Enhancing Retail Site Recommendation Using Large Language Model Embedding

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**Abstract.** In retail industry, suggesting a suitable location for a business establishment is challenging. Identifying factors that affect site suitability is difficult due to the lack of sales data and the lack of reliable and consistent datasets such as demographic, point of interest and many more. Although traditional methods such as statistical methods, machine learning, geospatial analysis, deep learning, and hybrid approaches have been explored, the growth of Large Language Models(LLMs) presents new opportunities to enhance retail site recommendations. LLMs can improve contextual understanding and decision making by using their ability to process unstructured data and produce useful embeddings. Therefore, this study has attempted (i) to construct an analytical dataset based on embedding that is useful for data modeling, (ii) to propose the LLM embedding framework for recommendation, and (iii) to evaluate the performance of the predictive model after applying the LLM embedding, incorporating LLM-based explainability techniques. The dataset consists of geographic information on target outlets, nearby stores, surrounding property data and popula- tion density. After converting the structured data into sentences, Ollama 3.1.8’s LLM processes location descriptions to generate embeddings, enabling to improve the accuracy of classification models. To address class imbalance, the SMOTE technique was applied. Several classifiers such as Random Forest, Logistic Regression, Support Vector Machine(SVM), XGBoost were created and the models were evaluated using the following metrics: accuracy, precision, recall and F1 score. The finding showed that the XGBoost Classifier produced the highest balanced accuracy of 86.9%. Furthermore, this study also leverages the natural language generation capabilities of LLMs to offer explanations to retailers at the prediction output step. The implementation of LLM em- beddings and explanations enhances user comprehension and model performance, making the system more useful for choosing retail locations in the real world.

# INTRODUCTION

Retail industry is considered the largest, most competitive and most dynamic market that plays a crucial role in the global economy. It refers to a business strategy that directly sells goods or services to consumers. Various businesses that match consumer needs can be involved, including food and beverage stores, convenience stores, clothing stores, etc. As the retail industry expands, the selection of a suitable location for the location of the store becomes significantly important because it affects the success of the commercial.

Site selection is an important component of business expansion. Choosing a suitable property site allows and im- proves operational efficiency, attracting more foot traffic, leading to the success of a business [1, 2, 3, 4]. To find the right location for a business, it is required to identify the critical factors such as foot traffic, demographic data, geospatial information, proximity to competitors etc. to choose the best site [5]. Using traditional approaches to site selection is less efficient and time consuming because it is primarily based on rules of thumb and human inspec- tions. Meanwhile, recent advancement of Artificial Intelligence (AI), especially the rise of LLMs have demonstrated new possibilities for handling unstructured data. LLMs are also effective in generating embeddings from textual data, which capture rich contextual information. Because of these, LLMs have the significant potential to transform traditional recommendation systems.

Even though location analytics for business recommendation has advanced significantly, there are still certain re- search challenges. First, the available data sets that determine the suitability of a business are difficult to obtain. However, it is extremely difficult to access such sales data due to the data privacy issues. It is necessary to create methods to analyze location features to address these issues. As the scale of data increases, handling large and un- structured data efficiently is one of the challenges in existing techniques. Textual location descriptions, demographic information are examples that frequently rich in useful information but are poorly utilized due to the lack of tools that can learn the insights from the complicated data. Therefore, improving the accuracy and adaptability of models and optimizing the performance is important. In addition, while LLM embedding have demonstrated potential in other domains, there is still a noticeable lack of systematic evaluation regarding their effectiveness when combined with several classification models for retail-to-site recommendation. It is necessary to determine the effectiveness of LLM embedding across a variety of classifiers. Furthermore, there is still a lack of research on the explainability of predictive models, which highlights the need to apply and evaluate LLM-based interpretability techniques to ensure efficient and flexible decision-making.

This study aims to construct an analytical dataset that provides a clear understanding of the business area’s sur- rounding characteristics for retail-to-site recommendation. Secondly, this paper’s objective is to implement LLM embedding for retail-to-site recommendation. Lastly, this paper also aims to evaluate performance of the predictive models after LLM embedding, incorporating LLM-based explainability techniques.

This paper will focus on food retail stores in Malaysia, specifically examining standalone establishments of major chains such as Chagee, Baskin Robbin, ZUS Coffee, Secret Recipe and McDonald’s outlets. The point of interest data sources is collected using Google API. In addition, property data from Brickz.my [6], provided by the Valuation and Property Services Department, will be used. Meta demographic data [7] will also be included, including information about the Malaysian population, the demographics of men and women, and the child population. However, this research proposes the integration of LLM embedding to retail to site recommendation to improve the performance.

# LITERATURE REVIEW

## Key Variables and Factors in Retail Site Selection

Retail-to-site selection is an essential procedure for businesses, but it can be challenging since it must determine the key factors influencing business decision making [8]. The factors have been roughly divided into demographic and geographic data. Geographical characteristics are considered to play a crucial role in suggesting a suitable location, including point of interest (POI), nearby property or neighborhood, and transportation. POI is a particular place on a map that has notable features that someone would find interesting or helpful, which includes its geographical coordinates or address. These researchers discussed the critical importance of POIs’ geographical regional characteristics in determining suitable sites for business [8, 9]. Furthermore, the surrounding neighborhood refers to the nearby geographic characteristics of a place. Previous studies show that the presence of user attracts, such as locations near walkable areas and high traffic areas such as schools, shopping centers, train stations, business areas, near residential areas, etc. has been shown to improve business success [1, 2]. Another important aspect that highlights the value of convenient access is transportation. In addition, the significance of transportation infrastructure, such as parking lots in improving customer satisfaction and business performance in retail and service-oriented businesses is covered [5]. Population, education, economy and POI customer number are characterized as demographic data, which is essential in impacting site selection. Population density is an essential factor in site selection, as a larger populated area provides a greater potential customer base, which will help the store success [1, 8]. Furthermore, the economic variables such as income levels, employment rates etc. can influence the business’s success [9]. Higher-end consumer goods and services are more likely to be supported by businesses in affluent communities. Using the number of POI customers also offers clear insights into possible foot traffic for a place, which aids in site selection, as highlighted by [2].

The comparison of demographic and geographic features used by other researchers is displayed in Table 1.

**TABLE 1.** Comparison of demographic and geographic features

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Authors** | **Geographical** | | | **Demographic** | | | |
| **POI** | **Nearby Property** | **Transportation** | **Population** | **Education** | **Economy** | **POI Customer Number** |
| [8] | ✓ | ✓ | ✓ | ✓ |  | ✓ |  |
| [1] | ✓ | ✓ |  | ✓ | ✓ | ✓ |  |
| [10] | ✓ | ✓ | ✓ | ✓ |  |  |  |
| [2] | ✓ | ✓ | ✓ | ✓ |  |  | ✓ |
| [5] | ✓ | ✓ | ✓ | ✓ |  |  |  |
| [11] | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |  |
| [9] | ✓ | ✓ | ✓ |  |  |  |  |

## Recommendation Techniques

A machine learning-based framework for suggesting a retail site through location profiling is proposed in [3]. Their methods convert various location characteristics into structured feature vectors and used classification algorithms to the data to recommend a retail business. By applying these methods, this study achieves high accuracy in location prediction and also highlights location data combined with machine learning to improve site recommendations. Furthermore, another work focuses on a multilabel classification deep learning model for retail recommendations [4]. This model enables retailers to forecast which multiple stores would be most successful in particular situations. In this study, the scalability and adaptability of deep learning in complex retail environments are emphasized. To screen retail shop locations, a sequential ensemble machine learning model is presented by [5]. When dealing with complicated, noisy, and high-dimensional retail site data, the study offers strong support in favor of employing ensemble approaches. In addition, a similarity measure with machine learning is proposed in [12]. The study demonstrated how well similarity-based modeling captures subtle interactions between customers and locations, especially when integrated into a predictive retail analytics pipeline.

## Large Language Models

Large Language Models (LLMs) are the key points that will be covered in this field. Recent research explores the potential of LLMs as effective embedding generators. The integration of LLMs into classical machine learning estimators shows significant improvements in prediction performance for binary classification and transfer learning tasks [13]. To facilitate effective model routing and performance forecasting, EmbedLLM suggests a framework for learn- ing compact vector representations of LLMs [14]. LLMs have also been shown to outperform traditional encoder-only models in generating embeddings [15]. Next, Llama 2 model’s embedding layer can be used to create vector representations that capture both the meaning of the text and its context [16]. These studies demonstrate the superior contextual understanding and pattern recognition capabilities of LLM embeddings in improving classification accuracy across diverse domains.

Due to its effectiveness, there has been a lot of interest in the application of LLMs to recommendation systems in recent years. Several studies have proposed approaches to the implementation of LLMs in recommendation systems. In recommendation systems, LLMs can analyze user preferences, therefore, provide recommendations for sites and activities, enhancing decision making [17, 18]. Besides, existing traditional methods often face the data sparsity issue, which affects the models’ poor accuracy. However, LLMs address this issue by word and sentence embeddings, which improves the accuracy and performance of recommendation systems [19, 20]. Besides, it has been demonstrated that LLMs perform better at creating embeddings than conventional encoder-only models [21]. To solve the long-tail problem in sequential recommendation systems, LLMEmb uses LLMs to create item embeddings [22].

# METHOD

Figure 1 illustrates the flow diagram of the methods used in this work. In this work, data pre-processing is performed to transform raw data into useful predictive models. The processes following involved data transformation that involved LLM embedding, model construction, evaluation and experiment setting. Each of the processes will be explored and explained in a more detailed way.



**FIGURE 1.** High-level framework for Retail-to-Site recommendation system

## Data Sources

The first process is to collect data from different aspects of location analytics. To achieve this, we have collected data from multiple sources, as demonstrated in Table 2. All the data will be used to construct an analytical dataset to perform the prediction in this paper.

The Base Data refers to individual food businesses brands such as Chagee, ZUS Coffee, Baskin Robbin , McDon- ald’s and Secret Recipe, extracting from the Google Application Programming Interface (Google API). Additionally, point-of-interest data, which captures nearby business types and their categories, is also gathered using the Google API. Property data is collected from brickz.my. The population data is a list of population in Malaysia and its source of population data is Humanitarian Data Exchange (HDX). Besides, the geographical data are from the Global Ad- ministrative Areas (GADM). After collecting all the data, we will process each dataset separately, then merge the entire dataset based on latitude and longitude values.

**TABLE 2.** Summary of datasets and their descriptions

|  |  |  |  |
| --- | --- | --- | --- |
| **Dataset** | **Description** | **Sources** | **Dimension** |
| Base Data | The food retail business data, which includes  different brands | Google API | 954,4 |
| Surrounding Environment Data | The nearby business name and type based on  base data | Google API | 19001,7 |
| Residential Property Data | The nearby residence and property | Brickz.my | 491721, 6 |
| Population Data | The population of men, women, women of re-  productive age, children, youth, and elderly | Humanitarian Data Exchange (HDX) | 3855823, 8 |
| Geospatial Data (Shapefile Format) | Malaysia geographic coordinates and related at-  tribute information | Global Administrative Areas (GADM) | — |

## Data Preprocessing

Data preprocessing is one of the essential steps in the data mining process. This step is necessary to ensure that the further data analysis result can be more accurate and efficient. To achieve optimal results, we will attempt to transform the raw data into a usable and suitable for further data analysis using a variety of data preprocessing methods. Data cleaning, which includes missing and duplicated data handling in these datasets has been done to ensure the further performance of method can be efficient. To maintain data integrity, we started by removing the dataset of rows with duplicate and missing values. We also filtered out the outlets operated in the shopping mall and gas station franchise from the base data to make it suitable to use. We extracted and converted store names to a consistent base name, such as "Chagee" to ensure brand naming consistency, especially because of variances made during data scraping using the Google API (such as entries like "CHAGEE Bukit Jalil"). Since the same business may appear with different names or variations in uppercase or lowercase, we also rename each row to maintain consistency. Using a shapefile with administrative boundaries, reverse geocoding was done to translate geographic coordinates into the appropriate city and state data. The ‘geopandas‘ Python package was used to spatially link the shapefile polygons with the latitude and longitude of each outlet. This made it possible to precisely assign city and state properties according to location. Besides, useless columns have also been removed from these datasets.

## Data Transformation

Data transformation is a crucial step in data mining because it transforms data into forms that are suitable for data mining procedures. The base data represents the main business of interest, while the surrounding area dataset expands from the base data for determining nearby businesses within a 2 km radius. These datasets are gathered using Google API. Therefore, merging the nearby area by business type and calculating the total number of each business type based on the surrounding area data is one of the transformation processes that are included in this study. In addition, property and population data are also integrated using haversine distance calculation within a 2 km radius based on the main business latitude and longitude. Each attribute also is briefly explained and converted into sentence in the column which is called “Description”, which can be used for embedding. Finally, an analytical dataset which includes business density, property characteristics, and population demographics, description is produced.

Ollama 3.1.8’s LLM embedding is applied to embed the column called ’Description’, which summarizes the textual data about the variable related to the retail location. By embedding the text, the predictive algorithm can concentrate on significant patterns. After that, SMOTE (Synthetic Minority Over-sampling Technique) would be applied to address the class imbalance problem. There were 245 McDonald’s, 211 Secret Recipe, 330 ZUS Coffee, 41 Baskin-Robbins, and 73 Chagee in the original label distribution, which was imbalanced. SMOTE improved the classifier’s capacity to generalize across all store types by assisting in the generation of synthetic samples for the minority classes, resulting in a more balanced dataset.

## Model Construction and Evaluation

After LLM embedding, a variety of classification models which include Random Forest, Logistic Regression, Support Vector Machine and XGBoost are used to predict the site selection. These models are used to evaluate performance after building, enabling us to compare their results and select the best model for retail-to-site recommendation system that will help us achieve our objectives. When evaluating classification model performance, the F1-score, recall, accuracy, and precision are often employed measures. The evaluation metrics are described as follows:

Accuracy: Accuracy is an important metrics to measure a model’s accuracy in identifying positive and negative occurrences. The Equation (1) is used to calculate the Accuracy.

(1)

Precision: The percentage of accurate positive forecasts is known as precision. The formula used to calculate the Precision is as Equation (2).

(2)

Recall: Recall evaluates a model’s ability to correctly identify all positive cases. Recall can be described as Equation (3).

(3)

F1 Score: The F1 score calculates the balanced mean of precision and recall, which provides a single, balanced score that incorporates both metrics. F1 Score can be defined as Equation (4).

(4)

## Experiment Setting

Based on the analytical dataset, four machine learning models will be developed in this study. Through the classification models, there are fixed primary point names to predict: Chagee, ZUS Coffee, Baskin Robbin, McDonald’s and Secret Recipe. These 5 point names will be generated into 10 sets of analytical datasets, as seen in Table 3. The Random Forest Classifier, Logistic Regression Classifier, Support Vector Machine Classifier and XGBoost Classifier are the classification models that will be trained for this project. The best outcome will be determined by comparing the models’ output after they have been trained.

**TABLE 3.** Combination of analytical dataset for experiment

|  |  |
| --- | --- |
| **Experiment** | **Point Name** |
| 1 | Chagee, Baskin Robbins, Secret Recipe |
| 2 | Chagee, McDonald’s, Baskin Robbins |
| 3 | Chagee, McDonald’s, Secret Recipe |
| 4 | Chagee, ZUS Coffee, Baskin Robbins |
| 5 | Chagee, ZUS Coffee, McDonald’s |
| 6 | Chagee, ZUS Coffee, Secret Recipe |
| 7 | McDonald’s, Baskin Robbins, Secret Recipe |
| 8 | ZUS Coffee, Baskin Robbins, Secret Recipe |
| 9 | ZUS Coffee, McDonald’s, Baskin Robbins |
| 10 | ZUS Coffee, McDonald’s, Secret Recipe |

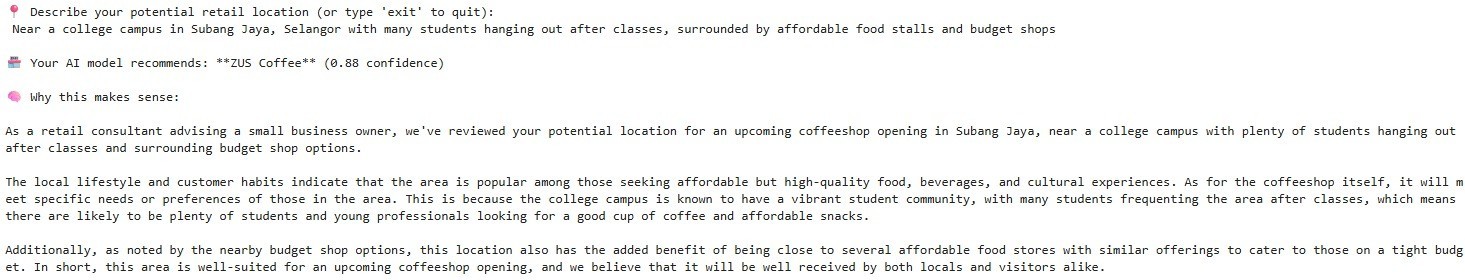
# FINDINGS

Each dataset contains a different combination of stores, while dataset 4 consists of three brands, Chagee, ZUS Coffee and Baskin-Robbins. Dataset 4 had the best classification accuracy among the 10 analytical datasets. Using this dataset, the XGBoost classifier produced the balanced accuracy of 86.9%, outperforming all other models. Random Forest and Logistic Regression also achieved with accuracies of 86.88% and 86.82% respectively. The accuracy score of each classification model is displayed in Table 4 to provide a summary of the overall performance on classification analysis.

**TABLE 4.** Performance of classification models

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Experiment** | **Model** | **Store** | **Balanced Accuracy** | **Precision** | **Recall** | **F1 Score** |
| 4 | Random Forest | Baskin Robbins  Chagee ZUS Coffee | 0.8688 | 0.93  0.80  0.88 | 1.00  0.91  0.69 | 0.96  0.85  0.78 |
| Logistic Regression | Baskin Robbins  Chagee ZUS Coffee | 0.8682 | 0.88  0.82  0.93 | 1.00  0.95  0.65 | 0.94  0.88  0.77 |
| Support Vector Machine | Baskin Robbins  Chagee ZUS Coffee | 0.3367 | 0.32  0.00  1.00 | 1.00  0.00  0.01 | 0.49  0.00  0.02 |
| XGBoost | Baskin Robbins  Chagee ZUS Coffee | 0.8690 | 0.92  0.82  0.87 | 1.00  0.90  0.70 | 0.96  0.86  0.78 |

After integrating the LLM-based explainability into the predictive model, the method produces a recommended retail brand and a human-readable explanation supporting the forecast. The LLM analyzed the location descriptions and provided detailed reasoning for each recommendation. Figure 2 presents the output generated for a sample location description, demonstrating how the integration of LLM-based explanations enhances the interpretability and credibility of the retail site recommendation system.



**FIGURE 2.** LLM-generated explanation output

# CONCLUSION

This study had constructed a dataset for the retail-to-site recommendations, fulfilling the objective of creating an analytical dataset. LLM embedding was applied for extract the key features for location selection. The SMOTE is applied to address class imbalance, particularly in underrepresented store categories. Furthermore, I created a prediction model, and it presently has a good level of accuracy. Besides, the models were assessed using the accuracy score, precision score, recall score and F1 Score. LLM-based explainability techniques to enhance model transparency and support efficient, flexible decision-making. The method proposed in this paper effectively integrates the LLM embedding and explainability with traditional classification techniques to improve the model performance, thereby achieving the project’s objectives. The approach transforms location descriptions into semantically rich embeddings, enabling it to capture contextual information that is often missed by traditional encoding methods.

Despite the approach’s potential, there are still several methodological limitations. For instance, crucial steps such as standardizing store names due to inconsistent Google API results and using shapefiles for reverse geocoding made the data preprocessing process more difficult and time-consuming, requiring close attention to guarantee accuracy and consistency. Furthermore, the lack of detailed cross-validation reporting constrains the generalizability of the results.

Future studies should focus on adding more features that could improve the model’s performance, due to the com- plexity of retail environment. Some of the demographic and geographic characteristics, such as the local economy, education, and transportation should be taken into account for future research in this paper. Furthermore, there is still room for improvement in terms of model interpretability, particularly for stakeholders who want fair decision-making. By expanding on the results and techniques offered in this paper, researchers can continue to enhance and create in- creasingly complex models in retail recommendation, assisting the retail industry in reaching more successful and customized decisions.

# REFERENCES

1. C.-Y. Ting, C. C. Ho, and H.-J. Yee, “Geospatial insights for retail recommendation using similarity measures,” Big Data **8**, 519–527 (2020), pMID: 33347366, https://doi.org/10.1089/big.2020.0028.
2. K. Z. Mazhi, L. E. Suryana, A. Davi, and W. R. Dewi, “Site selection of retail shop based on spatial analysis and machine learning,” in *2020 International Conference on Advanced Computer Science and Information Systems (ICACSIS)* (2020) pp. 135–140.
3. C.-Y. Ting and M. Y. Jie, “Location profiling for retail-site recommendation using machine learning approach,” in *Proceedings of the Interna- tional Conference on Computer, Information Technology and Intelligent Computing (CITIC 2022)* (Atlantis Press, 2022) pp. 48–67.
4. Z. Poo, C. Ting, Y. P. Loh, and K. Imran, “Multi-label classification with deep learning for retail recommendation,” Journal of Informatics and Web Engineering **2**, 218–232 (2023).
5. J. Lu, X. Zheng, E. Nervino, Y. Li, Z. Xu, and Y. Xu, “Retail store location screening: A machine learning-based approach,” Journal of Retailing and Consumer Services **77**, 103620 (2024).
6. “Brickz.my,” [https://www.brickz.my.](http://www.brickz.my/)
7. H. D. E. (HDX), “Malaysia high-resolution population density maps + demographic estimates,”.
8. N. Ghorui, A. Ghosh, E. A. Algehyne, S. P. Mondal, and A. K. Saha, “Ahp-topsis inspired shopping mall site selection problem with fuzzy data,” Mathematics **8** (2020), 10.3390/math8081380.
9. A. Fauzi, N. Indriyani, and A. B. H. Yanto, “Selection of coffee shop business locations using the analytical hierarchy process method,” Jurnal Teknologi dan Open Source **4** (2021), 10.36378/jtos.v4i2.1771.
10. Y. Liu, B. Guo, D. Zhang, D. Zeghlache, J. Chen, K. Hu, S. Zhang, D. Zhou, and Z. Yu, “Knowledge transfer with weighted adversarial network for cold-start store site recommendation,” ACM Trans. Knowl. Discov. Data **15** (2021), 10.1145/3442203.
11. H.-P. Fu, H.-P. Yeh, T.-H. Chang, Y.-H. Teng, and C.-C. Tsai, “Applying ann and tm to build a prediction model for the site selection of a convenience store,” Applied Sciences **12** (2022), 10.3390/app12063036.
12. A. Bhattacharijee, C. Ting, K. Imran, L. Peng, N. Hashim, W.-N. Mohd-Isa, I. Suvon, and W. Matsah, “Optimizing retail recommendation via similarity measures and machine learning approach,” JOIV : International Journal on Informatics Visualization **8**, 1192 (2024).
13. Y. Wu, Y. Wang, C. Wang, and Z. Zheng, “Large language model enhanced machine learning estimators for classification,” (2024), arXiv:2405.05445 [cs.LG].
14. R. Zhuang, T. Wu, Z. Wen, A. Li, J. Jiao, and K. Ramchandran, “Embedllm: Learning compact representations of large language models,” ArXiv **abs/2410.02223** (2024).
15. C. Tao, T. Shen, S. Gao, J. Zhang, Z. Li, Z. Tao, and S. Ma, “Llms are also effective embedding models: An in-depth overview,” ArXiv **abs/2412.12591** (2024).
16. S. Dreano, D. Molloy, and N. Murphy, “Embed\_Llama: Using LLM embeddings for the metrics shared task,” in *Proceedings of the Eighth Conference on Machine Translation*, edited by P. Koehn, B. Haddow, T. Kocmi, and C. Monz (Association for Computational Linguistics, Singapore, 2023) pp. 738–745.
17. J. Yao, “Elevating urban tourism: Data-driven insights and ai-powered personalization with large language models brilliance,” in *2023 IEEE 3rd International Conference on Social Sciences and Intelligence Management (SSIM)* (2023) pp. 138–143.
18. T. Wang and C. Wang, “Embracing llms for point-of-interest recommendations,” IEEE Intelligent Systems **39**, 56–59 (2024).
19. J. Lin, X. Dai, R. Shan, B. Chen, R. Tang, Y. Yu, and W. Zhang, “Large language models make sample-efficient recommender systems,” Frontiers of Computer Science **19** (2024), 10.1007/s11704-024-40039-z.
20. X. Lin, W. Wang, Y. Li, S. Yang, F. Feng, Y. Wei, and T.-S. Chua, “Data-efficient fine-tuning for llm-based recommendation,” in *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR ’24 (Association for Computing Machinery, New York, NY, USA, 2024) p. 365–374.
21. C. Tao, T. Shen, S. Gao, J. Zhang, Z. Li, Z. Tao, and S. Ma, “Llms are also effective embedding models: An in-depth overview,” (2024), arXiv:2412.12591 [cs.CL].
22. Q. Liu, X. Wu, W. Wang, Y. Wang, Y. Zhu, X. Zhao, F. Tian, and Y. Zheng, “Llmemb: Large language model can be a good embedding generator for sequential recommendation,” (2024), arXiv:2409.19925 [cs.IR].