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Abstract

The study proposes a multi-criteria framework for assessing geographic relevance(GR) in location-based services(LBS) focusing on topicality, spatial proximity, colocation and clustering for POI recommendations. The framework utilised OpenStreetMap data of Birmingham city, to implement NLP transformer-based model (S-BERT) and spatial algorithm (DBSCAN) to develop a computational model, which is examined through detailed ranking and statistical analyses including Pearson's correlation matrix, weight configuration sensitivity and comparative analysis of rankings. Results showed sparse criteria (colocation and clustering) affect limited POIs (1-1.4%) but disproportionately influence top recommendations (>96% overlap). Weight sensitivity testing showed model's responsiveness, with cluster-focused weights achieving highest relevance score (0.922). Colocation emerged as contextual filter than performance booster depicting optimal proximity thresholds specific to category pairs (e.g., café-restaurant: 19.5m), (barbershop-beauty: 57.5m). The model also addressed category ambiguity via partial matching, identifying 252 relevant beauty POIs. These findings collectively support the development of adaptive weighting strategies and context-aware techniques for enhancing geographic relevance in mobile cartography, contributing to LBS development.

1. Introduction

The widespread availability of smartphones with built-in telecommunication features has led to rapid advancements in Location-Based Services(LBS), changing the way people access and use geographic information in everyday life(Huang et al., 2018). LBS refers to mobile applications that leverage geographic data and spatial insights to deliver tailored contextually relevant information and recommendations based on user's current location and queries(Huang et al., 2018). LBS applications such as Uber and Google Maps ranging from ride hailing services and navigation systems to social media check-ins have become indispensable in providing situationally aware information for providing location-related services (Qian et al., 2020). Although these services have become indispensable, their effectiveness is significantly dependent upon the provision of location-specific information that aligns with user's particular needs and contextual circumstances (Huang and Gartner, 2018).

Despite the technological advancements, LBS encounters consistent challenges including contextual irrelevance, information mismatch and inadequacy, that can significantly impede user satisfaction and acceptance(Huang et al., 2018). To address such issues, the concept of Geographic Relevance (GR) has become an important framework for improving performance and facilitating the delivery of optimized and tailored recommendations. The traditional information retrieval methods, which focus on keyword-matching and textual-proximity often prove insufficient when addressing complex dynamic geospatial contexts. Thus, the integration of GR in LBS presents a promising approach in enhancing system performance.

Therefore, the aim of this study is to develop a LBS application capable of conducting search and recommendation of Points of Interests (POIs) by incorporating multi-criteria GR framework. By inculcating spatial, temporal and semantic relevance indicators, the study aims to enhance the contextual accuracy and user satisfaction of LBS application.

2. Literature Review

In recent years, the concept of Geographic Relevance has developed alongside several key iterations in Geographic Information Retrieval(GIR) models. De Sabbata and Reichenbacher (2012) established essential GR criteria such as colocation, clustering and hierarchical spatial structures, showcasing that traditional information retrieval(IR) indicators insufficiently address spatial context. They argued that users' perception of GR intrinsically relies on movement patterns and situational contexts revealing traditional limitations of traditional IR criteria. To address this, (Reichenbacher et al., 2016) developed ScoreGR, a computational model that incorporated topicality, directionality, clustering, spatiotemporal proximity and co-location. This model employed continuous preference logic (CPL) to adaptively balance criterion aggregation and outperform traditional IR methods like Vector Space Model (VSM). While ScoreGR showed improvements, the scalability concern revealed the demand for hybrid models capable of integrating human nuances in managing spontaneous user-inputs. Pablo et al., (2023) showed the potential of knowledge graphs via SeMaptics tool enhancing relevance understanding by mapping spatial-ontological linkages. While this approach demonstrated strong contextual understanding but encountered scalability limitation when dealing with dynamic geographic data indicating the lag when exposed to frequently updated scenarios. Likewise, the improved Okapi GRBM25 model proposed by De Sabbata and Reichenbacher (2010) revealed an improved ranking of relevant objects based on geographic connectedness post user queries demonstrating context aware relevance ranking, though requiring further validation from additional criterion to assess its effectiveness. A study by (Li et al., 2015) leveraged Foursquare check-in data to determine spatial and temporal drivers impacting user behaviour, developing an algorithm that connects a priori relevance to contextualized relevance. Zhang et al., (2021) promoted this developed approach with GeoGNN, a graph neural network for POI recommendations that models spatial connectedness via social-ties and temporal patterns, outperforming traditional matrix factorisation by 15%. Likewise, Wang et al., (2023) introduced LLM-Mob, utilising large language models to predict human mobility by integrating both long- and short-term contextual features, in spite of high accuracy, the model encountered occasional hallucinations when managing enormous data volumes and high computational costs making it unsuitable for large scale predictions.

3. Methods

3.1 Programming Language

Python was adopted as the primary programming language for the development of the application due to its robust support for geospatial analysis, natural language processing (NLP) and machine learning capabilities. The decision to use python was due to rich availability of libraries and frameworks within the python ecosystem essential in complex data manipulation and implementation of ML algorithms. Specifically, libraries like geopandas, osmnx, NumPy, scikit-learn and Fiona were collectively utilised to facilitate the integration and execution of spatial data and machine learning models.

3.2 Dataset and Study Area

The data utilised in this study was sourced from OpenStreetMap (OSM), which offers free accessible geospatial information under the Open Database License (ODbL) provided by Open Data Commons (Geofabrik, 2025). The study focused on a subset of OSM data covering Birmingham city as the selection is driven by the city's rich and varied OSM dataset, essential for testing and developing LBS functionalities. The city's diverse concentration of points of interests(POIs), complex urban layout made it a suitable area to implement and evaluate the performance of computational models.

3.3 Model for GR assessment

A computational model of De Sabbata (2013) was implemented to develop a reliable context-aware POI recommendation LBS system capable of evaluating the GR based on multiple criterion relevant to users queries and situational context. These criterions collectively respond to diverse user preferences, adapted to specific individual needs.

3.3.1 Topicality

Sentence-BERT (S-BERT) model was adopted to compute topicality score by assessing the semantic closeness between user generated queries and the POIs descriptions. Being a transformer-based architecture, S-BERT possesses the capability to determine relevancy by extracting the semantic essence of geographic information when expressed using varied wording structures as it operated by converting textual-inputs into vector-embeddings, allowing the use of cosine similarity to quantify and compare the target location's description with the user query and yielding a similarity score(Reimers and Gurevvych, 2019).

$$\cos_i = \frac{v_{\mathrm{POI}_i} \cdot v_Q}{\left|\left|v_{\mathrm{POI}_i}\right|\right| \left|\left|v_Q\right|\right|},$$

$$S_{\text{topicality}}(i) = \frac{\cos_i - \min_j \cos_j}{\max_j \cos_j - \min_j \cos_j}$$

3.3.2 Spatial Proximity

Spatial Proximity was considered as another GR criteria to assess how near the POIs were to user's specified location. Using geospatial coordinates, a spatial relevance score was computed via the Haversine formula which accounts for Earth's curvature when measuring the distance to each POIs. Then, an exponential decay function was applied to distances where higher points were given to POIs which were within the spatial threshold and lower to distant ones(De Sabbata and Reichenbacher, 2012).

$$d = 2R \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\Delta\lambda}{2}\right)}\right)$$

$$S_{\text{spatial}}(i) = \exp(-d_i/\lambda), \quad \lambda = 2 \text{ km}.$$

3.3.3 Clustering

A Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm was implemented to determine the clustering relevance score, grouping nearby POIs based on the predefined radius handling heterogenous distribution of OSM data where urban centre tend to form dense clusters of POIs. Clusters with high density were assigned a greater relevance score while isolating out tiny groupings as noise(Wang et al., 2020).

$$S_{\text{cluster}}(i) = \frac{\text{clusterSize}(i)}{\max_j \text{clusterSize}\,(j)}.$$

3.3.4 Colocation

To determine spatial patterns within the data, the rule mining was employed to identify frequently co-occurring POIs within a defined spatial threshold, grouping them as neighbourhoods. When two or more such POIs fall within the threshold, they were treated as the same spatial group. Such clusters where POIs categories frequently appear together receive higher GR score and vice versa(Maiti and Subramanyam, 2021).

$$c_i = |\{q : \text{dist}(i, q) \le r\}|,$$
$$S_{\text{coloc}}(i) = \frac{c_i - \min_j c_j}{\max_j c_j - \min_j c_j}.$$

3.4 GR score calculation and Statistical Analysis

The overall GR score was achieved using weighting factors assigned to each criterion and derived by including each of the four normalised sub-scores and forming their weighted sum. To evaluate GR model's performance, three methods including Correlation analysis with Pearson's coefficient initially determined the influence of scoring criterion on rankings. Second, weight sensitivity testing with five configurations quantified how prioritising different criteria impact top results, measured by overlap percentage. A comparative analysis evaluated colocation's impact by identifying POIs distinct to its inclusion and computing their mean minimum distances to buddy categories, validating urban spatial associations.

$$R(i) = \alpha . S_{\text{topicality}}(i) + \beta . S_{\text{spatial}}(i) + \gamma . S_{\text{cluster}}(i) + \delta . S_{\text{coloc}}(i).$$

3.5 Application User Interface

To visualise the recommended ranked POIs based on GR score, an interactive medium, using Dash framework of Python via Jupyter Notebook was implemented with input panels and slider bars to input queries, buffer distance and weighting factors.

Results

4.1 Multi-Criteria Scoring Performance and Correlations

The implementation of multi-criteria geographic relevance framework on 20,922 POIs showed clear patterns in score distributions and correlations. Among the evaluated criteria, spatial proximity had the highest association with final relevance score (r= 0.837), followed by topicality (r= 0.538), while clustering and colocation revealed moderate correlations (r=0.395 and r= 0.430) but exhibited strong inter-correlation with each other (r=0.560), indicating these criterions capture related aspects of GR.

Table 1: This table shows the correlation matrix of scoring criterion.

	S_topicality	**S_spatial**	**S_cluster**	**S_coloc**	**R**
S_topicality	1.000	0.052	0.162	0.226	0.538
S_spatial	0.052	1.000	0.137	0.155	0.837
S_cluster	0.162	0.137	1.000	0.560	0.395
S_coloc	0.226	0.155	0.560	1.000	0.430
R	0.538	0.837	0.395	0.430	1.000

The findings from relevance scores reveal significant disparities in distribution across criteria in how frequently each criterion contributed to POI evaluation. While topicality and spatial proximity produced scores for all POI (100%), clustering and colocation were highly selective, obtaining non-zero scores for only 217 POIs (1.0%) and 288 POIs (1.4%). Despite limited applicability, analysis of the top 10% of POIs ranked by each criterion showed clustering and colocation demonstrate high overlap with the overall ranking (97.5% and 96.4%), indicating these selective criteria have significant influence on high-ranking results. Consequently, spatial proximity overlapped with the top-ranked results at 87.1% and topicality at only 23.6%.

Further clustering analysis revealed 40 clusters with the largest containing 34 POIs, while colocation detected upto 7 co-located POIs. These spatial patterns varied by query type with restaurants formed 40 clusters, cafes formed 10 and barber shops formed 42, indicating spatial arrangement is influenced by the nature of the query.

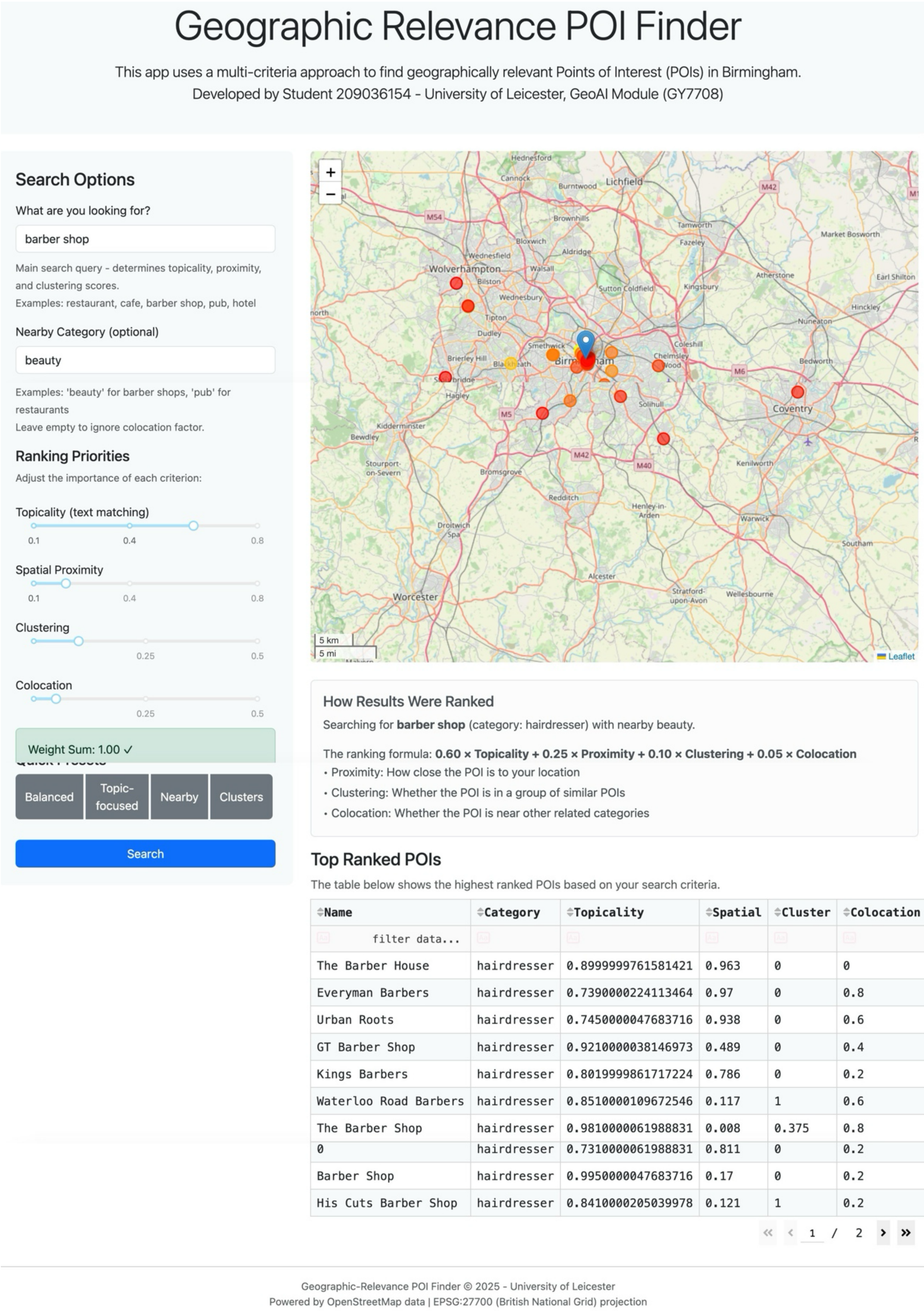

Figure 1: This screenshot shows the developed application interface demonstrating the multi-criteria POI ranking system in action. The panel on left shows controls for user queries, category filtering and ranking parameter for adjustments. While panel on right shows an interactive map with colour coded bubbles indicating relevance scores of POIs.

4.2 Weight Configuration Sensitivity Analysis

Five weight configurations were tested to assess multi-criteria system's sensitivity. Each setup yielded a unique maximum score. The configuration focusing on clustering produced the highest score (0.922), while the one prioritising topicality resulted in lowest (0.772). This outcome is significant, considering clustering affects only 1% of the POIs, suggesting that sparse yet relevant criteria can significantly impact the overall GR scores when prioritized.

Table 2: This table shows the maximum final relevance scores by weight configuration

Configuration	**Weight Distribution (T/S/C/Co)**	**Max Final R**
Balanced	0.25/0.25/0.25/0.25	0.806
Topic-focused	0.70/0.10/0.10/0.10	0.772
Spatial-focused	0.10/0.70/0.10/0.10	0.871
Cluster-focused	0.10/0.10/0.70/0.10	0.922
Colocation-focused	0.10/0.10/0.10/0.70	0.884

Upon evaluation of top 10 recommended POIs under different weight configurations, the Balanced and Cluster-focused configurations showed complete overlap 100%, suggesting that balanced weighting inherently emphasize clustered POIs. In contrast, spatial-focused configuration generated an entirely different set of recommendations as opposed to Balanced, Topic-focused and Cluster-focused showing 0% overlap. The Co-location focused setup demonstrated high overlap with Spatial-focused (80%) but minimal overlap with Topic-focused (10%), hinting that colocation and spatial proximity tend to determine similar POIs while their selections diverge substantially from those based on topical relevance.

Table 3: This table shows the overlap analysis of Top 10 POIs between weight configurations

Configuration 1	**Configuration 2**	**Overlap**	**Overlap %**
Balanced	Topic-focused	4	40.0%
Balanced	Spatial-focused	0	0.0%
Balanced	Cluster-focused	10	100.0%
Balanced	Colocation-focused	2	20.0%
Spatial-focused	Topic-focused	0	0.0%
Cluster-focused	Topic-focused	4	40.0%
Cluster-focused	Spatial-focused	0	0.0%
Cluster-focused	Colocation-focused	2	20.0%
Colocation-focused	Topic-focused	1	10.0%
Colocation-focused	Spatial-focused	8	80.0%

4.3 Impact of Colocation on POI Ranking

The comparative analysis showed that removing the colocation criterion consistently increased maximum GR score across all queries(Table.3), indicating that while colocation improves contextual relevance, it can limit the absolute relevance scores by adding spatial restrictions. Colocation also uniquely identified top-ranked POIs for restaurant-pub pairs, 46.7% (7/15) of the top POIs appeared only when colocation was considered, with an average distance of 47.6 meters to the nearest pub and colocation scores ranging from 0.571 to 1.000. Similar trends were observed for café-restaurant pair query.

Table 4: This table shows the impact of colocation criterion on Top 15 POI rankings

Query Type	**Buddy Category**	**Max R (with coloc.)**	**Max R (without coloc.)**	**Exclusive POIs**	**Avg Distance(m)**	**Colocation Score Range**
Restaurant	Pub	0.785	0.808	7/15 (46.7%)	47.6	0.571-1.000
Cafe	Restaurant	0.763	0.849	5/15(33.3%)	19.5	0.360-1.000
Barber shop	Beauty	0.718	0.829	7/15(46.7%)	57.5	0.200-0.800

The system also demonstrated robustness in handling missing categories as when no category when no exact “beauty” POIs were found, partial matching found 252 alternative POIs, enabling colocation scoring for barber shops. The strength of colocation varied by query-type as café-restaurant pairs showed highest maximum colocation value 25 compared to pub-restaurant 7 and barbershop- beauty 5, reflecting different spatial co-location patterns across the urban environment.

Discussion

5.1 Influence of Sparse Criteria on Rankings

The findings suggest that clustering and colocation as criteria, although applied to only 1.0% and 1.4% of POIs, exhibited exceptionally high overlap with top-ranked outcomes (97.5% and 96.4%). This aligns with recent findings in information retrieval, which suggests that data points with sparse representation can nonetheless exert a disproportionate influence on ranking algorithms (Moffat and Zobel, 2008). The strong inter-correlation observed between colocation and clustering (r=0.560) reflects findings in cluster-based retrieval that sparse clusters often obtain top-performing documents despite their small size (Belhadi et al., 2020). This pattern is consistent with cluster hypothesis framework proposed by (Jardine et al., 1971), indicating that this hypothesis remains robust even when applied to sparse data subsets.

Consequently, the low correlation coefficient of (r=0.052) between spatial proximity and topicality correlates with the observation of (Hu et al., 2014) who showed that semantic and geographical relevance capture distinct facets of POI relevance. Another study by (Zheng et al., 2009) further investigated that spatial proximity follows a power-law distribution while topicality is handled by patterns of semantic grouping, thus the distinct distributional characteristics explain the reasoning behind weak correlation within ranking systems.

5.2 Weight Configuration Sensitivity

The significant variation in recommendation outputs across different weight setups require adaptive weighting strategies, as demonstrated in recent POI recommendation systems (Wu et al., 2023; Yu et al., 2020). The findings show that cluster-centric configuration yielded the highest relevance score (0.922), aligning with Yatawatta's (2014) results that optimising criterion linked with sparse data lead to enhanced performance when appropriately weighted. Additionally, the complete overlap between Balanced and Cluster-focused configurations suggests that equal weighting inherently prioritize spatially structured POIs, also observed by (Li et al., 2019) in their model incorporating multi-dimensional auxiliary information.

In contrast, the absence of overlap between spatial-centric and topicality-centric configurations underscores the limitations of conventional averaging approaches in capturing complex, non-linear interdependencies among multiple objectives. These findings provide additional evidence to context-aware adaptive models such as the hierarchical attention-based model (HAGCN) developed by (Wu et al., 2023) which dynamically adjust weights based on contextual information rather than relying on fixed parameters.

5.3 Contextual Constraint of Colocation

The consistent reduction in GR score upon adding colocation as a criterion indicates that it serves more as a contextual constraint filter than a universal beneficial factor. This pattern aligns with findings by (Zhang et al., 2022), whose FG-CF model showed that integrating socially aware graph structures improved context sensitivity but reduced overall recommendation strength. The variation in average spatial distances between query and "buddy" categories was 19.5 meters for cafes-restaurants, 47.6 m for restaurants-pubs and 57.5 m for barber shops-beauty services, supporting the domain-specific proximity patterns and Gaussian mixture modelling results observed by (Zhao et al., 2013).

Moreover, by implementing partial category-matching, the system identified 252 "beauty" POIs for the barber shop scenario, showcasing robustness akin to (Feng et al., 2020) who achieved flexibility via hierarchical attention mechanisms to address category ambiguity challenges in sparse-data contexts. This form of adaptability is crucial in sparse-data settings aligning with (Liu et al., 2022) findings in the PDRM model, which exhibited that accommodating flexible category semantics lead to recommendation accuracy by 15-20% in data-sparse settings.

Conclusion

The implementation and evaluation of a multi-criteria geographic relevant framework for LBS, addresses critical challenges in POIs recommendation systems, providing deeper insights into the interplay between semantic, spatial and contextual relevant criteria. One notable finding was sparse criterion particularly colocation and clustering despite their limited coverage over POIs exert a significant influence on ranking outcomes. The framework's sensitivity to varied weighting configurations underscores the need of adaptive weighting strategies as observed in the convergence of results between balanced and cluster-focused setups. This suggests an implicit bias toward spatially clustered POIs under uniform weighting. The findings also revealed colocation to be context-dependent, functioning more as a constraint than an enhancer of relevance with optimal distances varying substantially across various domains. The developed prototype also demonstrated robustness in handling partial category matching where it identifies relevant POIs through semantic understanding beyond exact keyword matches, highlighting its flexibility in sparse or ambiguous data environments.

The study collectively contributes to a deeper understanding of GR in LBS applications and underscore the potential for developing more sophisticated, context aware recommendation systems. Future research directions should focus on inculcating dynamic weight adaptation strategies that respond to user context and query type and examine the generalizability of the observed patterns across diverse range of applicability settings.

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