# 대규모 언어모델 기반 자연어 처리를 통한 공간 추천 모델 향상

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# Enhancing Geospatial Recommendations through Natural Language Processing with Large Language Models

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**Abstract**

With the success of large language models (LLMs) such as OpenAI's ChatGPT, Meta's LLama, and Google's Gemmini, there is a growing trend to leverage natural language queries for database processing. For example, Chroma DB stores documents in an embedded representation, allowing it to find data that closely matches the embeddings of user queries. However, the application of this technology to geospatial data, such as places of interest on a map, remains underexplored. This paper presents an exemplary application of place recommendation by utilizing the user's location to crawl and filter a few recommended results, thereby finding the most relevant place based on the user's natural-language-based query. This approach offers new insights for enhancing location-based services, providing a framework for more contextually relevant and personalized user experiences.

## 1. Introduction

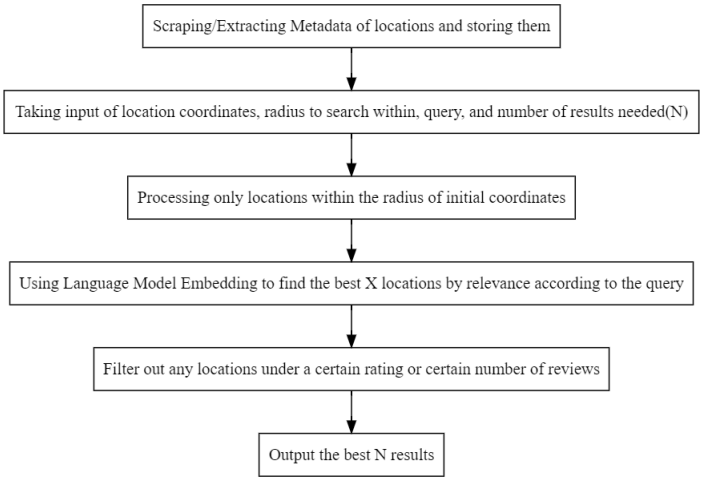
[1] The advent of large language models (LLMs) such as OpenAI's ChatGPT[1], Meta's LLama[2], and Google's Gemini[3] has revolutionized the field of natural language processing, excelling in generating human-like text and thus gaining widespread adoption across various sectors, from customer service automation to personalized content creation. One significant advancement is their integration into database querying systems, where they enable users to interact through natural language rather than traditional query languages like SQL, simplifying user interaction and enhancing data retrieval flexibility[4]. Chroma DB[2] exemplifies this innovation by storing documents as dense vectors that encapsulate semantic meanings, allowing the system to compute and retrieve the most semantically relevant documents based on the similarity between user queries and document embeddings. This approach not only enhances the precision of search results but also overcomes the limitations of traditional keyword-based search methods, offering more contextually appropriate data retrieval.

Despite the advancements in applying LLMs to traditional text-based databases, their potential in handling geospatial data has not been fully explored. Geospatial data, which includes information about geographic locations and features on Earth, presents unique challenges due to its complex and multidimensional nature. This paper aims to bridge this gap by demonstrating how LLMs can enhance location-based services. We propose a system that integrates LLMs with geospatial databases to provide place recommendations based on natural language queries. By incorporating the user's location and processing natural language queries, our system can crawl, filter, and recommend places that not only meet the user's expressed needs but also align with their contextual preferences. This approach significantly enhances user experience by offering more personalized and contextually relevant recommendations, thereby setting a new standard for interactive, location-based services.

In this paper, we propose a novel application solution that delivers personalized recommendations based on natural language queries. This solution harnesses metadata pertaining to the user's location at the time of the query and leverages this information to identify potential places of interest. Subsequently, we refine these results by crawling location data to determine sites that may align with the user's needs. To ensure the relevance and quality of the recommendations, we filter these locations based on specific ratings criteria before presenting the final results. This approach not only enhances the precision of location-based services but also tailors the user experience to individual preferences and context.

## 2. Method

We can summarize the process of the model as following:




1) This work was supported by Institute of Information & communications Technology Planning & evaluation (IITP) grant funded by the Korea government (MSIT) (No.2019-0-01126, Self-learning based Autonomic IoT Edge Computing)

2) https://docs.trychroma.com/

Our methodology, which combines the user's current location with their natural language input, provides a personalized and contextually aware recommendation system. This system not only responds to the explicit needs articulated in user queries but also anticipates underlying preferences and intentions. The potential for scaling this approach to encompass more complex queries and diverse datasets is substantial, offering pathways for significant advancements in both commercial and public sectors.

### 2.1 Scraping Places

We use Kakaomap API to extract all places' metadata including categorization of the place within an area or a city and store them to be processed later.

### 2.2 Select relevant places

Select only the places within the specified radius from the specified place to be processed.

### 2.3 Picking Top Suggested places

Select the top $X$ places suggested by the embedding model based on the query/question and the categorization of the place for final processing. We use Open AI embedding model(text-embedding-3-large) and Chroma DB as a database in python to handle the queries/questions.

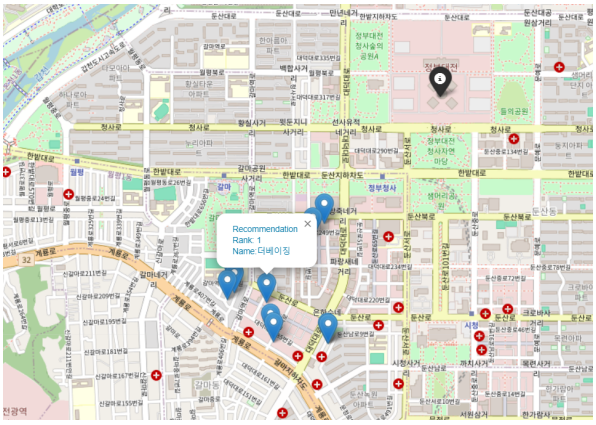
### 2.4 Final processing based on rating

Select the first $N$ places which has a rating higher than or equal than a certain value(3.8 in the current model) and the minimum number of ratings given that is required(10 in the current model). By selecting the first $N$ places, the output of the model is sorted by the relevance of the places suggested.

## 3. Use cases

With the help of NLP AI and embeddings, queries/questions can be understood in many different languages including minor mistakes in the structure sentence of the question and the result of the queries/questions can be interpreted visually which makes it simple for the user to interpret the results/places even for disabled users. It also saves time and effort for the user to look for nearby relevant places.
An example of visualizing the top 10 selected Chinese restaurants using branca[3]:

3) https://github.com/python-visualization/branca




Chinese restaurants around government complex

## 4. Test data

For the test data provided, the radius to look for restaurants will be set within $1.5km$ from the initial place and the number of results outputted by the model will be set to 10.
We will provide two different places in Daejeon: Gung dong, government complex Daejeon.

The categorization of each location is stored in Korean(as it is scraped from Kakaomap). But to demonstrate language model understanding, We will present 10 questions in English as follows:

| **Question** | **Criteria for Partially Related** |
|---|---|
| I am vegetarian. Where can I eat? | There is only sub-main vegetarian dishes |
| Where can I eat some sandwiches? | If it contains dough |
| Is there any place that sells Noodles? | If it is stew but with no noodles |
| I want to eat pizza. Suggest me some Pizza places. | If place sells pasta or dough related food but not pizza |
| Do you have any suggestions for chicken places? | None |
| Suggest me some Japanese restaurants. | Japanese style food but not Japanese |
| Where can I have Vietnamese food? | Southeast Asian cuisine |
| Are there any Western restaurants around? | None |
| I want to have some Indian food. | Indian style food but not Indian |
| Are there any Chinese food nearby? | Chinese style food but not Chinese |

## 5. Results

We will format the results such that each row describes each question with each cell being 1(matches criteria), 0(partially matches criteria), −1(does not match criteria).

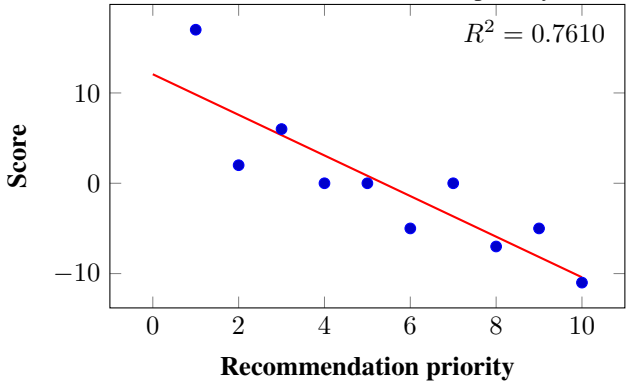
| Data | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Q1** | 1 | -1 | -1 | 0 | 1 | 1 | -1 | 1 | 1 | 0 |
| **Q2** | 1 | -1 | -1 | 0 | 0 | 0 | -1 | -1 | 0 | -1 |
| **Q3** | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |
| **Q4** | 1 | 1 | 1 | 1 | 1 | -1 | 1 | 1 | -1 | 0 |
| **Q5** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Q6** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | -1 | 1 | -1 |
| **Q7** | 1 | 1 | 0 | 0 | -1 | -1 | -1 | -1 | -1 | -1 |
| **Q8** | 1 | -1 | -1 | -1 | -1 | 1 | -1 | 1 | 1 | -1 |
| **Q9** | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 |
| **Q10** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | -1 | 1 |
| **Sum** | 8 | 1 | 1 | 3 | 3 | 3 | 0 | 1 | 1 | -3 |

Gung Dong results

| Data | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 1 | 0 | -1 | -1 | 0 | -1 | -1 | -1 |
| 2 | 0 | -1 | 0 | 0 | 0 | -1 | 1 | -1 | -1 | -1 |
| 3 | 1 | 1 | 1 | 1 | 1 | -1 | 1 | -1 | -1 | -1 |
| 4 | 1 | 1 | -1 | -1 | -1 | -1 | 0 | -1 | -1 | -1 |
| 5 | 1 | -1 | 1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 |
| 6 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 7 | 1 | 1 | 1 | 0 | -1 | -1 | -1 | -1 | -1 | -1 |
| 8 | 1 | -1 | 1 | -1 | -1 | -1 | 1 | -1 | 1 | -1 |
| 9 | 1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 |
| 10 | 1 | 1 | 1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 |
| **Sum** | 9 | 1 | 5 | -3 | -3 | -8 | 0 | -8 | -6 | -8 |

Government Complex results

Plotting the sum of scores of recommendations, we can show the relation between score and recommendation priority:




The results show that there is a correlation between how relevant the recommendation is and the priority of the location given by the embedding.

## 6. Conclusion

This paper demonstrates the potential of integrating large language models (LLMs) with geospatial data to enhance location-based services by enabling natural language queries within geospatial databases. Our solution facilitates a more intuitive and user-friendly interface, utilizing user location metadata and sophisticated query processing to generate personalized, contextually relevant recommendations. The use of LLMs not only improves the accuracy and flexibility of querying but also ensures high-quality recommendations through filtering criteria, significantly boosting user satisfaction. Looking forward, there are ample opportunities for refining this integration by incorporating dynamic data and more advanced predictive models to further enhance the utility and accuracy of the recommendations. This groundwork promises a transformative shift in how we interact with geospatial information, paving the way for more accessible and practical applications in everyday decision-making.

## References

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