# A TRIP ADVISOR BASED ON LIGHTRAG

Fanshi Meng (904055546), Junbo Zou (904145436)

## 1 Introduction

Recommender systems have become an essential component in the field of information retrieval and decision support, especially in tourism where users expect personalized suggestions for destinations and activities (Ricci et al., 2011; Felfernig et al., 2018). Traditional recommendation methods, such as collaborative filtering and content-based approaches, often struggle with capturing complex relationships among entities in a knowledge-rich domain like tourism (Adomavicius & Tuzhilin, 2005).

Recently, Retrieval-Augmented Generation (RAG) has emerged as a promising paradigm that integrates retrieval with large language models, thereby enabling systems to leverage structured or semi-structured knowledge in natural language tasks (Lewis et al., 2020). LightRAG, in particular, extends RAG into the graph domain by introducing graph-structured retrieval mechanisms (Zhu et al., 2024). This allows for modeling of entities and their relationships in a graph, which is highly suitable for domains such as tourism where destinations, attractions, and categories are inherently interconnected.

In this project, we focus on the U.S. state of Georgia as our case study. Georgia offers diverse tourist attractions including natural landscapes, cultural heritage sites, and urban experiences. By representing these attractions and their relationships in a graph structure, we can leverage LightRAG's graph-based retrieval capabilities to provide more meaningful and context-aware tourism recommendations.

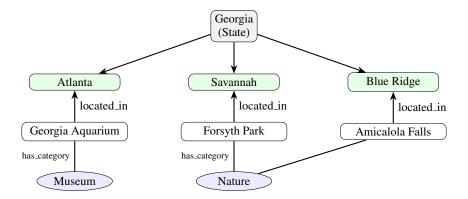


Figure 1: LightRAG-oriented tourism graph for Georgia: State  $\rightarrow$  City/Region  $\rightarrow$  Attraction, with bottom categories linked via *has\_category*; attractions link to their city by *located\_in*.

## 2 Related Work

RAG was first introduced as a framework combining neural retrieval with generative models, enabling language models to ground their outputs on external knowledge sources (Lewis et al., 2020). This approach alleviates the problem of parametric knowledge limitations by dynamically retrieving documents during inference. Since its introduction, RAG has become a fundamental paradigm in knowledge-intensive natural language processing.

RAG has been widely applied in domain-specific contexts. In healthcare, RAG-based systems have been developed to assist in clinical decision support and medical question answering, where accuracy and transparency are critical (Lee et al., 2023; Jin et al., 2023). In finance, RAG has been leveraged for tasks such as risk assessment, financial report analysis, and market intelligence, enabling domain-expert models to retrieve and reason over structured and unstructured documents (Wang

et al., 2023). These implementations demonstrate RAG's strength in handling knowledge-rich tasks across sensitive domains.

In the context of tourism, RAG is a natural fit given the heterogeneous information sources such as attractions, travel guides, reviews, and geographical knowledge. By constructing structured knowledge graphs or domain corpora, RAG can provide users with more personalized and context-aware recommendations. However, despite its promise, existing RAG systems are not without limitations.

Recent work has highlighted seven major failure modes of RAG, including issues such as retrieval insufficiency, hallucination, and context underutilization (Xu et al., 2024). These findings underscore the importance of addressing fundamental weaknesses in RAG pipelines, particularly when applied to recommendation scenarios where reliability and user trust are essential.

To overcome these shortcomings, LightRAG (Zhu et al., 2024) has been proposed as a simplified yet efficient graph-oriented variant of RAG. By integrating graph structures into retrieval, LightRAG is particularly suitable for domains like tourism, where entities and their relationships can be explicitly represented and exploited. Our project builds upon this line of research, focusing on the construction of a Georgia tourism attraction graph and its application to recommendation.

### 3 GOAL

The goal of this project is twofold:

- 1. **Contribution of a graph-structured tourism dataset:** We will construct a graph that represents tourism attractions in Georgia. The graph will encode not only the attractions themselves but also their semantic and geographical relationships, such as "located in," "similar to," or "recommended with."
- 2. **Implementation of a graph-based tourism recommender:** Using LightRAG, we will implement a retrieval-augmented recommendation system that can query this graph structure to suggest attractions to tourists. By combining graph-based retrieval with language model generation, the system aims to deliver context-aware and personalized recommendations, surpassing traditional keyword-based retrieval methods.

### REFERENCES

Gediminas Adomavicius and Alexander Tuzhilin. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering*, 17(6):734–749, 2005.

Alexander Felfernig, Gerhard Friedrich, Dietmar Jannach, and Markus Zanker. *Recommender Systems: An Introduction*. Cambridge University Press, 2018.

Di Jin et al. Towards trustworthy medical qa with retrieval-augmented large models. In *Proceedings* of ACL, 2023.

John Lee et al. Do large language models help clinical decision support? a rag-based evaluation. *Journal of Biomedical Informatics*, 2023.

Patrick Lewis, Ethan Perez, Aleksandra Piktus, Vladimir Karpukhin, Naman Goyal, Ankush Kulkarni, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Luke Zettlemoyer. Retrieval-augmented generation for knowledge-intensive nlp tasks. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2020.

Francesco Ricci, Lior Rokach, and Bracha Shapira. *Recommender Systems Handbook*. Springer, 2011.

Xinyi Wang et al. Finrag: Retrieval-augmented generation for financial applications. In *Proceedings* of *EMNLP Industry Track*, 2023.

Frank Xu, Weijia Shi, et al. Seven failure modes of retrieval-augmented generation, 2024.

Yiming Zhu, Yangyi Chen, Zixuan Ma, Zhijing Jin, Wayne Xin Zhao, and Ji-Rong Wen. Lightrag: Simple and fast retrieval-augmented generation, 2024.