ICAM: Interactive-Constructive-Active Learning Machine

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1 Overview

The **Interactive-Constructive-Active Learning Machine (ICALM)** is an Intelligent Tutoring System (ITS) designed to enhance student engagement through dynamic learning pathways. ICALM includes:

- **Concept Map Generation**: Converts flashcards into structured concept maps by extracting relationships and forming a **knowledge graph**. The information extraction pipeline transforms unstructured text into structured data, typically in the form of a knowledge graph. It involves several steps: **coreference resolution**, which links pronouns to their entities; **named entity recognition** (NER), which identifies key entities in the text; **entity disambiguation**, which clarifies ambiguous entities; and **relationship extraction** [6], which defines relationships between entities. LLMs have made this process more accessible, enabling users to automate tasks like multi-hop question-answering and data analytics using tools like Neo4j [3].
- **Knowledge-Graph-Based Recommendations**: Suggests new topics based on the knowledge graph by leveraging user preferences, learning history, and topic interconnections. Knowledge graphs provide a structured representation of academic concepts, allowing for more intelligent, tailored recommendations. The pipeline begins by extracting subject-relation-object triplets from flashcards using models like KnowGL [6]. These triplets form the backbone of the knowledge graph, which is subsequently used to suggest learning paths via systems like RippleNet [7]. This process identifies relevant topics for the student by propagating preferences across the graph, thus facilitating deeper exploration and structured learning.
- **LLM-Facilitated Active Learning**: Supports learning through chatbot interactions, reflections, and feedback by generating contextually relevant learning tasks and reflective essays. Large Language Models (LLMs), such as GPT, are integrated into ICALM to foster active learning. LLMs assist students by providing feedback, answering complex queries, and generating personalized learning tasks. After students engage in reflective exercises, the system compares their written work with LLM-generated summaries, enhancing comprehension [2]. Furthermore, LLM-based tools are fine-tuned to create in-class portfolios, assess notes, and provide students with real-time, actionable feedback on their learning progress.

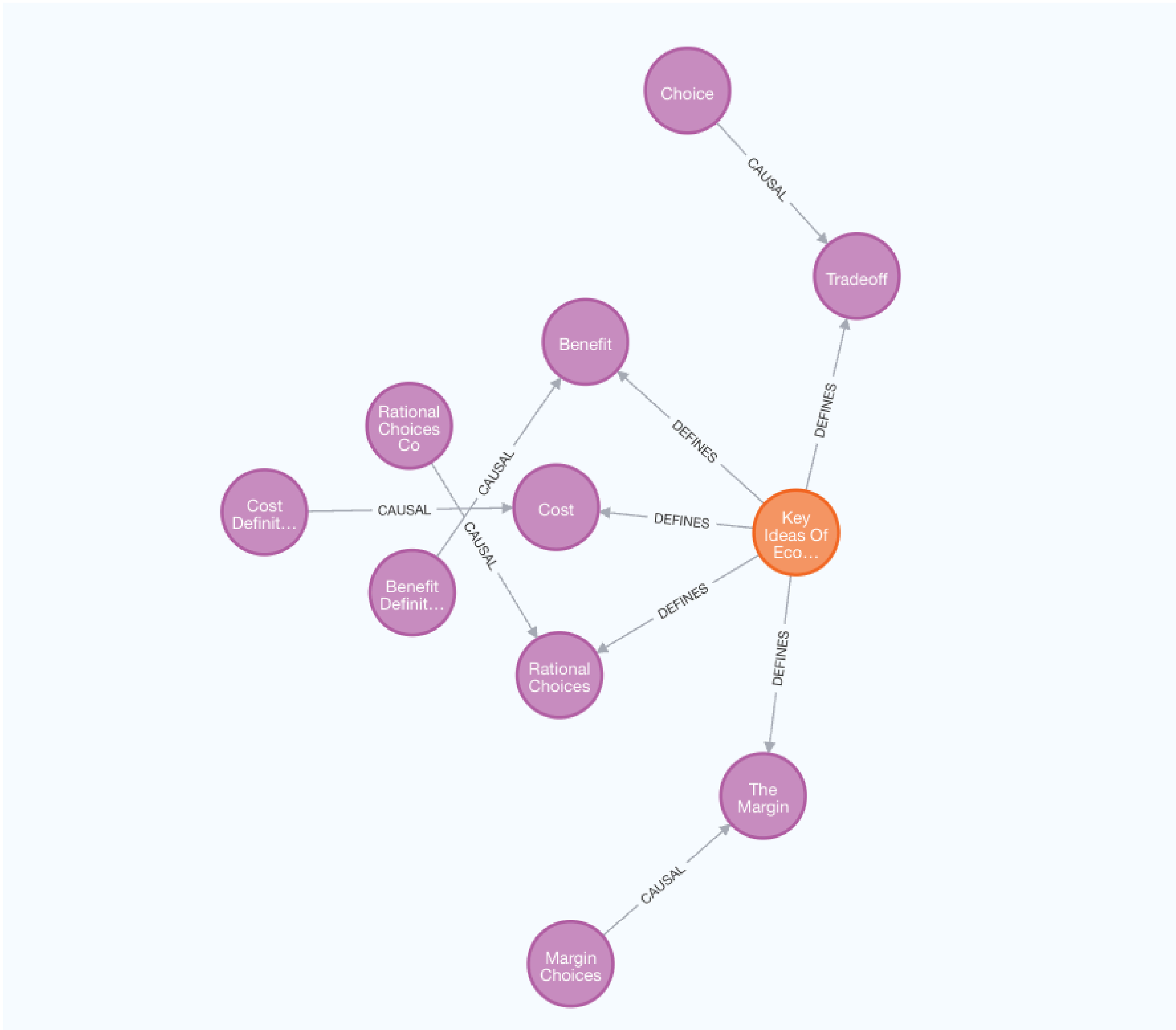
2 Core Components

- **Entity-Relation Extraction**: Transforms CSV-based flashcards into nodes and relationships in a knowledge graph using entity-relation extraction and OpenAI models.

  In ICALM, entity-relation extraction is the foundation for converting unstructured textual flashcard data into structured knowledge graphs. This process begins with the use of LLMs, such as OpenAI's GPT models, to identify key entities and their relationships within the flashcards. By applying Named Entity Recognition (NER), the system extracts meaningful subjects and objects, followed by relationship extraction [6], which defines how these entities are connected. This structured format enables the system to visualize complex educational content and supports downstream applications like recommendation systems and active learning. For example, in an economics flashcard, "inflation" might be linked to "interest rates" through the relation "affects", forming the foundation for conceptual understanding and further recommendations.

Economics Concepts
Economics is best defined as, making choices with unlimited wants but facing a scarcity of resources.
"When an economy produces more houses and fewer typewriters, this deals with the question of", what?
Marginal benefit from a good is the benefit from consuming one more unit of a good.

The figure and text represent how ICALM applies **relationship extraction** to build a knowledge graph from raw data. By linking entities like "Economics," "Cost," and "Benefit" through logical relationships, ICALM enhances students' understanding of interrelated concepts in economics.



Knowledge graph for Economics concepts and relationships

- **Recommender System**: Leverages the knowledge graph to suggest interconnected concepts, fostering exploration and deeper understanding. The knowledge-graph-based recommender system in ICALM exploits the graph's structure to suggest the next logical learning topics for students. Once the knowledge graph is built using entity-relation extraction, ICALM employs path-based algorithms like RippleNet to propagate user preferences across the graph [7]. The system can predict a learner's needs by tracking their journey through the graph and recognizing patterns in content consumption. For instance, if a student shows interest in "inflation" and "monetary policy", the system might suggest exploring related topics like "central banking" or "interest rate control", enhancing their understanding of the broader economic framework. This approach is particularly effective in fostering exploratory learning, where students are encouraged to delve deeper into interconnected ideas.

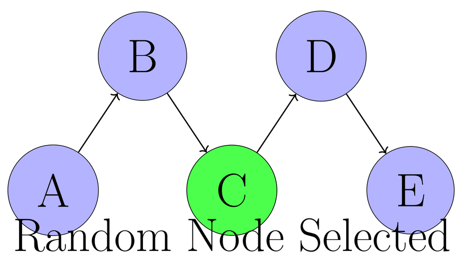
- **Chatbot Interaction**: Engages students with a large language model to ask questions, verify their understanding, and defend their perspectives. ICALM uses LLM-based chatbots to facilitate active learning [2]. After students are presented with a topic or concept map, they can interact with the chatbot to clarify doubts, ask questions, and engage in deeper discussions about the material. The chatbot is equipped with pre-trained LLMs capable of generating human-like responses, guiding students through the material and encouraging them to defend their understanding. For example, after learning about "inflation," the student might ask the chatbot to explain the causes of inflation in specific historical contexts, pushing them to think critically and verify their comprehension. The chatbot also provides personalized feedback, making the learning process interactive and engaging.

- **Reflective Learning**: Students compare their written reflections with LLM-generated summaries to deepen their learning experience. At the end of each learning session, ICALM prompts students to write reflective essays summarizing what they have learned. These essays serve as an opportunity for metacognitive reflection, allowing students to process and internalize the material [2]. The system then generates a summary using an LLM, which is juxtaposed with the student's reflection. The comparison helps identify gaps in understanding and highlights areas for improvement. For example, if a student's reflection on "monetary policy" misses critical details about "interest rate adjustments," the LLM-generated summary can bring those details to their attention, thereby reinforcing learning through reflection and feedback. This reflective exercise not only enhances retention but also promotes self-assessment.

3 Pathway Selections

- **Random Flashcard Pathway**: Presents random flashcards from the knowledge graph, facilitating **Active learning** [2] by exposing students to new content and reinforcing memory recall.

  The Random Flashcard Pathway engages students by presenting previously unexplored flashcards from a knowledge graph in random order. This method ensures students encounter fresh material with each session. Students interact with the flashcards by attempting to answer, requesting hints, or reviewing correct answers. Each interaction is tracked, allowing for real-time feedback, mistake review, and marking progress. This pathway promotes active learning by encouraging continuous engagement, recall practice, and iterative improvement.



- **MetaNode Pathway**: Prioritizes high-entropy nodes, focusing on concepts with many interconnections. This pathway fosters **Constructive learning** by helping students build structured knowledge and connections.

  In the MetaNode Pathway of ICALM, the learning path is dynamically generated by prioritizing nodes (concepts) in the knowledge graph with the highest entropy, representing the concepts with the most connections. The system begins by identifying the node with the highest entropy, followed by traversing its neighbors based on their entropy levels, leading students to explore interconnected concepts. If a node's neighborhood is exhausted, the system uses cosine similarity to find and move to the closest unvisited node with high entropy. This structured approach encourages **Constructive learning**, helping students form deeper connections between abstract ideas while progressively exploring complex concepts.

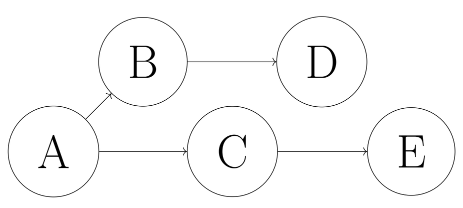
  For instance, the algorithm first locates the flashcard (node) with the highest entropy and moves to neighboring nodes based on their entropy. If the immediate neighbors are already explored, it searches for another high-entropy node, ensuring that the learner consistently encounters new and challenging material. This pathway is designed to foster a comprehensive understanding of the subject by guiding students through the most connected and conceptually rich areas of the knowledge graph.

Illustration of MetaNode Pathway

The following series of node and edge graphs illustrates the process of the MetaNode Pathway, where the system prioritizes nodes with the highest entropy, helping students build structured knowledge by exploring interconnected concepts [6].

Step 1: Initial Step - High Entropy Node Selection

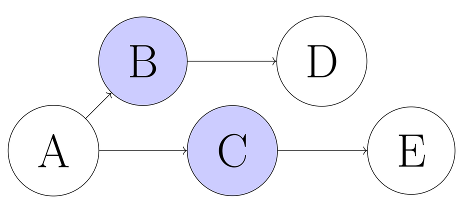
The system starts by selecting the node (flashcard) with the highest entropy (most interconnections).



Here, node **A** is selected because it has the highest entropy (the most interconnections).

Step 2: Traversing to Neighboring Nodes

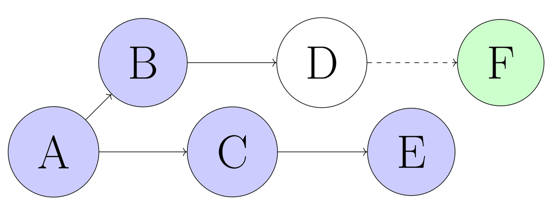
Once the high-entropy node is selected, the system traverses its neighboring nodes based on their entropy values.



Nodes **B** and **C** are visited after node **A** based on their entropy values.

Step 3: Exhausting Neighbors and Selecting a New Node

If the neighbors of the current node are exhausted, the system uses cosine similarity to find a new high-entropy node to explore.



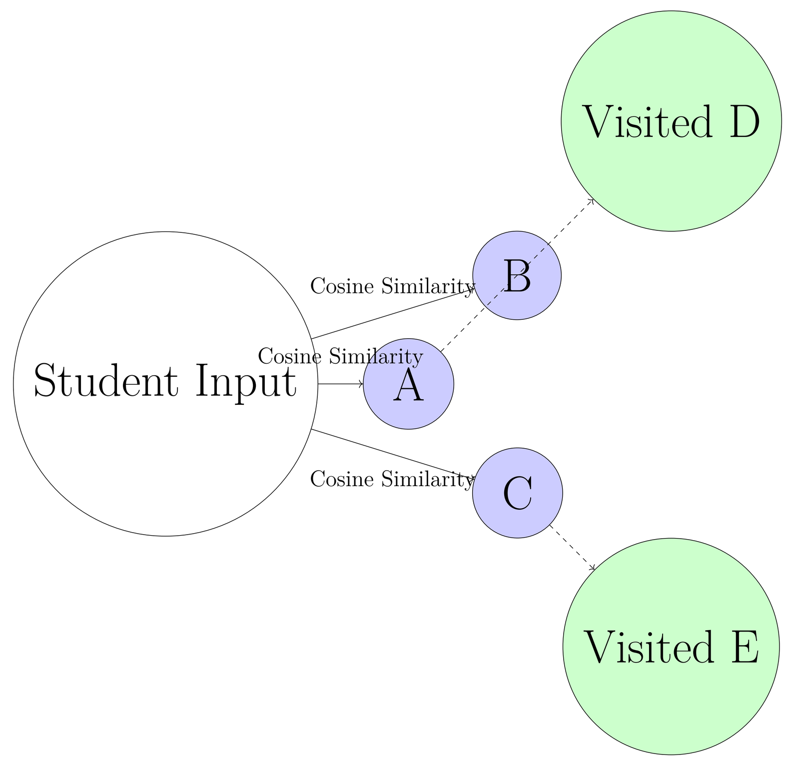
In this step, node **F** is selected using cosine similarity after exploring all neighboring nodes of the initial high-entropy node.

- **Interest-Based Pathway**: Students input areas of interest, and ICALM matches relevant nodes using cosine similarity. This pathway encourages **Interactive learning** through personalized, dynamic exploration.

  In the Interest-Based Pathway of ICALM, students begin by inputting topics or areas they are interested in. The system then retrieves flashcards from the knowledge graph that align with the student's input using cosine similarity to match the student's input with relevant concepts [2]. To facilitate this, the system embeds the student's input using a pre-trained language model. These embeddings are compared with the stored embeddings of flashcards in the knowledge graph using a similarity function, such as the cosine similarity metric, to rank flashcards by relevance.

  The process begins by filtering out previously visited nodes (flashcards) and using the Neo4j Graph Data Science API to return the most similar nodes to the student's input. This ensures that students are exposed to flashcards that align with their learning interests while avoiding redundancy. Once the flashcards are selected, the student is presented with options to answer questions, receive hints from a large language model (LLM), and explore the flashcards further. If a flashcard is particularly challenging, the student can add it to their mistake list for further review.

  This personalized and interactive approach fosters deeper engagement, as students dynamically explore topics they are most interested in. As students continue exploring flashcards, they progressively build a customized learning pathway tailored to their preferences and knowledge gaps, promoting both interest-driven discovery and conceptual understanding.



4 Educational Approach

Grounded in the **ICAP Framework** [2], ICALM promotes a progression from **passive** to **active**, **constructive**, and **interactive** learning. By converting flashcards into concept maps and generating knowledge graphs, ICALM provides structured pathways that enhance cognitive engagement and comprehension.

5 Future Work

The next phase of development for ICALM will focus on several key areas:

- **Expanding Subject Diversity**: ICALM will be extended to cover a wider range of subjects beyond general education, incorporating more specialized fields such as STEM, humanities, and vocational studies. By expanding the knowledge base, we aim to cater to diverse student needs and promote inclusivity in educational access [2].
- **Enhanced Personalization with AI**: We plan to further enhance ICALM's ability to personalize learning by refining the recommendation system using advanced AI algorithms. This will include deeper integration of Large Language Models (LLMs) with Knowledge Graphs (KGs) to generate even more tailored content based on student learning styles and behaviors. The introduction of adaptive learning mechanisms will allow ICALM to adjust the difficulty and depth of flashcards based on the student's progress and comprehension levels [5].
- **Exploring the Impact of Knowledge Graphs vs. LLM Interactions**: A significant research question revolves around how explicit representations of Knowledge Graphs influence student comprehension compared to simple turn-wise conversations with LLMs. Future studies will involve controlled experiments comparing both methods. Pre- and post-tests will be conducted, alongside structured interviews to gauge student preference and understanding. This research will help in refining the approach that ICALM uses for content delivery [5].
- **Adapting to Shortening Attention Spans**: With increasing concerns regarding student attention spans, the future versions of ICALM will include features that present content in bite-sized formats and visually structured using knowledge graphs. A/B testing will be employed to evaluate the effectiveness of this method in improving learning outcomes compared to traditional methods [4].

- **Integration of Structured Reflections and Peer Learning**: ICALM will also explore the integration of structured reflection activities and peer learning techniques, both of which are recognized for their effectiveness in fostering deeper engagement. We will deploy prototypes of the platform with these features and track their impact on student performance and satisfaction over an academic term [1].
- **Evaluating Engagement Metrics**: In future research, we plan to develop metrics to track engagement more precisely, analyzing how students interact with flashcards, their knowledge pathways, and the effectiveness of tailored recommendations. The goal is to use these metrics to continuously refine the user experience and promote sustained cognitive engagement.

Through these research endeavors, ICALM aims to advance its pedagogical techniques, ultimately offering a richer, more adaptive, and student-centered learning experience.

References

[1] Elizabeth F. Barkley. Student engagement techniques: A handbook for college faculty. *Google Books*, May 2020.

[2] Michelene T. H. Chi and Ruth Wylie. The icap framework: Linking cognitive engagement to active learning outcomes. *Educational Psychologist*, 49(4):219–243, 2014.

[3] R.F. Flippo and T.W. Bean. Academic preparedness. In *Handbook of College Reading and Study Strategy Research*, pages 181–190. Taylor & Francis, 2018.

[4] G. Mark. *Attention Span: Finding Focus for a Fulfilling Life*. HarperCollins Publishers Limited, 2023.

[5] Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks, 2019.

[6] Gaetano Rossiello, Md Faisal Mahbub Chowdhury, Nandana Mihindukulasooriya, Owen Cornec, and Alfio Massimiliano Gliozzo. Knowgl: Knowledge generation and linking from text, 2022.

[7] Hongwei Wang, Fuzheng Zhang, Jialin Wang, Miao Zhao, Wenjie Li, Xing Xie, and Minyi Guo. Ripplenet: Propagating user preferences on the knowledge graph for recommender systems. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, CIKM '18, page 417–426, New York, NY, USA, 2018. Association for Computing Machinery.