchically, and (c) revisited information they had previously interacted with more frequently.**

#### 5.1 RQ1. Does Sensecape support exploration?

Analysis of system usage logs shows that participants issued a similar number of prompts in both the Baseline ( $M = 5.8$ ,  $SD = 2$ ) and Sensecape conditions ( $M = 7.3$ ,  $SD = 5.2$ ),  $t(11) = 0.9$ ,  $p = 0.37$ . They also created a similar number of nodes in their knowledge structure: Baseline ( $M = 23.5$ ,  $SD = 8.3$ ) and Sensecape ( $M = 26.8$ ,  $SD = 10.1$ ),  $t(11) = 0.8$ ,  $p = 0.45$ . And made a similar number of connections in their knowledge structure: Baseline ( $M = 15.8$ ,  $SD = 9.3$ ) and Sensecape ( $M = 14.3$ ,  $SD = 8.5$ ),  $t(11) = 0.4$ ,  $p = 0.72$ .

However, when using Sensecape, participants explored significantly more concepts ( $M = 68.3$ ,  $SD = 49.1$ ) than when using the Baseline system ( $M = 22.8$ ,  $SD = 7.7$ ),  $t(11) = 3.1$ ,  $p = 0.01^{**}$  (see Fig. 9a).

This suggests that the participants got more information out of issuing a similar number of prompts. P10 described the content of their responses as “*presenting the littlest amount of information with the most punch*”. P12 said, “*I definitely would use [Sensecape] to explore a complex topic because it helps me answer questions, generate content, and helps me automatically lay it out to make sense of.*” Many participants found expand bar features such as subtopic generation and question generation “*very helpful*” in supporting their exploration, as they helped “*articulate information needs better*” (P7) and “*know about concepts or terms [to explore next]*” (P1). P7 explained: “*If I were looking on my own, I would not know what to look for. I would Google, I would find an article, then look at multiple articles, and try to pick out common subtopics from there.*”

## 5.2 RQ2. Does Sensecape support sensemaking?

When using Sensecape, participants structured their topic knowledge more hierarchically ( $M = 4.3$ ,  $SD = 1.2$ ) by adding more hierarchical levels to their knowledge representations than when using the Baseline system ( $M = 2.6$ ,  $SD = 1.6$ ),  $t(11) = 2.7$ ,  $p = 0.02^*$  (see 9b). P9 stated, “*you can focus your attention on one specific subtopic and dive deeper into each subtopic in a natural way*”, showing that Sensecape provided the participant with a more conducive environment to structure their thinking. P5 said, “*it helps me identify connections between topics and reflect on them. This is really helpful to see my knowledge at different levels.*”

Participants also revisited information they had previously interacted with (either as a prompt or in their knowledge representation) more when using Sensecape ( $M = 12.8$ ,  $SD = 10.9$ ), compared to when using Baseline ( $M = 0.7$ ,  $SD = 1$ ),  $t(11) = 3.8$ ,  $p = 0.00^{**}$  (see 9c). P11 stated, “*I actually have that hierarchy in my mind, and it's actually better to remind me what I have done.*” P3 talked about how Sensecape helped her “*easily move from one level to another and better follow [her] structure of thinking and come back to it, to reflect on.*”

The participants also felt that Sensecape helped structure their thoughts. P8 liked the way it “*helped [him] structure [his] thinking*” and “*everything is automatic*” and he does not “*need to manually organize the information.*” P7 also highlighted this by comparing Sensecape with commercial softwares Miro and Google doc:

*“I think it helps a lot that each subtopic has its own canvas, but when you are in the hierarchy view, you can still see the subtopics listed within that canvas. This is nice because when it comes to a Miro board, it can get very confusing pretty quickly, so it's nice that each level of information has its own page in Sensecape. On Google Doc, if all the information is set just linearly from top to bottom, it can be hard to find information in the middle. Here you get a sense of where ideas are connected in relation to one another because you're able to lay out things spatially rather than being forced to put things in a linear top to bottom order.”*

## 5.3 RQ3. What is the perceived utility of Sensecape’s features?

We analyze responses to the post-study survey and interview to review the perceived utility of Sensecape’s features.

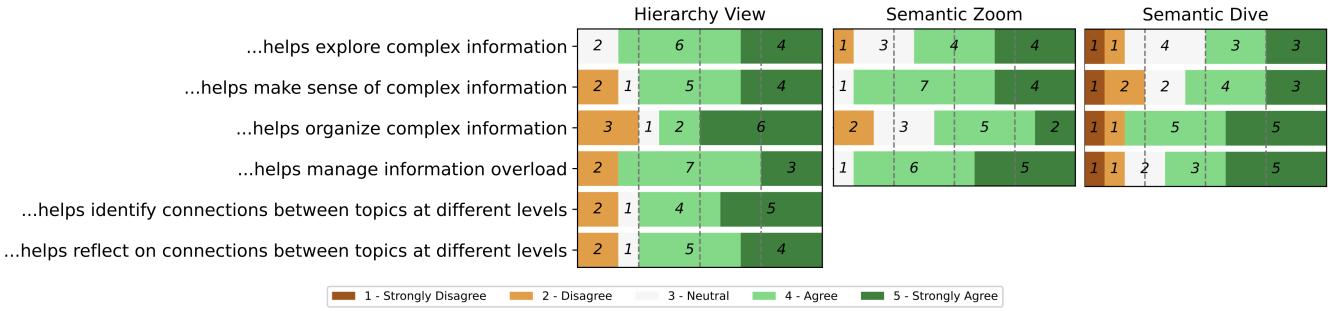
**5.3.1 Expand Bar.** The expand bar allowed users to seek information using PROMPT, EXPLAIN, QUESTIONS, or SUBTOPICS prompts. On average, participants used the expand bar 7.25 times ( $SD = 5.15$ ) during the study. They used PROMPT 4 times ( $SD = 4.26$ ), EXPLAIN 3.41 times ( $SD = 4.52$ ), QUESTIONS 0.41 times ( $SD = 0.52$ ), and SUBTOPICS 3.83 times ( $SD = 5.27$ ).

P7 used the EXPLAIN prompt to “dive deeper.” He said: “*when you generate a subtopic, you can simply click EXPLAIN versus writing the prompt, to say, oh ‘jobs rotation’ maybe it is something I should look more into.*” P3 found the QUESTIONS prompt gave an overview of the topic, saying: “*I like that it generates questions and gives me an overview on the topic... I struggle to get a big picture of the topic, but with the generated questions I can dive into many different aspects.*” P7 noted that the SUBTOPICS prompt taught him new ways of exploring and articulating his information needs: “*without the prompt for generating subtopics, I might not have thought to do that. But now that I've been exposed to [Sensecape], I think I would know to ask this to generate more information or more ways of articulating information needs.*” Similarly, P3 said the SUBTOPICS prompt is “*great to have because it allows you to get that breadth faster.*”

**5.3.2 Text Extraction.** To help break down the generated responses, participants chose to extract and curate parts of the response, on average, 6.25 times per session ( $SD = 5.65$ ). Most participants used this feature to organize the information and their thinking. P6 said, “*system helped me structure my notes and thinking because of the ability to drag and drop and then organize things spatially on a 2D plane.*” They further explored these extracted parts of the response, on average, 4.2 times per session ( $SD = 3.97$ ). This ability to follow up helped P6 dive deeper to explore more. P6 said it “*helped [her] dive deeper into the subtopics within the topic and allowed [her] to continue asking follow-up questions.*”

**5.3.3 Semantic Zoom.** On average, participants used semantic zoom 12.58 times per session ( $SD = 8.92$ ) to manage the information overload from generated responses. When asked to rate the effectiveness of this feature on Likert-type statements, almost all participants agreed that it helped them explore complex information, make sense of, organize, and manage complex information, as shown in Figure 10. P3 explained her rating: “*it does allow you to manage information overload because it offers different levels of granularity. You can identify keywords, but also structure information in the summary or in the lines. By traveling across the two, you can get an idea of the complex information.*” Similarly, P11 said, “*it did not really directly help me organize, but it gave me some of the views and ideas on how to organize.*”

**5.3.4 Semantic Dive.** On average, participants used the semantic dive feature 6.58 times per session ( $SD = 5.12$ ). Most participants agreed that the semantic dive feature helped them explore complex information, make sense of, organize, and manage complex information (see Figure 10). P7 found this feature helped them navigate easily: “*I think it helps a lot with organizing complex information since you can flow directly between subtopics... versus having to go back out to the hierarchy and back into the topic.*” P9 identified a trade-off, saying that “*you can focus your attention on one specific subtopic and dive deeper into each subtopic in a pretty natural way. But that might also cost your cognitive load and attention.*”



**Figure 10: Evaluation of Sensecape’s features**

**5.3.5 Hierarchy View.** Participants visited the hierarchy view, on average, 6.33 times per session ( $SD = 5.26$ ). Moreover, participants agreed that the hierarchy view helped them explore complex information, make sense of, and manage complex information. It was also helpful in helping them “*identify and reflect on connections between topics at different levels*” (P11). Most participants strongly agreed that the hierarchy view helped them manage the information overload (see Figure 10). Additionally, as mentioned in Section 5.2, participants structured their thinking and topic knowledge more hierarchically in Sensecape using this view. P6 explained, “*I really like the ability to zoom out of certain canvas. I feel that it helped me organize an even more complex topic than what I have already seen before in other mind mapping tools or relational graphics. The ability to see how each canvas is zoomed out and related with that 3D view was refreshing to me.*” Additional benefits of the hierarchy view included making the explored information easier to “remember” (P11) and motivating exploration into the information space the user has not visited yet. P5 said that seeing the hierarchy view taught him “*how to search, what to search*” and “*motivate[d] [him] to search more and explore more complicated information*.”

#### 5.4 How do people see Sensecape being useful in their everyday knowledge work?

To understand how Sensecape might be useful in complex information work outside of the bounds of the evaluation study, we asked participants from diverse fields of knowledge work how they might imagine using Sensecape in their work. Four of the participants identified as Researchers, 4 as Designers, and 4 as Engineers. An analysis of post-study interviews found that participants wanted to use Sensecape in several ways for their knowledge work. We discuss them in this section.

**5.4.1 To explore and learn about new topics.** Most participants talked about how Sensecape’s features could help them explore and learn about new, complex topics in their everyday work. For example, Machine Learning Engineer P8 said, “*as an engineer, I sometimes need to do something that I didn’t know how to, I need to learn some new fields or a new technique. And this is a very good tool for me to explore a new concept. Especially with the hierarchical view, I can navigate the topic much better, and it saves me a lot of time.*”

**5.4.2 To generate novel ideas and develop them.** Some participants talked about how Sensecape could help them generate ideas and

develop them. Researcher P3 spoke about his experience starting a new project in a new domain and how Sensecape might help find relationships between two seemingly disconnected topics: “*it was challenging for me at first to find a specific topic [for my research]. I knew I wanted to work on invisible illness or chronic illness or disabilities, and I had to tie it in with a piece of pop culture. But I don’t watch so much pop culture, and then I didn’t know how to tie that into invisible illness. But I could have used this and it could have helped generate ideas. And then, after getting the broad topic, being able to organize it according to subtopic would’ve been nice. Because in one giant linear block, it was really hard to reason with it or see how the argument is laid out. So I think the system with the hierarchy view will be very helpful with that. It would’ve also helped me find keywords to look into.*” Researcher P1 echoed how this might also be useful in a collaborative setting: “*It’s easier to generate ideas, even with collaborators, because it’s easy for people to point and say, ‘I don’t think it makes sense’, ‘this concept is related to this picture’, or ‘maybe we should add this in this layer’*”

**5.4.3 To collaborate: share understanding.** Modern knowledge work is often collaborative. Although collaboration has benefits, effectively coordinating work in a team can be challenging. Collaborators must spend time dividing and assigning search goals and tasks, locating, sharing, and synthesizing information to create a shared mental model [52]. Challenges may include repeated work across collaborators, confusions about the process and resultant understanding [9, 52].

Researcher P1 wanted to use Sensecape to share understanding and their exploration process with their research collaborators: “*In our research meetings, many times we have to share what we have explored so far in our project. The way we’ve been doing it is mostly using a document where the information is linearly presented. Having [Sensecape’s] visual structure to the knowledge, it’ll be easier to guide the discussion. It might also be easier for the other group members to make sense of the overall topics of our discussion.*”

**5.4.4 To collaborate: share process and hand-off.** Designer P7 shared, “*the web app I’m building has become very complex. So onboarding new software engineers to the project has become very hard. So say, I’m onboarding new engineers and I want to show how one part of the system is designed and the process we used to build it. Then, I think this would be very helpful for showing the connection to the other parts of the system and diving deeper into the specifics of each part.*”

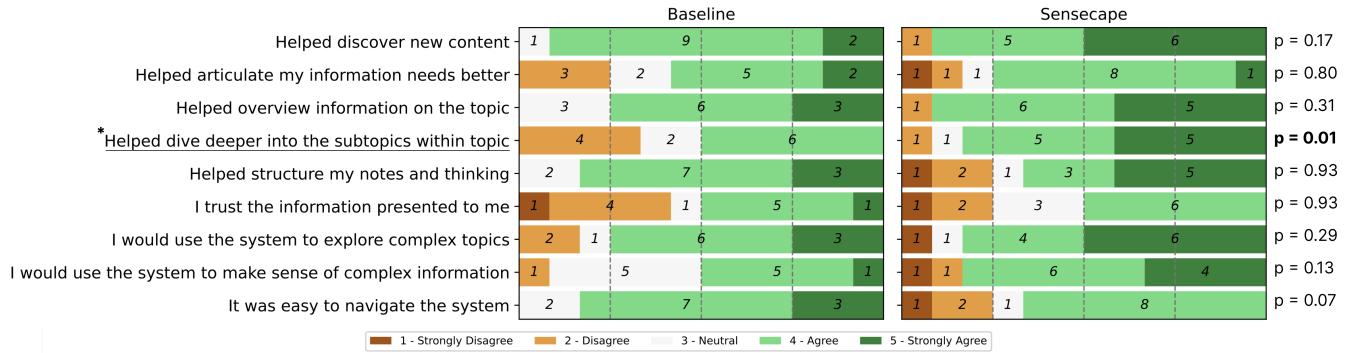


Figure 11: System evaluation results. Statistical significance ( $p < 0.05$ ) is marked with \*.

## 5.5 Participants Preferred To Use Sensecape for Deeper Understanding of a Topic

At the end of the study, participants were asked which system they preferred using – Baseline or Sensecape. All 12 participants preferred Baseline and Sensecape over linear interfaces without an integrated note-taking area like ChatGPT. Seven of the 12 participants reported that they generally preferred Sensecape to work with. Nine out of the 12 participants preferred to use Sensecape to gain a deeper understanding of a topic. To get a broad understanding of a topic, 6 out of 12 participants preferred using the Baseline and 1 had no preference, while 5 said they preferred Sensecape.

In a post-study survey about participants’ opinions about the two systems, they thought the Sensecape system helped them significantly more than the Baseline to ‘dive deeper into subtopics within a topic’. Participants reported that the Baseline was marginally easier ‘to navigate.’ (The p-values from Wilcoxon signed-rank tests for the statements are reported in Fig. 11).

Overall, the interview revealed that each system may be more useful for certain contexts for some participants and that the flexibility to switch between the two may offer benefits to users. P10 said, “[For getting a] broad overview, [Baseline] would help more, while [for] deeper understanding, [Sensecape] would help more.” They reasoned that on Sensecape, they could explore deeper into suggested keywords and would be able to “work in more complex environments.” Many mentioned that one of the trade-offs is the learning curve versus the complexity of the task they were working on. Participants who preferred Baseline mostly cited the steep learning curve as the reason. P4 said, “The more advanced features can get more complex things done and much faster, but getting used to them can take some time.” Similarly, P12 said, “the learning curve [for Sensecape] is a bit high compared to [Baseline]. So I probably prefer [Baseline] but I can imagine that if there’s a huge information that need to be digested, [Sensecape] would be really useful.”

## 6 DISCUSSION

### 6.1 Summary

In this work, we explored how we can leverage LLMs to support complex information work by developing Sensecape, an interactive system designed to support information exploration and sensemaking in a structured manner. The user evaluation study found that

Sensecape enables users to discover more topics and explore more broadly compared to Baseline thanks to the many features that support exploration through an instant generation of subtopics, questions, explanations, and prompting. Sensecape’s expand bar supports the wide variety of prompts and responses users need to explore information productively. For example, when users perform semantic dive, Sensecape instantly recommends subtopics to give the user a head start rather than leaving them with a blank slate, addressing the common challenge people with little knowledge of the topic experience when searching [37].

Furthermore, Sensecape supports participants in developing a deeper understanding of a topic. This is evidenced in their self-report and in the multiple levels of hierarchy in their knowledge representation. This may be because Sensecape enables users to externalize their sensemaking in a more nonlinear, hierarchical manner. On the other hand, the enhanced sensemaking and exploration seen when using Sensecape might be explained by *schema theory*, which states that explicitly forming links of new information to the learners’ knowledge and schema that they already possess can help them integrate new information into their schema [43, 62].

## 6.2 Limitations and Future Work

**6.2.1 Study Limitations.** When we introduce new technologies and tools, the novelty effect can bias people’s perceived usefulness of the introduced tools. At the same time, if people have a limited time with the tool, they might also not be able to fully assess its usefulness. This seemed to be true given a number of features in Sensecape and the complexity of learning how to think and organize information across multiple levels of abstraction – a mental maneuver that can be unfamiliar and challenging for some [54]. In fact, participants who preferred Baseline commonly cited the learning curve as the reason. While some participants, such as P1, who claim to apply hierarchical thinking to their everyday knowledge work, felt they used Sensecape productively, several participants stated that they could not fully learn and utilize all of Sensecape’s features within the given time frame. Interestingly, P11 said that if people were given more time (i.e., more than 20 minutes), they would realize the “need for the hierarchy view, to organize [their workspace] better.” To test this, a longitudinal study spanning a few weeks to months in a real-world setting should be conducted.

**6.2.2 Supporting Switching Between Linear and Nonlinear Interfaces.** With a greater degree of freedom, users can position objects in various ways in nonlinear interfaces. While this empowers users proficient in navigating them, it can have an unintended effect on users with less experience and skills. This was one of the observations in our study, as a few participants preferred the Baseline interface and found the option to leverage additional space (e.g., hierarchy view) rather overwhelming. While linear conversational interaction is also possible in Sensecape as it adds an input box below the generated response, users were still required to pan and position their view. If we want to accommodate users with varying needs and preferences, we may need to offer users the option to switch to Baseline where the interface (Fig. 8) is *locked in* to the left side of the interface. In fact, P5 alluded to the need for such an option, saying that for a topic he is unfamiliar with, he would like to use Baseline first to collect information, and then when he “reaches a particular familiarity, then [he] would move to [Sensecape]” and “abstract everything.”

**6.2.3 Supporting Collaborative Sensemaking.** A significant portion of our information gathering and sensemaking is done through interaction with others. For example, people ask questions and collect information and opinions from Q&A platforms such as Quora and communities such as Reddit. Sensecape, at its current implementation, is not designed to support collaborative exploration and sensemaking, but enabling such capabilities may open doors to discovering ways people can collectively explore and make sense of the information space through the collaborative construction of the knowledge hierarchy.

**6.2.4 Supporting Context-Aware Recommendations.** We envision various ways in which Sensecape can be augmented, especially with respect to intelligently supporting users during their exploration and sensemaking processes. For example, we can envision Sensecape analyzing content in users’ canvas and hierarchy and providing content-based recommendations and guidance. Examples of these recommendations can include suggesting potential subtopics or questions when users seem stuck and potential grouping and connections between existing nodes can be inferred. In the hierarchy view, Sensecape could suggest potential canvas layers while users browse or restructure the hierarchy to match the granularity of each canvas’ topic. This could extend existing work on context-aware recommendations for complex information work. Additionally, since most creative tasks are done across multiple application contexts, Sensecape could be extended to support complex information work across applications.

**6.2.5 Supporting Multiple Representations and Other Frameworks.** In Sensecape, we used a hierarchical representation to encode information. This is because hierarchy is a robust structure for representing knowledge and empowering seamless switching between divergent and convergent thinking inherent in exploratory and sensemaking tasks. While powerful, hierarchy is not the only structure for sensemaking. For example, a graph can more effectively reveal the similarity between information. Thus, in the future, enabling users to leverage more representations, e.g., graph, depending on the task may open up additional ways of facilitating exploration and sensemaking.

The spatial exploration in the hierarchy view, especially the ability to move up and down the levels of abstraction, is inspired by the abstraction ladder [23, 54, 59]. While Sensecape allows users to move between the overarching topic and its subtopics, there exist other forms of abstraction ladders that it does not yet support. For example, some abstraction ladders employ different representations in each level of abstraction (e.g., code  $\Leftrightarrow$  story  $\Leftrightarrow$  comic) [55, 56]. There are frameworks that list abstraction levels for specific fields such as computing (e.g., problem  $\Leftrightarrow$  object  $\Leftrightarrow$  program  $\Leftrightarrow$  execution) [1]. In the future, it would be interesting to extend this idea of navigating the information space in the 3D space to explore moving up and down the levels of abstraction that correspond to different representations and abstraction levels used in specific domains.

**6.2.6 Supporting Fact-Checking.** The LLMs’ tendency to “hallucinate” has been a large threat to their use for information-related tasks. Recently, researchers and industries have been exploring ways to address this. For example, Microsoft recently released its search engine, Bing, coupled with ChatGPT. To address the concern with ChatGPT returning incorrect facts, Bing included references to the information sources. Recent start-ups have also taken the same approach of adding references to information sources to address this concern. We believe that such a mechanism should be implemented in all LLM-powered systems that return factual information, and we considered adding it to Sensecape — such as adding links to top search results from the Google search engine. However, because the goal of our study was to test whether Sensecape facilitates exploration and sensemaking and how it may support other kinds of complex information work, we intentionally avoided adding this feature, as it adds an additional work and distraction during the search process and influences their experience and perception. Regardless, for Sensecape to be used in actual settings, there should be ways to check and know to what extent the LLM-generated information can be trusted.

### 6.3 Design Implications

The user challenges identified in this study and how we address them may have useful implications for designing future systems that support information tasks with LLMs. Some of these challenges may be specific to exploratory tasks (**C1. Slow Start**) and conversational interfaces (**C2. Hard to Revisit; C3. Lack of Structure**). However, they might still be valuable for instances where one is developing non-conversational but linear interfaces, such as timeline-based interfaces that leverage LLMs for information tasks. On the contrary, the challenges common to a wide variety of systems may be information overload (**C4. Information Overload**) and visual clutter (**C5. Visual Clutter**). While LLMs’ power comes from their ability to *instantly* generate high-quality responses, this also means they can generate a large volume of information that quickly exceeds our bandwidth for processing information. To take full advantage of LLMs, we may need techniques such as *semantic zoom*. Our study found that participants greatly appreciated features such as semantic zoom for managing information overload and making sense of complex information. We imagine a similar type of support tailored to given systems and domains will be essential for future systems supporting people’s complex information tasks with LLMs.

## 7 CONCLUSION

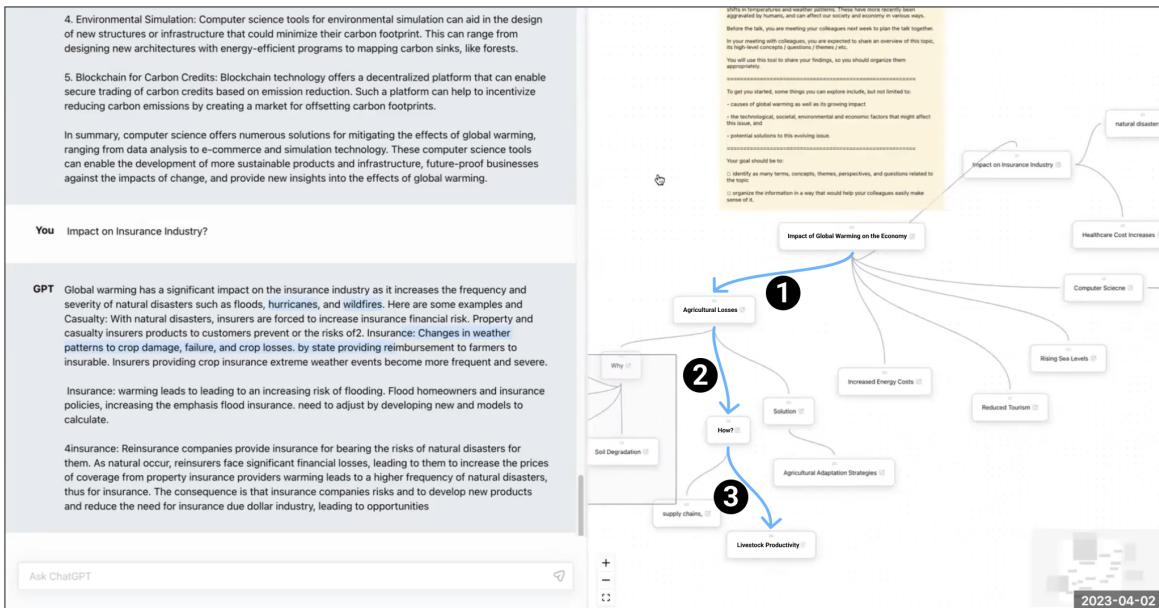
In this work, we introduced Sensecape — an intelligent interactive system that is powered by LLMs and supports structured information exploration and sensemaking. We use sensemaking theory and user studies of complex information work to ground the design of Sensecape. A user evaluation study found that Sensecape’s approach helps users explore more concepts, construct a deeper understanding, and revisit information more frequently to develop a holistic understanding of the complex information space. In addition to our contributions of Sensecape and the user study, our work shows that the externalization of multilevel abstraction motivates people to explore further and helps them with their exploration and sensemaking of the information space. As a whole, our work contributes an exciting first step to powering complex information workflows with large language models.

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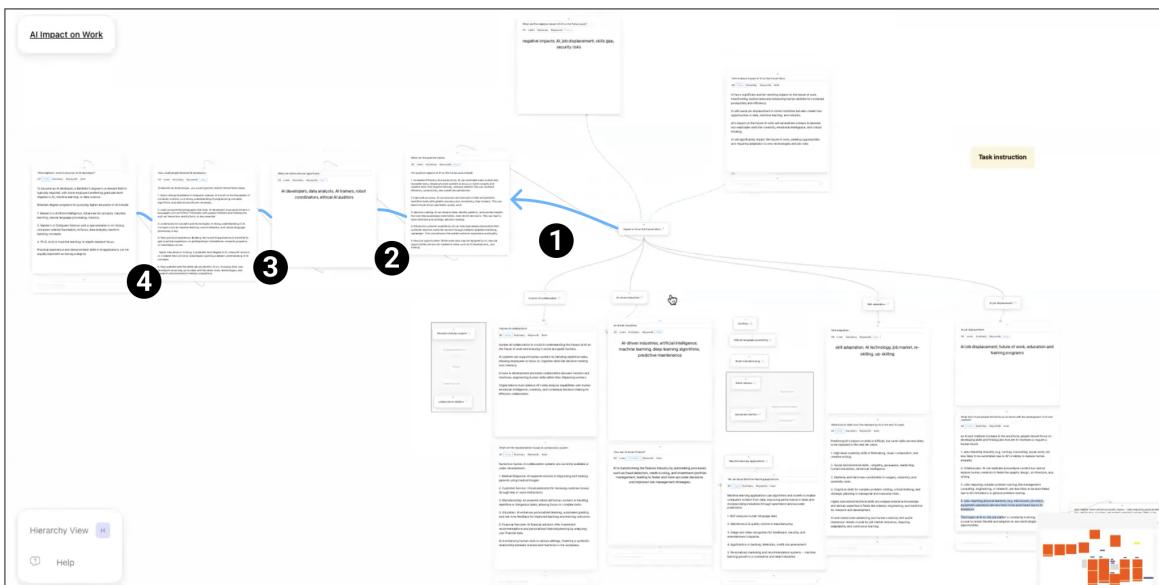
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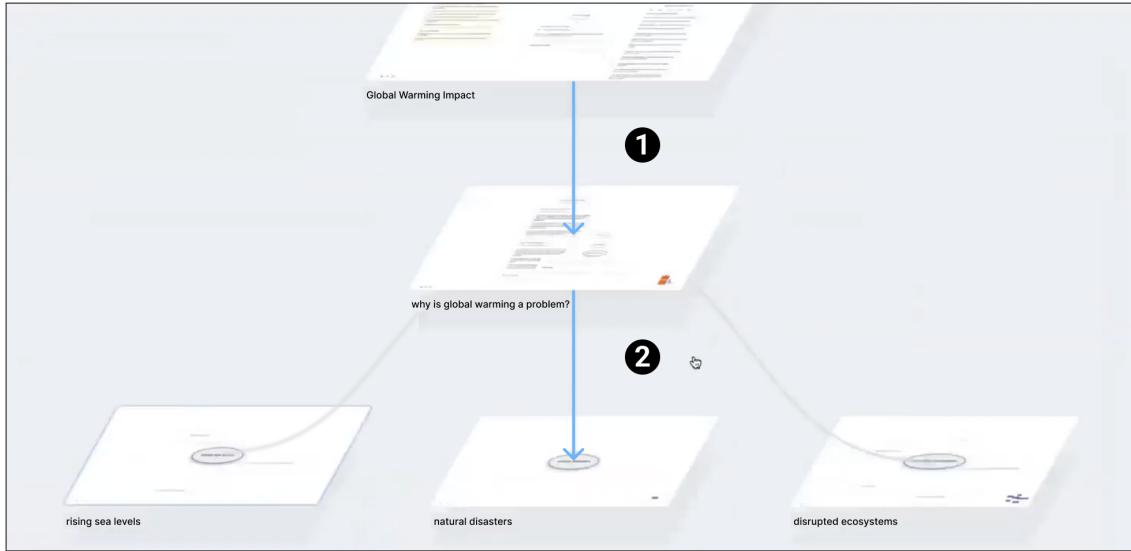
## A APPENDIX



**Figure 12: P11's Baseline canvas view:** this canvas displays P11's exploration – to discover the impact of global warming in the economy – also spreads to agriculture and livestock. P11 traverses through three levels to come to this discovery. The first traversal is shown (1) connecting ‘Impact of Global Warming on the Economy’ to ‘Agricultural Losses’. The second traversal (2) connects ‘Agricultural Losses’ to ‘How?’. Finally, the third traverse (3) connects ‘How?’ to the node ‘Livestock Productivity’.



**Figure 13: P12's Sensecape canvas view:** P12 dove deeper into learning about potential job opportunities in AI. After the participant follows up on the LLM's response three times, creating four traversals to new ideas and concepts, they take a step back to restructure their canvas. They orient their most recent conversation towards the left edge of the canvas shown as (1 - 4), to position the main topic at the center of all exploration.



**Figure 14: P3’s Sensecape hierarchy view:** P3 explored the impact of global warming by (1) diving into a question (“why is global warming a problem?”). With possible answers organized by subtopics, the participant (2) generated subtopics (“rising sea levels”, “natural disasters”, “disrupted ecosystems”) as answers to the question layer. During their exploration of global warming impact, P3 constructed a hierarchy with two levels to externalize her thought process.

**Table 1: LLM prompts used for each Expand Bar feature (Section 3.2.1)**

Prompt Type	Prompt	Example Input(s)	Example Response
QUESTIONS	I need to learn about {text}. Give me a total of 25 questions, with 5 questions starting with ‘why’, 5 questions starting with ‘what’, 5 questions starting with ‘when’, 5 questions starting with ‘where’, and 5 questions starting with ‘how’. Do not add numbers in front of the questions.	Moving to San Francisco	Why move to San Francisco?, Why is the cost of living so high?, Why is San Francisco known as the tech hub?, ... What areas offer great value for your money when you are looking for property prices?
SEMANTIC ZOOM: LINES	{line} If the text stated above is a paragraph, summarize it into a sentence. If the text is a bullet point or numbered list item, keep both the bullet point/number and main topic/term that represented the entire line, but just summarize the description into keywords.	3. Fisherman's Wharf is a popular place to visit for seafood in San Francisco	Fisherman's Wharf: Fresh seafood, fishermen, Pier 39
SEMANTIC ZOOM: SUMMARY	Summarize this text in 1-2 phrases: {text}	Fisherman's Wharf is a popular tourist destination located in San Francisco, California, USA. It is a historic waterfront district that dates back to the mid-1800s, when it was primarily a fishing village.	Fisherman's Wharf is a popular tourist destination in San Francisco. It was primarily a fishing village.
SEMANTIC ZOOM: KEYWORDS	Extract 3-5 of the most important keywords from this text in CSV format: {text}	Fisherman's Wharf is a popular tourist destination located in San Francisco, California, USA. It is a historic waterfront district that dates back to the mid-1800s, when it was primarily a fishing village.	Fisherman's Wharf, tourist, San Francisco, fishing village.
SUBTOPICS	Give me {numOfTopics} give or take {numOfMargin} new subtopics in the form of terms in 1 to 3 words each given this context: {context}. Format your response in CSV (comma separated values).	5, 0, Fisherman's Wharf	Pier 39, Street Performers, Seafood Restaurants, Historic Ships