

# Latent Lab: Large Language Models for Knowledge Exploration

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## Abstract

This paper investigates the potential of AI models, particularly large language models (LLMs), to support knowledge exploration and augment human creativity during ideation. We present “Latent Lab” an interactive tool for discovering connections among MIT Media Lab research projects, emphasizing “exploration” over search. The work offers insights into collaborative AI systems by addressing the challenges of organizing, searching, and synthesizing content. In a user study, the tool’s success was evaluated based on its ability to introduce users to an unfamiliar knowledge base, ultimately setting the groundwork for the ongoing advancement of human-AI knowledge exploration systems.

## Introduction

The untapped potential of collective knowledge holds significant implications for idea evolution and innovation across various entities (Curley and Salmelin 2013). Despite the digital revolution, information organization remains strikingly similar to traditional methods, limiting exploration across diverse sources and impeding the discovery of interconnected relationships. Current search approaches prioritize quick answers and display results in a list format. This hinders the discovery of interconnected relationships required for meaningful exploration and undermines the context of search terms by prioritizing keywords over semantics.

In contrast, synthesis tools like ChatGPT<sup>1</sup> offer a paradigm shift in user interface design through conversational interaction, though they have drawbacks such as the opaqueness of information sources and limited text-based interaction. This paper outlines the development of Latent Lab<sup>2</sup> and evaluates it in the context of the MIT Media Lab data set of 4,000+ research projects. This exploration tool surpasses previous search and synthesis tools by incorporating scanning and active visual interaction. Leveraging data manipulation libraries, interactive visuals, and LLMs, Latent Lab overcomes the constraints of keyword-centric search, allowing users to engage in semantically meaningful exploration and synthesis across diverse data sets. The iterative design process of the tool itself highlights the importance of

exploration in the creative process, offering a glimpse into the potential of AI-assisted idea generation.

We make the following contributions to the field of human-AI interaction systems.

- We present the design and implementation of an interactive knowledge visualization tool, including a novel automated technique to label idea clusters using an LLM.
- We report the results from a user evaluation study, demonstrating the utility of a hybrid search/synthesis system to find meaningful insights and connections often missed by traditional search and synthesis tools.

## Related Work

### Knowledge Organization

Vannevar Bush’s memex laid the foundation for hypertext and associative indexing (Bush 1945). Richard Feynman’s triangulation method emphasized understanding relationships between concepts (Feynman, Gottlieb, and Leighton 2006). These ideas influenced the development of Google Knowledge Graph (Carr 2007). Our approach to knowledge organization builds on these works to enable fluid exploration of linked information.

### Information Visualization

Shneiderman’s taxonomy established information visualization principles, with the “overview, zoom and filter, details-on-demand” mantra guiding the design of visual interfaces for interacting with large data sets. (Shneiderman 1996). Bostock et al. presented D3.js for interactive visualizations (Bostock, Ogievetsky, and Heer 2011). Heer and Shneiderman highlighted the importance of interaction in visual analysis (Heer and Shneiderman 2012). Our work integrates these principles to create an informative interface for users.

### Information Retrieval

Spärck Jones introduced the tf-idf weighting scheme for keyword-based search (Spärck Jones 1972). Mikolov et al. proposed the Word2Vec model for embedding-based search (Mikolov et al. 2013). Devlin et al. developed the BERT model, which further improved semantic search (Devlin et al. 2018). Latent Lab extends this work by leveraging embedding-based search to provide users with relevant results in complex information landscapes.

<sup>1</sup><https://chat.openai.com/>

<sup>2</sup>Try Latent Lab at <https://latentlab.ai/>

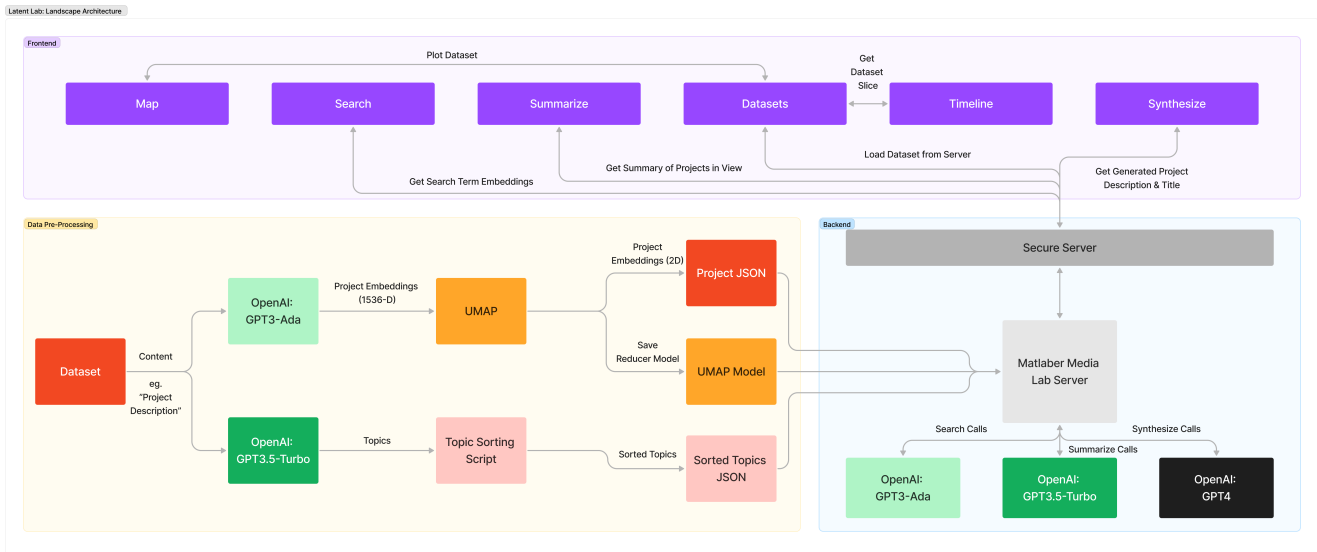


Figure 1: System Architecture of Latent Lab

## Human-AI Collaboration

Minsky’s Society of Mind proposed human intelligence as a result of interacting agents (Minsky 1988). Influential works that consider humans and intelligent systems as interacting agents include TRIZ, Polya’s work on invention, and Weis and Jacobson’s DELPHI framework (Weis and Jacobson 2021; Polya 1945; Altshuller 1999). Our work further examines human-AI collaboration, aiming to create a system that amplifies human capabilities and positions AI as a “copilot” rather than an “autopilot.”

## Methods

### System Overview

Latent Lab is an AI-powered knowledge exploration system. High-dimensional unstructured data is condensed and visualized in an interactive 2D map. The interface allows users to explore labeled clusters of similar topics, search by semantic context, and synthesize new ideas.

### System Architecture

The system, designed for performance and scalability, utilizes Fast API<sup>3</sup> and Python, for the back end, while the front end employs Vercel<sup>4</sup>, Next.js<sup>5</sup>, React<sup>6</sup>, and TypeScript. The initial approach was to execute all operations on the front end. However, due to the absence of a fully JavaScript-supported version of UMAP (McInnes, Healy, and Melville 2018), we decided to incorporate a back end server. This also facilitated server-side rendering to expedite data set loading. See Figure 1 for the system architecture diagram.

<sup>3</sup><https://fastapi.tiangolo.com/>

<sup>4</sup><https://vercel.com>

<sup>5</sup><https://nextjs.org>

<sup>6</sup><https://reactjs.org>

## Data Processing

The data processing pipeline is mostly automated and runs independently of the web app back end for each new data set. It generates three primary artifacts:

- A project JSON containing the unstructured data and embedding data for mapping every project on the front end
- A sorted research topics JSON containing all topics produced by the pipeline, ordered by topics with the most associated projects, used for the labels on the front end
- A pickled UMAP model to reduce project and topic embeddings to 2 dimensions on the back end

## Topic Extraction

Latent Lab’s automated topic extraction feature sets it apart from other embedding visualization tools, which don’t provide insights into cluster meanings. The system uses GPT-3.5-Turbo to distill topics for each project, count occurrences of unique topic labels, and identify related projects. It then calculates label positions using the centroid of the UMAP-reduced coordinates for each associated topic.

## Components

The Latent Lab interface has four main components, shown in Figure 2. It includes a Map Visualization, Generation Workbench, Search Bar, and Timeline Slider.

## Map Visualization

The main visualization displays an organized map of project data, with dots representing research projects and clusters indicating semantic similarity. Dot colors correspond to different Media Lab groups and can be customized to represent other discrete data set attributes.

Contour lines in the map indicate data density within clusters, a concept borrowed from topographic maps where they

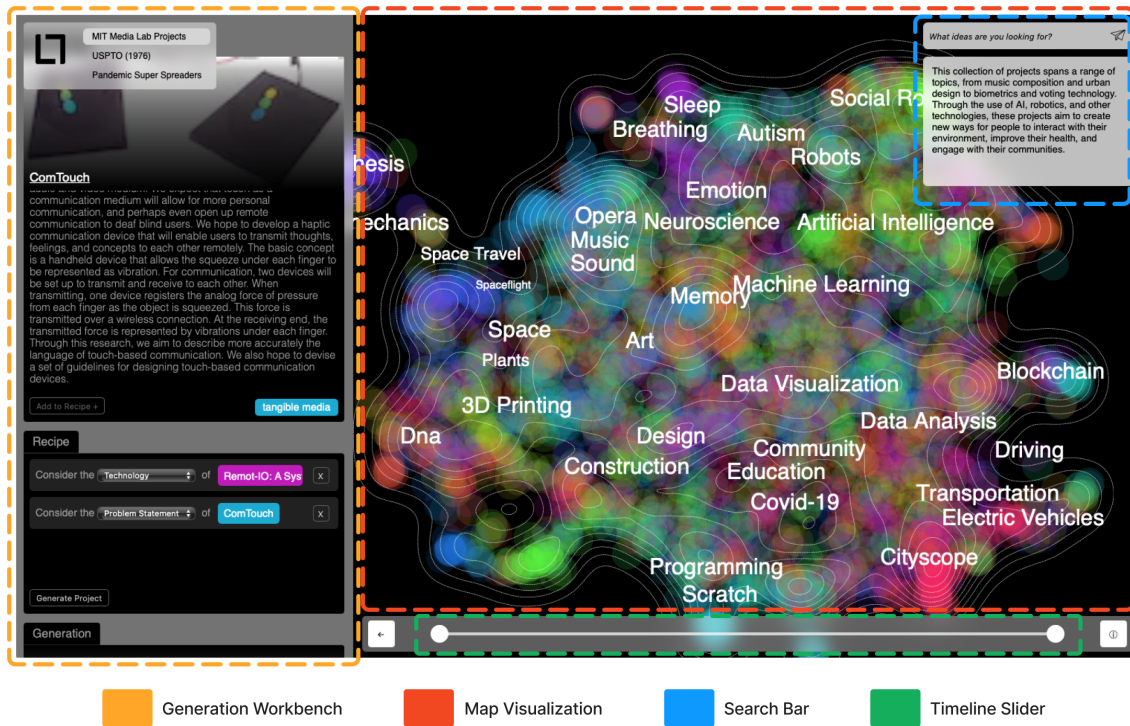


Figure 2: Latent Lab Interface, Annotated to Differentiate Between Components

represent elevation. Paired with the timeline, the changing contour lines reveal the evolution of research concentration.

Users can pan and zoom, uncovering varying levels of information. High-level labels and contour lines are shown at the highest zoom level, while sub-topic labels and project details appear when zooming in. An occlusion algorithm determines label visibility based on popularity and bounding box overlap.

### Generation Workbench

Latent Lab’s Generation Workbench allows users to create a “recipe” for collaboratively synthesizing new research project ideas. Users can choose whole projects or specific aspects, such as community, problem statement, or technology, to include. After designing the recipe, selecting “generate” submits a preset prompt with selected project elements to GPT-4 via the OpenAI API, producing a synthesized project title and description. Users can view the exact prompt by clicking the “What was used to generate this?” information button. See Figure 3 for the user flow diagram.

### Search & Summarization

Latent Lab employs embedding-based search for semantic meaning instead of simple keyword-matching, enabling more intuitive project exploration through contextual relationships. When a user searches, the query is sent to the back end server, and the GPT-Ada API returns a 1,536-value embedding. This is passed to the UMAP reducer, yielding x and y coordinates, which are sent to the front end to dynamically zoom and highlight the relevant map region. Figure

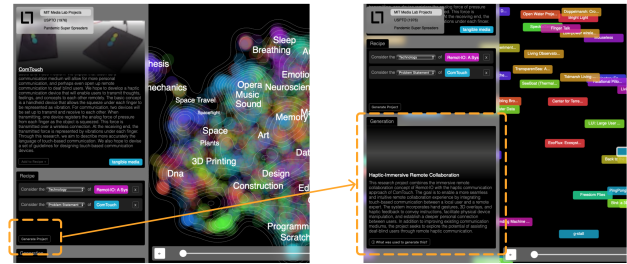


Figure 3: Generating a Research Project Idea

4 demonstrates this process using “quadratic voting” as the search term. Below the search bar, Latent Lab displays summaries that provide users with a quick overview of projects in the currently viewed map region.

### Timeline Slider

Latent Lab’s Timeline feature enables users to explore data set progression over a selected period using start and end date sliders. This functionality, particularly useful alongside the search bar, allows for efficient examination of current or ongoing projects in specific areas. Figure 5 illustrates timeline filtering for projects since 2018.



Lab realizes the long-sought goal of information technology experts for an intuitively accessible wealth of interconnected information. AI-assisted exploration has turned this vision into reality, setting the stage for future human-AI co-invention systems and fostering more intuitive and productive collaborations that are capable of generating novel and impactful creations.

### Author Contributions

TP and KD are leading authors. TP, KD, and AL contributed to the conception of Latent Lab. TP, KD, and AP all contributed to the development of Latent Lab.

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