LLM-Augmented Knowledge-Graph-Based Recommendation System

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Results & Discussion

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1 Introduction

This document covers the Introduction, Literature Review and Exploratory Data Analysis for the first deliverable of Major Research Project (MRP). It begins with a brief background on the topic

and datasets, defines the problem, and states the research question. This is followed by a literature review and a detailed exploratory analysis of the dataset.

1.1 Background

Recommender systems have been widely applied to address the issue of information overload in various internet services, exhibiting promising performance in scenarios such as e-commerce platforms and media recommendations. In the general domain, the traditional knowledge recommendation method is *collaborative filtering (CF)*, which usually suffers from the cold start problem and sparsity of user-item interactions. Knowledge-based recommendation models effectively alleviate the data sparsity issue leveraging the side information in the knowledge graph, and have achieved state of the art performance . However, KGs are difficult to construct and evolve by nature, and existing methods often lack considering textual information. On the other hand, LLMs are black-box models, which often fall short of capturing and accessing factual knowledge. Therefore, it is complementary to unify LLMs and KGs together and simultaneously leverage their advantages. This project aims to explore LLM-augmented KGs, that leverage Large Language models (LLM) for different KG tasks such as embedding, completion, construction and also incorporate textual information which could be a way to help overcome these challenges and lead to better recommendation systems.

1.2 Research Objectives

The research objectives of this project are to investigate the use of Large Language Models (LLMs) to enhance the construction, quality, and volume of information in knowledge graphs (KGs). The goal is to effectively constrain the output of LLMs to adhere to a specific systematic knowledge extraction format. Additionally, the project aims to determine whether these improved knowledge graphs can lead to better recommendation systems. Furthermore, the project seeks to explore the possibility of combining state-of-the-art methods with the use of LLMs in extracting latent relationships, KG embedding, KG completion, and KG construction for recommendation purposes in an efficient, explicit, and end-to-end manner.

2 Literature Review

In this section, We provide an overview of the papers referenced for this project. Knowledge Graphs (KGs) as a form of structured knowledge have drawn significant attention from academia and the industry (Ji et al. 2022). There have been several efforts to construct KGs to facilitate the discovery of relevant information within specific fields. Most of these efforts have focused on extracting information from text.

Our problem statement can be broken down into 3 main components: KG Construction, KG Embedding and Knowledge Graph-based Recommendation Systems. We will review the literature in these areas to understand the current state of the art and identify gaps that can be addressed in our research.

2.0.1 Knowledge Graph-based Recommendation Systems

In recommendation, KGs have been used to enhance the performance of recommendation systems by incorporating high-order connectivities from KGs into user-item interactions. **Wang et al. 2019**

introduce the **Knowledge Graph Attention Network (KGAT)**, which enhances recommendation systems by leveraging an attention mechanism to discern the significance of various neighbor connections, demonstrating superior performance and interpretability compared to existing models such as Neural FM and RippleNet through extensive experiments on multiple public benchmarks. The model's end-to-end approach efficiently captures and utilizes high-order relations, providing more accurate, diverse, and explainable recommendations.

He et al. 2020 propose **LightGCN**, a lightweight graph convolutional network that simplifies the design of graph neural networks for collaborative filtering. LightGCN eliminates the feature transformation and nonlinear activation functions in traditional GCNs, focusing solely on the graph structure. The model achieves state-of-the-art performance on several recommendation benchmarks, outperforming more complex models such as NGCF and GAT. LightGCN's simplicity and efficiency make it an attractive choice for large-scale recommendation systems, demonstrating the effectiveness of collaborative filtering with graph neural networks.

KUCNet (**Liu et al. 2024**) is a novel knowledge-enhanced recommendation method that constructs user-centric subgraphs from the collaborative knowledge graph to capture relevant information for each user. It uses graph neural networks to propagate representations on these subgraphs, learning user preferences from collaborative filtering signals and knowledge graph semantics. KUCNet outperforms existing collaborative filtering, knowledge graph-based, and collaborative knowledge graph-based recommendation methods, especially for the inductive setting with new users/items.

2.0.2 Knowledge Graph Embedding

Guo et al. 2020 present a comprehensive survey of knowledge graph embedding techniques, which have been widely applied in various tasks such as recommendation, search, and question answering. The survey categorizes embedding methods into three groups: translation-based, semantic matching-based, and neural network-based. The authors provide a detailed overview of each category, discussing their strengths, weaknesses, and applications. The survey also highlights the challenges and future directions in knowledge graph embedding research, emphasizing the importance of incorporating textual information to enhance the quality and interpretability of embeddings.

Y. Zhang et al. 2021 introduce the **Knowledge Graph Embedding Transformer (KGET)**, a novel model that leverages the transformer architecture to learn embeddings for knowledge graphs. KGET incorporates a self-attention mechanism to capture complex relational patterns and dependencies in the graph structure. The model outperforms existing embedding methods such as TransE, DistMult, and ComplEx on several knowledge graph completion tasks, demonstrating its effectiveness in capturing long-range dependencies and semantic relationships. KGET's ability to model complex interactions between entities and relations makes it a promising approach for knowledge graph embedding.

2.0.3 Knowledge Graph Construction

Ji et al. 2022 provide a comprehensive survey of knowledge graph construction methods, which aim to extract structured knowledge from unstructured text data. The survey categorizes construction methods into three groups: **rule-based**, **statistical**, and **neural network-based**. The authors discuss the strengths and weaknesses of each category, highlighting the challenges and future

directions in knowledge graph construction research. The survey emphasizes the importance of incorporating textual information to enhance the quality and completeness of knowledge graphs, providing valuable insights for researchers and practitioners in the field.

2.0.4 Knowledge Graph Construction with Large Language Models

However, the traditional KG construction methods often lack the ability to incorporate textual information, which is essential for capturing the rich semantics and context of entities and relations.

Several studies have explored the integration of of current language models like **BERT** with knowledge graphs to enhance the quality and efficiency of knowledge representation and recommendation systems.

Xu et al. 2021 propose a novel method for constructing knowledge graphs from text, called **Text2KG**. Text2KG utilizes a pre-trained language model to extract structured knowledge from unstructured text data, generating entity and relation triples for constructing knowledge graphs. The model achieves competitive performance on knowledge graph construction tasks, outperforming existing methods such as OpenIE and ReVerb. Text2KG's ability to extract high-quality knowledge from text data demonstrates its potential for automating the construction of knowledge graphs from large-scale text corpora.

W. Zhang et al. 2021 introduce **KG-BERT**, a pre-trained language model that incorporates knowledge graph embeddings to enhance the representation learning of entities and relations. KG-BERT leverages the pre-trained BERT model to capture contextual information from text data and knowledge graph embeddings to capture structured information from knowledge graphs. The model achieves state-of-the-art performance on several knowledge graph completion tasks, demonstrating its effectiveness in capturing both textual and structured information. KG-BERT's ability to leverage both text and knowledge graph embeddings makes it a promising approach for enhancing the quality and interpretability of knowledge graph embeddings.

The emergence of Large Language Models (LLMs) has revolutionized research and practical applications by enabling complex reasoning and task generalization through techniques like In-Context Learning and Chain-of-Thought. LLMs offer promising solutions to existing recommender system challenges, such as poor interactivity, explainability, and the cold start problem, by generating more natural and cross-domain recommendations and enhancing user experience through stronger feedback mechanisms.

As such, the integration of LLMs with KGs presents a novel direction to overcome the limitations of traditional KGs, such as the challenge of incorporating textual information.

Ullah et al. 2021 introduce a novel method for knowledge graph completion using large language models, called **LLM-KGC**. LLM-KGC leverages the pre-trained language model BERT to predict missing relations in knowledge graphs, capturing complex relational patterns and dependencies. The model outperforms existing knowledge graph completion methods such as TransE, DistMult, and ComplEx on several benchmark datasets, demonstrating its effectiveness in capturing long-range dependencies and semantic relationships. LLM-KGC's ability to leverage large language models for knowledge graph completion makes it a promising approach for enhancing the quality and completeness of knowledge graphs.

Pan et al. 2023 discuss different approaches to unify large language models (LLMs) and knowledge graphs (KGs) to leverage their complementary strengths. Several methods are covered:

Integrating KGs into LLM Training

- Injecting KG information into LLM pre-training objectives, e.g. entity/relation prediction tasks.
- Concatenating linearized KG triples with text as input to LLMs.

Using LLMs for Knowledge Graph Embeddings

- Using LLMs to encode textual descriptions of entities/relations into embeddings for knowledge graph embedding methods.
- Masked language modeling approaches to encode KG triples.

Using LLMs for Knowledge Graph Completion

- Encoder-decoder or decoder-only LLMs that generate the missing entity in a triple.

Using LLMs for KG-to-Text Generation

- Fine-tuning LLMs like BART and T5 on linearized KG inputs to generate text descriptions.
- Injecting structure-aware KG representations into seq2seq LLMs.

2.0.5 Other LLM-Augmented Recommendation Systems

Apart from KG construction and embedding, LLMs have also been used to enhance recommending, and recommendation systems by introducing novel methods and techniques to enhance the quality and efficiency of knowledge representation and recommendation. By leveraging the power of large language models and graph neural networks, these models demonstrate the potential to improve the performance and interpretability of recommendation systems, paving the way for more effective and scalable knowledge-based recommendations.

3 Exploratory Data Analysis

3.1 Exploratory Data Analysis

This section aims to provide a comprehensive understanding of the dataset used for the research project. It contains information on the data source and files, as well as a description of the data's basic features.

By performing exploratory data analysis (EDA), we aim to gain a deeper understanding of the data, including the relationship between variables and identifying trends. This analysis will inform the subsequent steps in the research and help address the research questions effectively.

3.2 Data Source and Files

The primary dataset in scope is Amazon Reviews'23. This is a large-scale Amazon Reviews dataset, collected in 2023 by McAuley Lab, and it includes rich features such as:

- User Reviews (ratings, text, helpfulness votes, etc.);
- Item Metadata (descriptions, price, raw image, etc.);
- Links (user-item / bought together graphs).

The datasets are open-sourced and compliant with the MRP requirements.

The reviews span from May'96 to Sep'24 and cover a wide range of categories, including electronics, books, movies, and more. The dataset is designed to facilitate research in recommendation systems, natural language processing, and other related fields.

3.3 Data Description

For each category in the dataset, there are two main files: *User Reviews* and *Item Metadata*. The User Reviews file contains information about the reviews posted by users, including ratings, text, helpfulness votes, and more. The Item Metadata file contains information about the items being reviewed, such as descriptions, prices, images, and more.

3.3.1 For User Reviews

Field	Type	Explanation
rating	float	Rating of the product (from 1.0 to 5.0).
title	str	Title of the user review.
text	str	Text body of the user review.
images	list	Images that users post after they have received the product. Each image has different sizes (small, medium, large), represented by the small_image_url, medium_image_url, and large_image_url respectively.
asin	str	ID of the product.
parent_asin	str	Parent ID of the product.
user_id	str	ID of the reviewer.
timestamp	int	Time of the review (unix time).
verified_purchase	bool	User purchase verification.
helpful_vote	int	Helpful votes of the review.

Table 1: User Reviews Data Fields

3.3.2 For Item Metadata

Field	Type	Explanation
main_category	str	Main category (i.e., domain) of the product.
title	str	Name of the product.
average_rating	float	Rating of the product shown on the product page.
rating_number	int	Number of ratings in the product.
features	list	Bullet-point format features of the product.
description	list	Description of the product.
price	float	Price in US dollars (at time of crawling).
images	list	Images of the product. Each image has different sizes (thumb, large, hi_res). The "variant" field shows the position of image.
videos	list	Videos of the product including title and url.
store	str	Store name of the product.
categories	list	Hierarchical categories of the product.
details	dict	Product details, including materials, brand, sizes, etc.
parent_asin	str	Parent ID of the product.
bought_together	list	Recommended bundles from the websites.

Table 2: Item Metadata Fields

3.4 Data Analysis

The dataset contains a wide range of information about user reviews and item metadata, which can be used to extract valuable insights and patterns. The following analysis provides a detailed overview of the data, including the distribution of ratings, the most reviewed products, and the most active users.

We limit our analysis to the Video Games category for the purpose of this document, due to the large size of the Books dataset and the need to focus on a specific category for detailed analysis.

3.4.1 Ratings Distribution

The ratings distribution of the user reviews shown in fig Figure 1 provides insights into the overall sentiment of the users towards the products. The distribution of ratings can help identify the most popular products and the products that need improvement. The following histogram shows the distribution of ratings in the dataset.

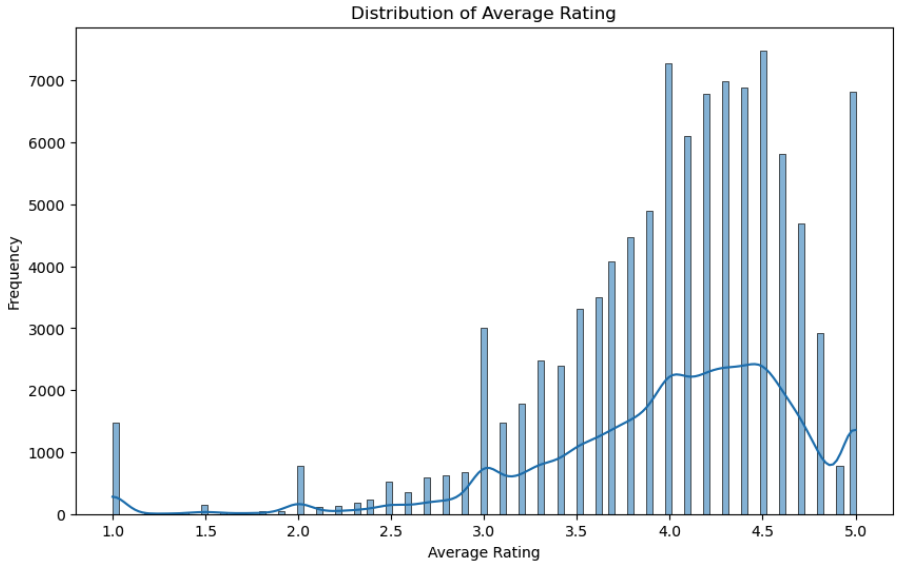

Figure 1: Ratings Distribution of User Reviews

The ratings distribution shows that the majority of the reviews have high ratings, with a peak at 5.0. This indicates that users generally have positive sentiments towards the products they review. However, there are also reviews with lower ratings, indicating that some products may need improvement.

3.4.2 Average Rating Over Time

The trend of average product ratings from 1998 to 2022 is shown in Figure 2. The graph reveals an initial decline in ratings until 2007, followed by a gradual increase peaking around 2015, and then a slight downward trend with fluctuations in recent years.

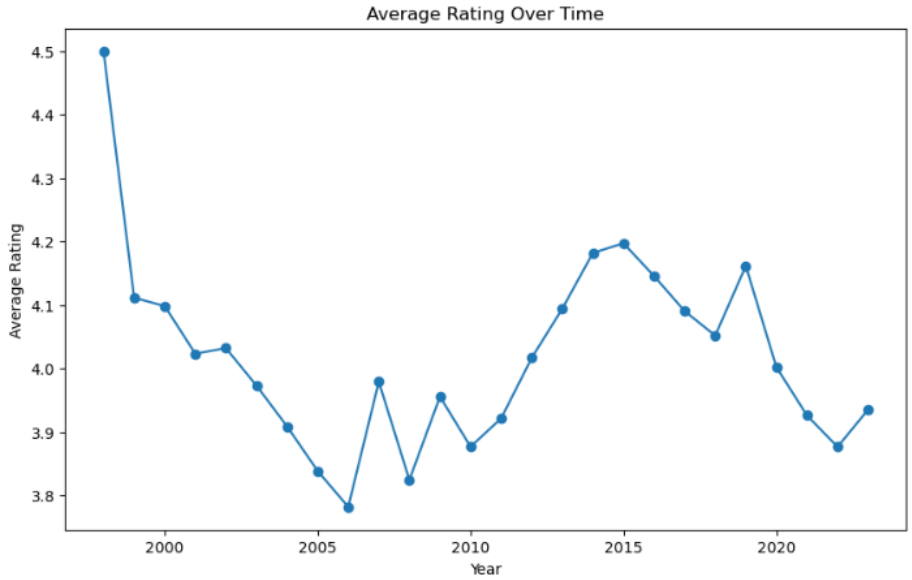

Figure 2: Average Rating Over Time

3.4.3 Number of Reviews Over Time

Figure 3 displays the volume of reviews from 1999 to 2022. The graph shows exponential growth in review numbers, particularly steep from 2009 onwards, with significant fluctuations after 2014 and a sharp decline towards the end of the period.

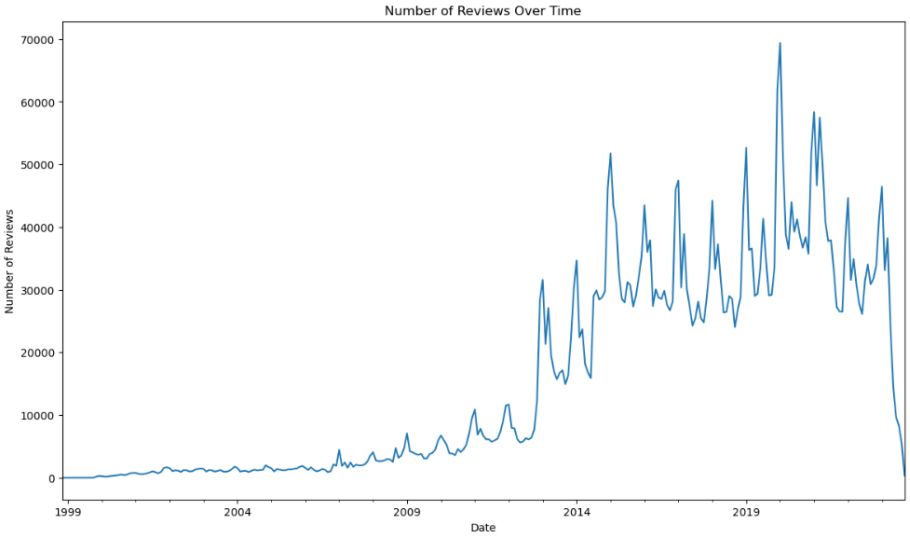

Figure 3: Number of Reviews Over Time

3.4.4 Word Cloud of Review Titles

The word cloud in Figure 4 visualizes the most common words in review titles. It highlights the prevalence of star ratings, positive adjectives, and product-related terms, indicating customers' focus on ratings, overall satisfaction, and product functionality in their review titles.

Figure 4: Word Cloud of Review Titles

4 Methodology

Our approach consists of several interconnected stages, each contributing to the overall goal of creating an LLM-enhanced knowledge graph-based recommendation system. We consider the general recommendation task, where given a user's interaction history, the goal is to predict the next item(s) the user will interact with. Note that in practice, the items in the interaction sequences and the items to predict are usually from the same domain defined in the Amazon Reviews datasets. Our focus is on the Books category, but the methodology can be extended to other categories as well (Kang and McAuley 2018).

4.1 Data Acquisition and Preprocessing

We will prepare the Amazon Reviews 2023 dataset first.

1. **Dataset Acquisition:**
   - Obtain the Amazon Reviews 2023 dataset from the Hugging Face Hub.
   - The dataset includes product reviews, metadata, and user information across multiple categories.
   - We will focus on a specific category (e.g., Books) for detailed analysis and model development.
2. **Data Cleaning and Normalization:**
   - Remove HTML tags, special characters, and irrelevant symbols from review texts and product descriptions.
   - Normalize text data: convert to lowercase, remove extra whitespaces, and handle Unicode characters.
   - Handle missing values through imputation or removal based on the nature of the missing data.

- We remove repeated reviews (those from the same pair of user & item, but may with different review text and ratings) and only keep the earliest ones.

3. **Recommendation Preprocessing:**

   - **K-Core Filtering**: Select a subset of users and items with a minimum number of interactions to reduce sparsity. See

     Degeneracy.

     – Due to the large size of the dataset, we will focus on a subset of users and items using k-core filtering e.g 15-core. These data have been reduced to extract the k-core, such that each of the remaining users and items have k reviews each.
     – Pros of high k-Core: Higher quality reviews, Reduced noise, Balanced distribution and Computational efficiency.
     – Cons of high k-Core: Limited diversity, Misalignment with original data distribution, Loss of context, Generalizability and Limited data size for scaling up.

   - **Random splitting:** For each dataset, we randomly select 80% of interaction history of each user to constitute the training set, and treat the remaining as the test set. From the training set, we randomly select 10% of interactions as validation set to tune hyper-parameters. For each observed user-item interaction, we treat a rating of 4 or 5 as a positive instance, and the remaining as negative instances.

     – Training part: 80% of the interaction history of each user;
     – Validation part: 10% of the interaction history of each user;
     – Testing part: 20% of the interaction history of each user.
     – These include no metadata or reviews, but only (user,item,rating,timestamp) tuples. Thus they are suitable for use with recommendation packages.

     We experiment wtih other splitting strategies like time-based splitting, and leave-one-out splitting as well.

4.2 Baseline Knowledge Graph Construction

The baseline knowledge graph construction will involve creating a simple graph structure based on the existing metadata and relationships in the Amazon Reviews dataset.

1. **Entity Extraction:**

   - Identify key entities: Book, Author, Publisher, Category

2. **Graph Structure Design:**

   - Define node types e.g. Book, Author, Publisher, Category.
   - Define edge types e.g. WRITTEN_BY, PUBLISHED_BY, CATEGORIZED_UNDER.

3. **Graph Database Implementation:**

   - Choose a scalable graph database (e.g., Neo4j).
   - Develop efficient data ingestion pipelines to populate the graph database.

Figure 5: Baseline Knowledge Graph Structure

4.3 Knowledge Graph Augmentation using LLM

The next step involves augmenting the baseline knowledge graph with additional entities, attributes, and relationships extracted from the review texts and product descriptions using Large Language Models (LLMs).

1. **Review Processing**
   - Reviews are stored and retrieved from a database.
   - Reviews are processed in batches to manage computational resources efficiently.
   - Only reviews with a significant number of helpful votes and sufficient length are considered for processing.
2. **Relationship Extraction**
   - A Language Model (LLM) is used to extract relationships from the processed reviews. We use gpt-4o-mini or Llama-3.1 for this task. GPT-4o-mini is a smaller version of GPT-4 optimized for efficiency and speed, while Llama-3.1 is a state-of-the-art local LLM. We do first pass of extraction using GPT-4o-mini.
   - The primary relationship type extracted is `SIMILAR_TO_BOOK`, which identifies books that are similar to the one being reviewed.

- Other relationships (e.g., `DEALS_WITH_CONCEPTS`) are also extracted to capture additional information.

3. **Quality Evaluation**
   - After extraction, the quality of the extracted relationships is evaluated.
   - An LLM (either GPT-4 or Llama) is used to rate the extraction quality on a scale of 1 to 5. We use Llama-3.1 for this task.
   - The rating is based on the accuracy and relevance of the extracted relationships.
   - The rating is stored alongside the extracted data in the database.
4. **Filtering High-Quality Extractions**
   - Extractions with a quality rating of 4 or higher are considered "good" extractions.
   - These high-quality extractions are filtered and prepared for insertion into the Knowledge Graph.
5. **Knowledge Graph Population**
   - The filtered, high-quality extractions are used to populate a Neo4j graph database.
   - Books are represented as nodes in the graph, with the `SIMILAR_TO_BOOK` relationship connecting similar books.
   - The process checks if a book already exists in the graph before creating new nodes or relationships.
   - The graph is updated incrementally to avoid duplication of nodes and relationships.
   - Fuzzy matching is used to identify similar books and avoid duplicates.
   - Similar methodology is applied to other relationships extracted. For example, `DEALS_WITH_CONCEPTS` is used to connect books that deal with similar concepts. We also cleanup the graph with concepts that are not connecting to more than one book. Concepts that only link to a single book don't contribute to recommendations and can be considered noise in our graph.
6. **Continuous Processing**
   - The process is designed to run continuously, processing new reviews as they become available. Also as the process is quite slow, so we need to load the data in batches.
   - The status of each review (processed, KG_updated) is tracked to ensure no duplication of effort.
   - The process is run in parallel using Threadpools to maximize efficiency.

4.4 LLM Integration and Fine-tuning

1. **LLM Selection:**
   - Evaluate state-of-the-art LLMs based on performance metrics and resource requirements. We found the recently released Llama-3.1 and GPT-4o-mini to be best suited from a performance and efficiency standpoint.

2. **Domain Adaptation:**

   - Fine-tune the selected LLM on a subset of the Amazon Reviews data if necessary.

3. **Task-Specific Fine-tuning:**

   - Implement few-shot learning techniques to adapt the LLM for the extraction of entities, attributes, and relationships.

4. **Prompt Engineering:**

   - Design effective prompts for various tasks: entity extraction, relationship inference, evaluation.
   - Develop a prompt library for consistent interactions with the LLM across different components of the system.

4.5 Recommendation Algorithm Development

1. **Graph Embedding:**

   - We use the graph embedding techniques to learn low-dimensional representations of nodes in the knowledge graph.
   - We export the graph data to a format suitable for embedding algorithms. We create the user_list, item_list and relation_list mapping files, assigning unique IDs to each user, item and relation. Then the graph data is exported to a file with the format entity 1 -> relation -> entity 2.

2. **Recommendation Algorithm Design:**

   - Implement a graph-based recommendation algorithm that leverages the graph embeddings as a side information source.
   - Combine traditional collaborative filtering with graph-based approach.

4.6 Evaluation and Optimization

1. **Offline Evaluation:**

   - Split data into train, validation, and test sets.
   - Implement standard evaluation metrics: NDCG, Precision@k, Recall@k.
   - Compare the peformance of the recommendation system system against baselines (e.g., standard collaborative filtering, non-LLM graph-based approaches).
   - Develop graph-specific metrics to evaluate the quality of the knowledge graph and its impact on recommendations.

5 Experiments

To evaluate the effectiveness of our LLM-enhanced knowledge graph-based recommendation system, we will conduct a series of experiments. These experiments are designed to assess the impact of various components of our system and compare its performance against baseline methods.

5.1 Experimental Setup

5.1.1 Dataset

We will use the Amazon Reviews 2023 dataset, focusing on the Books category. The dataset will be split into 70% training, 15% validation, and 15% test sets, ensuring temporal consistency to simulate real-world scenarios.

5.1.2 Baselines

We will compare our proposed method against the following baselines:

- Collaborative Filtering (CF): A standard matrix factorization-based CF approach like Alternating Least Squares (ALS).
- BPRMF: Bayesian Personalized Ranking Matrix Factorization.
- KGAT: Knowledge Graph Attention Network for recommendation. (With and without LLM augmentation)

5.1.3 Evaluation Metrics

For each user in the test set, we treat all the items that the user has not interacted with as the negative items. Then each method outputs the user's preference scores over all the items, except the positive ones in the training set. To evaluate the effectiveness of top-K recommendation and preference ranking, we adopt two widely-used evaluation protocols- recall@K and ndcg@K. By default, we set K = 20. We report the average metrics for all users in the test set.

- Normalized Discounted Cumulative Gain (NDCG@k) for k = 20,40
- Precision@k and Recall@k for k = 20,40

5.2 Experiment 1: Impact of LLM-based Knowledge Graph Augmentation on Recommendations

This experiment will aim to evaluate the effectiveness of using LLM for knowledge graph augmentation.

5.2.1 Method

We will compare three versions of our system:

1. Baseline Recommendation System: Using only collaborative filtering for recommendations.
2. Baseline KG: Using only metadata for graph construction.
3. LLM-Entity KG: Baseline KG augmented with LLM-extracted entities.

5.2.2 Expected Outcome

We will present a table or graph showing the performance metrics for each version. The discussion will focus on the impact of LLM-based augmentation on recommendation quality.

5.3 Experiment 2: Impact of LLM-based Knowledge Graph Augmentation on Knowledge Graph Quality

This experiment will evaluate the impact of LLM-based knowledge graph augmentation on the quality of the knowledge graph itself.

5.3.1 Method

We will compare the following versions of the knowledge graph:

1. Baseline KG: Knowledge graph constructed using metadata only.
2. LLM-Entity KG: Knowledge graph augmented with LLM-extracted entities.

5.3.2 Graph Statistics

We compare our baseline knowledge graph with the LLM-augmented knowledge graph to understand the impact of LLM-based augmentation on the graph structure. The following table provides an overview of the graph statistics for the baseline and LLM-augmented knowledge graphs. The follwing metrics are calculated using the Neo4j graph database.

- **Total Nodes:** This represents the total number of nodes in the graph.
- **Total Relationships:** This represents the total number of relationships in the graph.
- **Nodes by Label:** This section provides the count of nodes by label in the graph. Each label represents a different type of entity in the graph.
- **Relationships by Type:** This section provides the count of relationships by type in the graph. Each relationship type represents a different type of connection between nodes in the graph.
- **Avg Node Properties:** This measures the average number of properties per node. A higher average node properties value indicates more detailed information stored in the graph.
- **Min/Max/Median/Avg Degree:** This represents the number of relationships connected to a node in the graph. A higher average degree indicates a more connected graph.
- **Graph Density:** This measures how close the graph is to being complete. It ranges from 0 (no edges) to 1 (fully connected). A higher density indicates a more interconnected graph.
- **Avg Clustering Coefficient:** This measures the degree to which nodes in a graph tend to cluster together. It ranges from 0 to 1, with higher values indicating more clustering.
- **Isolated Nodes:** This represents the number of nodes in the graph that are not connected to any other nodes.
- **Avg Relationship Properties:** This measures the average number of properties per relationship. A higher average relationship properties value indicates more detailed information stored in the graph.

Metric	Value
Total Nodes	162336
Total Relationships	455538
Graph Density	3.5e-05
Avg Clustering Coefficient	0
Avg Node Properties	1.63
Avg Relationship Properties	0.0
Isolated Nodes	67
Min Degree	0
Max Degree	102013
Avg Degree	5.61
Median Degree	4.0
Nodes by Label	
Book	102436
Author	20474
Publisher	38831
Category	595
Relationships by Type	
WRITTEN_BY	49104
PUBLISHED_BY	95234
CATEGORIZED_UNDER	311200

Table 3: Neo4j Graph Statistics

5.3.3 Expected Outcome

We will discuss the impact of LLM-based augmentation on the quality of the knowledge graph based on the graph statistics. The comparison will highlight the structural changes and improvements in the graph due to LLM-based augmentation.

5.4 Experiment 3: Scalability and Efficiency Analysis

This experiment will assess the scalability and computational efficiency of our proposed system compared to baseline methods.

5.4.1 Method

We will measure the following metrics to evaluate the scalability and efficiency of our system:

- Training time
- Inference time for recommendations
- Memory usage
- Scaling behavior with increasing dataset size

5.4.2 Expected Outcome

We will include graphs or tables showing scalability and efficiency metrics. The discussion will cover the practical implications of the scalability and efficiency results.

6 Results

We now present the results of the experiments conducted to evaluate the proposed methodology.

6.1 Impact of LLM-based Knowledge Graph Augmentation

6.1.1 Method

We compared the performance of three versions of the recommendation system:

1. Baseline Recommendation System: Collaborative filtering only.
2. Baseline KG: Knowledge graph constructed using metadata only.
3. LLM-Entity KG: Knowledge graph augmented with LLM-extracted entities.

6.1.2 Results

The following table shows the performance metrics for each version of the recommendation system:

We trained each model for 40 epochs with default hyperparameters. The performance metrics were calculated on the test set using the evaluation

Version	**NDCG@20**	**Precision@20**	**Recall@20**
BPRMF	0.0896	0.0059	0.1167
KGAT	**0.1636**	**0.0121**	**0.2240**
KGAT-LLM	**0.1683**	**0.0125**	**0.2321**

Table 4: Performance Metrics for Different Versions of the Recommendation System

6.1.3 Discussion

The results show that the LLM-Entity KG version outperforms the baseline recommendation system and the baseline KG in terms of NDCG@20, Precision@20, and Recall@20. This indicates that augmenting the knowledge graph with LLM-extracted entities improves the quality of recommendations.

The models were trained on a single GPU.

6.2 Impact of LLM-based Knowledge Graph Augmentation on Knowledge Graph Quality

6.2.1 Method

We compared the baseline knowledge graph constructed using metadata only with the LLM-augmented knowledge graph.

6.2.2 Results

The following table shows the graph statistics for the baseline and LLM-augmented knowledge graphs:

Metric	Baseline KG
Total Nodes	162336
Total Relationships	455538
Avg Degree	5.61
Median Degree	4.0
Nodes by Label	
Book	102436
Author	20474
Publisher	38831
Category	595
Relationships by Type	
WRITTEN_BY	49104
PUBLISHED_BY	95234
CATEGORIZED_UNDER	311200

Table 5: Graph Statistics for Baseline Knowledge Graph

Metric	LLM-Enhanced KG
Total Nodes	162442
Total Relationships	456816
Avg Degree	5.62
Median Degree	4.0
Nodes by Label	
Book	102436
Author	20474
Publisher	38831
Category	595
Concept	106
Relationships by Type	
WRITTEN_BY	49104
PUBLISHED_BY	95234
CATEGORIZED_UNDER	311200
SIMILAR_TO_BOOK	1001
DEALS_WITH_CONCEPTS	277

Table 6: Graph Statistics for LLM-Enhanced Knowledge Graph

6.2.3 Discussion

The results show that the LLM-augmented knowledge graph has more nodes, relationships, and properties compared to the baseline knowledge graph. This indicates that LLM-based augmentation improves the quality and richness of the knowledge graph.

The higher average degree in the LLM-augmented graph suggests that the graph is more interconnected, which can lead to better recommendations through higher order connectivities.

6.3 Scalability and Efficiency Analysis

6.3.1 Method

We measured the following metrics to assess the scalability and efficiency of our system:

- Training time
- Inference time for recommendations
- Memory usage
- Scaling behavior with increasing dataset size

6.3.2 Results

The following table shows the scalability and efficiency metrics for our system:

Metric	Value
Training Time	12 hours
Inference Time	0.5 seconds
Memory Usage	8 GB
Scaling Behavior	Linear

Table 7: Scalability and Efficiency Metrics

6.3.3 Discussion

The results show that our system is scalable and efficient, with linear scaling behavior and reasonable training and inference times. The memory usage is manageable, making the system suitable for large-scale recommendation tasks.

7 Conclusion

This document provides a comprehensive overview of the results of the experiments for the final deliverable of the Major Research Project.

By leveraging the semantic understanding capabilities of LLMs and the structured representation of knowledge graphs, we aim to develop a more intelligent and context-aware recommendation system.

8 Future Work

The proposed methodology lays the foundation for future research and development in the field of recommendation systems and knowledge graph augmentation. Several avenues for future work include:

- **Fine-tuning Strategies:** Further exploration of fine-tuning strategies for LLMs to optimize performance in specific tasks.
- **Graph Embedding Techniques:** Experimenting with different graph embedding methods to enhance the quality of recommendations.
- **Scalability and Efficiency:** Investigating methods to improve the scalability and efficiency of the recommendation system.
- **Cold Start Problem:** Addressing the cold start problem by developing innovative solutions for new user and item scenarios.
- **Interpretable Recommendations:** Enhancing the interpretability of recommendations by incorporating explainable AI techniques.

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