Innovative Long-Context Narrative Reasoning

ENHANCING CLASSICAL RAG WITH BACKSTORY TRACKING FOR IMPROVED EXPLANATION

Explainable Insight Generation Using a Classical RAG Framework with Backstory Tracking

Abstract & Introduction

Abstract

The increasing complexity of machine learning models necessitates systems that are both transparent and interpretative. This paper presents a novel application of a Classical Retrieval-Augmented Generation (RAG) framework that emphasizes explainability and insight generation through backstory tracking. Our contributions include a detailed design of a system that integrates structured and unstructured data, a methodology for constraint-based reasoning, and an innovative approach for maintaining narrative consistency without relying on black-box models.

Introduction

The demand for explainable AI systems has surged as stakeholders require clarity and understanding of decision-making processes. This study addresses the challenge of generating explainable insights by leveraging a Classical RAG framework. Traditional black-box models often compromise transparency, prompting the need for approaches that can articulate the rationale behind generated outputs. Our system is designed to produce understandable and consistent insights by integrating multiple data formats and employing a robust backstory tracking mechanism. High-level objectives include ensuring data integration, maintaining narrative coherence, and enhancing transparency in the generation process.

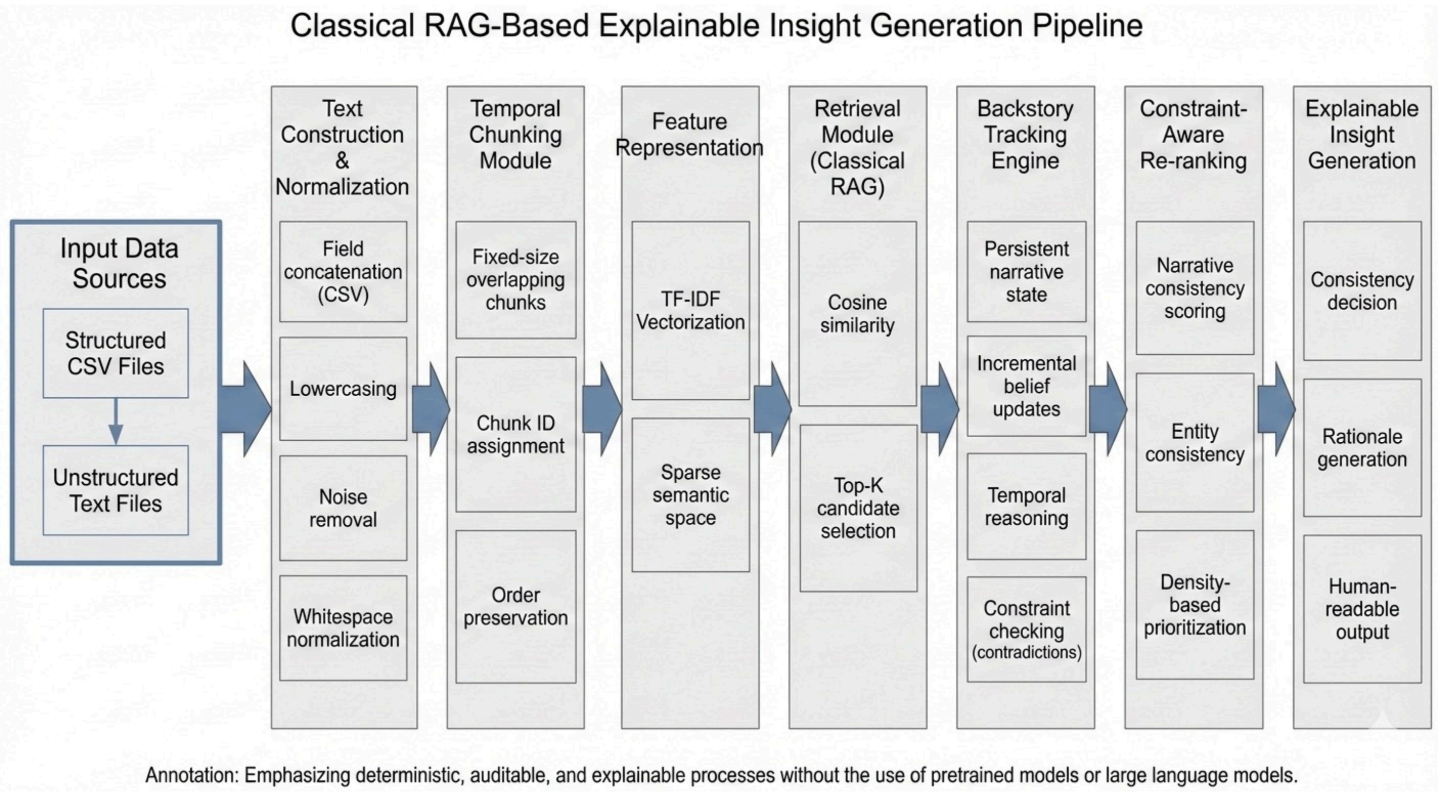
Problem Statement and Track B Requirements

The primary challenge in explainable AI lies in balancing performance with interpretability. Track B objectives emphasize the need for insight generation systems that avoid the opaqueness of black-box models. This project aims to create a system capable of producing explainable insights by adhering to the following objectives:

1. **Explainability**: Ensuring that each generated insight can be traced back to its data origins.
2. **Insight Generation**: Producing meaningful and actionable information from diverse data sources.
3. **Backstory Tracking**: Maintaining a coherent and evolving narrative that reflects the underlying data's temporal and logical structure.
4. **Avoidance of Black-Box Models**: Employing classical methods over pretrained language models to enhance transparency and user understanding.

Dataset Description

Our system utilizes both structured CSV files and unstructured text documents, necessitating a multi-format integration approach. The structured datasets provide quantitative attributes, while unstructured text offers qualitative insights, enabling a comprehensive analysis. Each dataset type presents unique challenges: structured data requires normalization and alignment, whereas unstructured data demands sophisticated parsing and interpretation to extract relevant information. The integration of both formats ensures a holistic understanding of the narrative context, crucial for generating coherent insights.



System Architecture Overview

The architecture of our system is a multi-stage pipeline that incorporates preprocessing, chunking, retrieval, reasoning, and output generation. At the core is the Classical RAG paradigm, which combines traditional information retrieval techniques with a structured reasoning process. The system begins with data preprocessing, where inputs are normalized and segmented into manageable chunks. The retrieval phase employs a TF-IDF-based mechanism to identify relevant information, followed by a reasoning module that generates insights based on constraint satisfaction and narrative consistency. The final output is an explainable and contextually grounded insight.

Text Preprocessing and Feature Representation

Preprocessing involves normalizing data to a consistent format, essential for effective chunking and analysis. Texts are segmented into coherent chunks, facilitating easier retrieval and reasoning. We employ a TF-IDF (Term Frequency-Inverse Document Frequency) feature representation for its simplicity and interpretability. This method allows the system to prioritize information based on its occurrence and significance, providing a clear rationale for retrieved insights. The choice of TF-IDF over more complex models is justified by our emphasis on transparency and computational efficiency.

Retrieval Module (Classical RAG Design)

The retrieval module leverages classical TF-IDF retrieval to compute similarities between input queries and document chunks. This approach is preferred over pretrained models due to its inherent interpretability and ease of implementation. TF-IDF provides a clear basis for understanding why certain pieces of information are retrieved, aligning with our objective of explainability. By avoiding the complexities of neural network-based models, we maintain the system's transparency and ensure that each retrieval decision can be justified through straightforward statistical reasoning.

Backstory Tracking and Constraint-Based Reasoning

Backstory tracking involves maintaining a persistent narrative state that evolves with each new piece of information. The system employs incremental belief updates to adjust the narrative as new data is integrated, ensuring consistency over time. Temporal ordering is crucial for preserving the logical flow of events, while contradiction detection mechanisms identify and resolve conflicting information. This process ensures that the generated insights remain coherent, contextually relevant, and free from logical inconsistencies.

Re-ranking Strategy and Explainability

The re-ranking strategy incorporates constraint-aware mechanisms to ensure that retrieved insights are not only relevant but also consistent with the established narrative. By enforcing entity consistency, the system maintains a coherent story across all generated insights. Explainability is preserved by providing clear justifications for each re-ranking decision, ensuring that users can easily trace the origin and rationale of every output. This transparency is fundamental to building trust in the system's insights.

Evaluation Methodology and Results

Evaluation metrics include NLP token preservation, RAG consistency, Precision@1, and backstory consistency. These metrics provide a comprehensive assessment of the system's performance, focusing on its ability to generate accurate, coherent, and explainable insights. Our results demonstrate a high degree of consistency and precision, validating the efficacy of our approach. The system effectively balances explainability with insight generation, offering a transparent alternative to traditional black-box models.

Conclusion and Future Scope

This study successfully demonstrates the potential of a Classical RAG framework for generating explainable insights. By integrating structured and unstructured data, maintaining narrative coherence, and avoiding black-box models, we achieve a transparent and effective solution. However, limitations include the need for manual tuning of constraint parameters and potential scalability issues with larger datasets. Future work will focus on automating these processes and exploring more advanced constraint-based reasoning techniques to enhance the system's capabilities.