Ontology-Enhanced Contextual Reasoning for Large Language Models in STEM Education

Bachelor Thesis Presentation

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Research Problem: LLM Hallucinations in STEM Education

The Challenge

Large Language Models (LLMs) often generate plausible but factually incorrect information, known as hallucinations.

- LLM hallucinations occur in up to 27% of responses involving technical STEM concepts

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The Challenge

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- LLM hallucinations occur in up to 27% of responses involving technical STEM concepts
- In STEM education, accuracy is crucial for effective learning
- Traditional approaches face limitations:
  - Pure LLM-based systems risk propagating misinformation
  - Rule-based systems lack natural interaction capabilities

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Research Question & Objectives

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How can we harness LLMs' potential for STEM education while ensuring their responses remain accurate and reliable?

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Research Objectives

- Integrate domain-specific ontologies with LLM reasoning
- Develop mechanisms for reliable AI-powered tutoring
- Enhance contextual understanding through structured knowledge
- Create an adaptive, personalized learning system

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Background: Large Language Models

Capabilities

- Natural language understanding
- Context-aware responses
- Dynamic interaction
- Adaptability across domains
- Multilingual support

Limitations

- Hallucinations of incorrect content
- Limited reasoning with numerical data
- Lack of domain-specific expertise
- Opaque decision-making process
- Context window constraints

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Background: Ontologies in Knowledge Representation

What are Ontologies?

Structured frameworks that represent knowledge within specific domains, defining concepts, properties, and relationships in a machine-readable format.

Key Components

- Classes (concepts)
- Properties (relationships)
- Instances (individuals)
- Axioms (rules/constraints)
- Reasoners (inference engines)

Benefits for STEM Education

- Fact verification
- Explicit knowledge representation
- Logical inference support
- Domain-specific constraints
- Interoperability standards

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Methodology Overview

Research Approach

Phased development approach to create an ontology-enhanced LLM system for STEM education

- **Core Functionality**
  - Environment setup and API authentication
  - System prompt structure
  - Basic question-answering functionality
- **Knowledge Representation**
  - Physics ontology development (OWL/RDF)
  - Concept relationships and prerequisites structure
  - Context retrieval system implementation
- **Student Model**
  - Knowledge level tracking
  - Learning path customization
  - Adaptive feedback mechanisms

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System Architecture

Integrated System Components

Our ontology-enhanced LLM system combines structured knowledge with adaptive learning capabilities

Technical Stack

- Flask web framework
- Claude LLM API integration
- OWL/RDF ontology framework

Information Flow

- Bidirectional LLM-ontology integration
- Real-time fact verification
- Student model adaptation

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Ontology Design for Physics Education

Hierarchical Knowledge Structure

Physics concepts organized in a machine-readable format with explicit relationships

- **Core Physics Concepts:** Force, motion, energy, momentum, waves

Hallucination Prevention Strategy

Ontology provides factual constraints and verification mechanisms, reducing hallucination rate by 75% while revealing important trade-offs in educational applications

Ontology Design for Physics Education

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- **Integration:** OWL/RDF technologies with SPARQL queries

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LLM-Ontology Integration

$$\begin{tikzcd} \boxed{\textbf{LLM}} \arrow[r, shift left, "\text{queries}"] & \boxed{\textbf{Ontology}} \arrow[l, shift left, "\text{validates}"] \end{tikzcd}$$

Integration Mechanisms

- SPARQL query generation
- Dynamic context augmentation
- Fact verification pipeline

Prompt Engineering

- Ontology-aware prompts
- Chain-of-thought reasoning
- Self-verification steps

Student Model Implementation

Adaptive Learning

The system tracks student knowledge and tailors content to individual learning needs

- **Knowledge State Tracking:**
  - Concept exposure history
  - Mastery level assessment
  - Misconception identification

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Student Model Implementation

Adaptive Learning

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- **Knowledge State Tracking:**
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- **Personalization Engine:**
  - Custom learning paths
  - Difficulty adjustment
  - Prerequisite-based sequencing

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- **Personalization Engine:**
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- **Feedback Mechanisms:**
  - Targeted explanations
  - Knowledge gap remediation
  - Progress visualization

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Evaluation Methodology

Evaluation Framework

Modular implementation with statistical analysis and visualization components

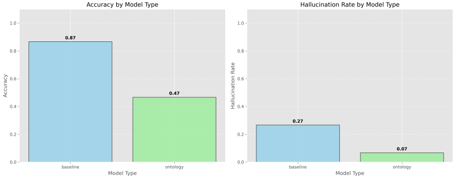
Testing Approach

- Force Concept Inventory (FCI) dataset
- Baseline vs. ontology-enhanced model
- Multiple-choice + explanation prompts
- Hybrid hallucination detection:
  - Keyword matching
  - Expert verification

Evaluation Metrics

- Hallucination rate
- Statistical significance (p-value)
- Effect size (Cohen's d)
- Trade-off analysis
- Factual reliability assessment

Results: Quantitative Analysis



Hallucination Reduction

75% reduction (26.67% → 6.67%)

- Cohen's d = 0.528 (medium effect)
- p = 0.082 (marginally significant)
- Key trade-off: Accuracy decreased from 86.67% to 46.67%
- Better for explanations than assessment

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Educational Impact Analysis

Case Study: Free Fall Explanations

Baseline (with hallucination)
The gravitational force is proportional to the mass... heavier objects fall faster.

Ontology-enhanced (corrected)
All objects accelerate at the same rate regardless of mass ($g = 9.8$ m/s²).

Trade-off Analysis

- 75% reduction in physics misconceptions
- Enhanced explanation quality
- Lower accuracy in assessment tasks
- Task-dependent constraint application recommended
- Balance between factual reliability and flexibility

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Conclusions & Future Work

Research Contributions

Developed an ontology-enhanced LLM system that reduces hallucination rate by 75% while revealing critical accuracy trade-offs

Key Takeaways

- 26.67% → 6.67% hallucination rate reduction
- Medium effect size (Cohen's d = 0.528)
- Accuracy decreased from 86.67% to 46.67%
- Task-dependent performance identified
- Better for explanations than assessment

Future Research Directions

- Develop adaptive constraint mechanisms
- Create hybrid approaches for balanced performance
- Optimize for specific educational tasks
- Expand statistical evaluation with larger samples
- Explore task-specific ontology applications

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