

Analego: Let’s build analogies together!

Bhavya Bhavya, Yang Zhou, Shradha Sehgal, Suma Bhat, ChengXiang Zhai

University of Illinois at Urbana-Champaign
{bhavya2, yz96, ssehgal4, spbhat2, czhai}@illinois.edu

Abstract

Analogies are a useful instructional tool to understand difficult concepts by connecting them to more familiar ones. We present a system that leverages Generative AI to enable learners and teachers to co-create analogies about a given concept with the ability to create personalized analogies about topics that are familiar and interesting to them. The generated analogies can be added to our ever-growing repository, thereby allowing future users to search and provide feedback on them¹.

Introduction

By connecting unfamiliar concepts (called the target) to more familiar ones (called the source), analogies play a huge role in education as they help with understanding concepts, problem-solving, increasing learners’ interest and motivation (Thagard 1992; Novick and Holyoak 1991; Glynn et al. 1989). However, manually creating effective analogies can be challenging (Kim et al. 2023) and it is impossible to manually generate adaptive analogies suitable for *every* learner. Thus it would be beneficial to build a general analogy search engine to enable all the students and all the teachers to find suitable analogies, for learning and teaching a concept, respectively. A major challenge in building such a system is how to generate many analogies to explain all kinds of concepts and grow the system over time to include alternative analogies or new analogies to explain emerging new concepts in a sustainable way.

In this paper, we address this challenge and present a system where users (learners and teachers) can collaboratively generate useful analogies by leveraging Large Language Models (LLMs). The system, called *Analego*², has two synergistic innovative functions: (1) Given a target concept, users can generate analogies, by leveraging the OpenAI ChatGPT model³, to explain it by using a suitable prompt (Bhavya, Xiong, and Zhai 2022). Users can also specify a source domain, i.e., a topic of their interest that

they would like the analogy to be about. The generated analogy can then be edited and also added to our back-end repository. (2) Users can search for a suitable analogy from the growing repository of all the generated analogies, implemented using Elasticsearch⁴. Users can also provide feedback by upvoting or downvoting the analogies, enabling the search engine to naturally improve ranking of analogies based on the votes over time.

Our system is an example application of AI-human collaboration. Recently, large language models (LLMs) have shown great promise in automatically generating analogies for concepts (Kim et al. 2023; Bhavya, Xiong, and Zhai 2022), which make good candidates for our system. As those LLMs are computationally expensive and not every user has access to such a model, it is not desirable to have every user interact with an LLM whenever the user needs an analogy; instead, it would be more cost-effective to add every newly generated analogy to a repository so as to avoid regenerating a similar analogy if a user can already find one in the repository. Our system is designed based on such a cost-effective way of human-AI collaboration.

Related Work

LLMs have recently been used to assist with creating educational content such as questions, explanations, and grading (Moore et al. 2023; MacNeil et al. 2022), as well as generating analogies (Bhavya, Xiong, and Zhai 2022, 2023; Kim et al. 2023). We build a system to enable students and teachers to benefit from the new technology of using LLMs to generate analogies. An LLM-based analogy-generation system for assisting science writers with creating scientific analogies has been developed recently (Kim et al. 2023) with the goal of generating coherent and original analogies; in contrast, we emphasize creating personalized analogies to accurately explain a concept, which is more appropriate for education applications. Other related systems include an analogy search engine for education (Kumar, Bhat, and Pedanekar 2015) and an online analogy submission platform *metamia.com*. Compared to them, our search engine is based on analogies generated by AI. As AI capabilities continuously improve, such an AI-based system would allow us to continuously add new analogies that do not exist on the Web.

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¹Code at https://github.com/yangzho12138/analogy_search_gen_web

²Lego is a popular toy with pieces that can be flexibly assembled to construct objects. Similarly, our system allows users to flexibly connect concepts to create analogies.

³<https://platform.openai.com/docs/api-reference/chat>

⁴<https://www.elastic.co/elasticsearch>

System Architecture

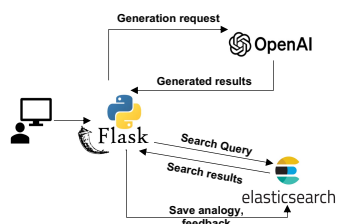


Figure 1: Analogo system architecture

Figure 1 shows the overall system architecture. Analogo is developed using Python Flask⁵ web framework. The front end is developed using Javascript, HTML, and CSS. For analogy generation, GPT3.5 (gpt3.5-turbo) is used by calling OpenAI API. For efficient search, we use Elasticsearch as the search engine and index for storing analogies.

User Workflow

We now describe our interface and interaction workflow.

Generating Analogies

Figure 2 shows the analogy generation interface. Users enter their OpenAI API key, the target concept, and optionally a source domain of their interest that the analogy should be about. Additionally, we provide a list of prompts that the user can select from. For personalized analogies about a source concept, we design prompts like “Explain <target> using an analogy about <source>.” Moreover, we expose all generation configuration parameters with tooltips to explain them. In this way, users have a high agency over analogy generation in a human-machine collaborative manner. Further, following human-AI system design guidelines, the system allows users to develop a mental model (Bansal et al. 2019) of the underlying AI. Moreover, it could also be used as a sandbox to learn Generative AI by exploring with the impact of hyperparameters on the generated analogy.

Finally, upon clicking the ‘generate’ button, the generated analogy is shown in the text box below. Users (e.g., teachers) could then edit it as needed (e.g., make them more accurate or understandable). The final analogy can then be saved to the repository by clicking on the Save button.

Searching Analogies

Figure 3 shows the search interface. Users enter a query in the search box with auto-complete. Users can also filter the results based on the prompt and temperature entered while generating the analogy. Upon pressing the ‘search’ button, the relevant search results are shown. For each analogy in the search results, the target concept, prompt, and temperature are also displayed as metadata in the top-left. Further, there is a ‘like’ and a ‘dislike’ button in the bottom-left corner, and the number of likes and dislikes are displayed next to

The screenshot shows the Analogo generation interface. It includes fields for 'OpenAI API Key', 'Target Concept' (set to 'cell'), and 'Source Domain (Optional)' (set to 'sports'). A dropdown menu for 'Prompt' is open, showing 'Explain <target> using an analogy involin...'. Below these are sliders for 'Randomness' (0.2), 'Maximum Length' (800), 'Top P' (1), 'Frequency Penalty' (0), and 'Presence Penalty' (0). A 'Best Of' field is set to 1. A 'Generate' button is at the bottom right. Below the form, a text box displays the generated analogy: "Imagine a cell as a sports team. Just like a team, a cell is made up of different players or components that work together to achieve a common goal."

Figure 2: Generating analogies on Analogo

the buttons. Upon clicking the buttons, the respective number of likes or dislikes gets updated in the backend Elasticsearch collection and is also reflected on the interface. Below the search results, a button saying “Not found a useful analogy? Generate a new one.” shows up that takes them to the analogy generation page, where the target concept field is automatically populated with the search query.

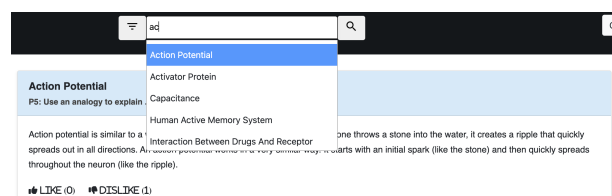


Figure 3: Searching analogies on Analogo

Conclusion and Future Work

We introduced Analogo, an online platform for generating and searching analogies. It leverages Generative AI to generate analogies for education, including personalized analogies. The generated analogies can then be edited and saved to our repository. Additionally, by leveraging Elasticsearch, we enable users to search over and provide feedback on the analogies. Given that well-crafted and familiar analogies play a significant role in explaining challenging topics, we believe Analogo is an essential first step toward building a large-scale, interactive analogy search and generation engine. As the system continues to grow, future work could explore how to incorporate user feedback to better prompt-tune and personalize the generated and ranked analogies.

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⁵<https://flask.palletsprojects.com/en/3.0.x/>

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