Massive-STEPS: Massive Semantic Trajectories for Understanding POI Check-ins – Dataset and Benchmarks

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Abstract

Understanding human mobility through Point-of-Interest (POI) recommendation is increasingly important for applications such as urban planning, personalized services, and generative agent simulation. However, progress in this field is hindered by two key challenges: the over-reliance on older datasets from 2012-2013 and the lack of reproducible, city-level check-in datasets that reflect diverse global regions. To address these gaps, we present Massive-STEPS (Massive Semantic Trajectories for Understanding POI Check-ins), a large-scale, publicly available benchmark dataset built upon the Semantic Trails dataset and enriched with semantic POI metadata. Massive-STEPS spans 12 geographically and culturally diverse cities and features more recent (2017-2018) and longer-duration (24 months) check-in data than prior datasets. We benchmarked a wide range of POI recommendation models on Massive-STEPS using both supervised and zero-shot approaches, and evaluated their performance across multiple urban contexts. By releasing Massive-STEPS, we aim to facilitate reproducible and equitable research in human mobility and POI recommendation. The dataset and benchmarking code are available at: `https://github.com/cruiseresearchgroup/Massive-STEPS`.

1 Introduction

Importance of Human Mobility Data and Modeling Human mobility data and modeling are essential for understanding how individuals interact with and move through physical spaces. This understanding enables a wide range of applications, including urban planning [63], travel service recommendations [7], improved commercial advertising strategies [59], and Point-of-Interest (POI) recommendation [6, 22, 68]. Recently, human mobility data has become even more crucial with the increasing use of large language models (LLM) agents to simulate human-like behavior and routines [71, 20]. However, while simulated human mobility data are starting to gain popularity [31, 9], they may not accurately reflect real-world human behavior [33], highlighting the value of evaluating on real-world data. These advancements are enabled by and large with the rise of Location-based Social Networks (LBSNs), which generate vast amounts of spatio-temporal data through user check-ins [68, 22]. This rich data source has allowed the development of POI recommendation systems that leverage users' historical visiting behaviors to suggest relevant locations. Such systems enhance user engagement through personalization and provide commercial value to both users and businesses by aligning recommendations with individual preferences and available services [68, 6].

Literature Gaps Our paper addresses three critical gaps in POI recommendation research and datasets, as detailed in Section 2.1. First, as shown in Fig. 1, the field remains dominated by studies focused on just two cities, New York and Tokyo, based on the Foursquare dataset curated in [57].

Table 1: **Comparison of check-in datasets commonly used for POI recommendation tasks**. GSCD [57, 56] and Semantic Trails [29] are global datasets not grouped into individual cities, whereas others perform city-level grouping. †Replicable indicates whether city boundaries are clearly defined or can be reliably reconstructed.

Dataset	Scale			Completeness	Usability	
	#cities	**Years**	**#months**	**POI Attributes**	**Replicable†**	**Open-source**
GSCD [57, 56]	Varies	2012-2013	17	Coordinates, Category	N/A	✓
Semantic Trails [29]	Varies	**2012-2013, 2017-2018**	**24**	Category	N/A	✓
NYC and Tokyo [57]	2	2012-2013	11	Coordinates, Category	✓	✓
Gowalla-CA [4, 62]	1	2009-2010	21	Coordinates, Category	✓	✓
AgentMove [7]	12	2012-2013	17	Coordinates, Category	✗	✗
Massive-STEPS	12	**2012-2013, 2017-2018**	**24**	**Coordinates, Category, Name, Address**	✓	✓

This dataset, collected in 2012-2013, raises concerns about its temporal quality, as many POIs may no longer exist and user behavior may have changed [61]. While some recent studies have expanded to other cities [65, 28, 7], they often rely on the Global-scale Check-in Dataset (GSCD) [55, 56], which, despite its large coverage, is also from 2012-2013 and contains nearly 50% erroneous entries [29].

Second, most existing studies are difficult to reproduce, either due to the lack of clearly defined geographic boundaries or the unavailability of the datasets themselves, hindering fair comparison and replication. Finally, we join recent efforts [63] in advocating for the inclusion of low-resource and underrepresented cities in evaluation. Expanding beyond well-studied urban centers is essential for building more generalizable and universally applicable POI recommendation models. Table 1 summarizes these limitations in terms of geographic coverage, temporal span, and reproducibility.

Massive-STEPS Dataset In this paper, we introduced the Massive Semantic Trajectories for Understanding POI Check-ins (Massive-STEPS) Dataset, derived from the Semantic Trails dataset (STD) [29]. Massive-STEPS includes high-quality check-ins from 2012-2013 and 2017-2018, providing more modern and updated POI check-in data. This supports longitudinal POI recommendation studies and addresses the limitations of older datasets commonly used in prior studies. The dataset covers 12 diverse cities across multiple regions, including East, West, and Southeast Asia, North and South America, Australia, the Middle East, and Europe. Notably, we placed a deliberate emphasis on under-explored regions by including cities such as Jakarta, Kuwait City, and Petaling Jaya, filling a key gap in POI recommendation research that has largely focused on major urban centers. We further enriched STD by aligning it with Foursquare's Open Source Places dataset, incorporating metadata such as POI coordinates, POI names, and addresses—details unavailable in the original STD.

Benchmark Tasks To demonstrate the utility of this dataset, we conducted an extensive benchmark on two tasks: (1) supervised POI recommendation and (2) zero-shot POI recommendation. Our benchmark covers a wide range of models, including traditional approaches, deep learning-based models, and more recent LLM-based methods. The goal of POI recommendation task is to predict a set of POIs that a user is likely to visit based on their current check-in trajectory and historical behavior. This reflects real-world applications such as personalized POI recommendations in location-based services. In addition, the scale of our dataset allows us to examine how urban features influence POI recommendation accuracy. Building on prior hypotheses, we propose a new insight: cities with more evenly distributed POI categories tend to be harder to model, as the absence of a dominant POI category makes user behavior less predictable.

Contribution This paper introduces the Massive Semantic Trajectories for Understanding POI Check-ins (Massive-STEPS) dataset, addressing gaps in existing POI recommendation research. Current POI check-in datasets are often only from 2012-2013, skewed to a few cities, and lack semantic metadata, hindering the development of robust and globally applicable models. While datasets like GSCD and STD offer broad geographic coverage, they either suffer from an older timespan, contain erroneous data, or have missing information. Massive-STEPS overcomes these issues by providing high-quality check-ins from 2012-2013 and 2017-2018, improving temporal quality for longitudinal POI recommendation studies. The dataset spans 12 diverse cities across multiple regions, with a focus on low-resource cities overlooked in previous research. Additionally,

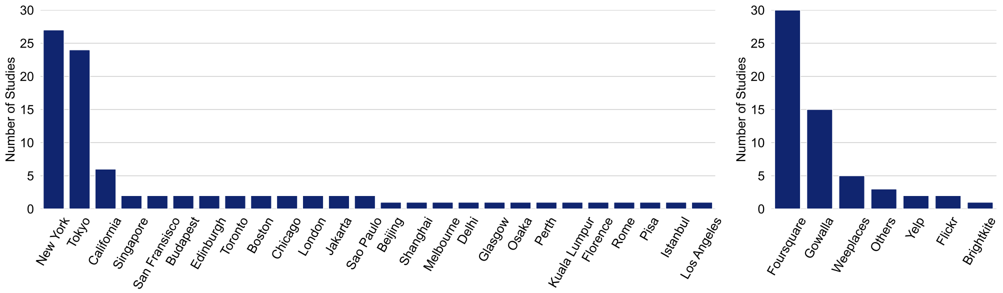

Figure 1: **Distribution of POI recommendation studies** modeled on specific cities, filtered from Table IV in [68]. We identified and counted studies that explicitly mentioned city names, revealing the skewness of existing research, which is saturated around New York and Tokyo. In addition, we include the distribution of studies by LBSN platform, showing that Foursquare is by far the most commonly used source of check-in data. The list of identified studies is shown in Table 5.

Massive-STEPS is enriched with metadata through alignment with Foursquare's Open Source Places, providing crucial details such as POI geographical coordinates, POI names, and addresses. We also conducted an extensive benchmark on both supervised and zero-shot POI recommendation tasks, evaluating a wide range of models, including traditional methods, deep learning approaches, and recent LLM-based techniques. We further analyzed which urban features affect POI recommendation accuracy and found that cities with no dominant POI category tend to be harder to predict. By releasing this dataset and benchmark code publicly, we facilitate open and reproducible research, enabling future advancements in POI recommendation studies.

2 Related Works

2.1 Existing Datasets

A survey conducted by [68] outlines the broad landscape of POI recommendation research, covering a wide range of models and architectures used in prior studies. While it offers a high-level overview of the datasets used, it lacks a dedicated discussion or evaluation of POI datasets. We address this gap by analyzing commonly used datasets in the field and positioning our dataset within this context.

LBSN Check-in Data Sources Building on the tabular summary provided in [68], which offers a representative overview of the broader POI recommendation literature, we investigated which datasets are most commonly used in prior studies. From their original table (Table IV), we filtered entries pertaining specifically to POI and next POI recommendation tasks and identified (1) the most frequently used LBSN check-in data sources and (2) the most commonly studied cities. As shown in Fig. 1, Foursquare remains the dominant source of LBSN data in existing studies, appearing in almost 50% of the surveyed works. While several variants of Foursquare datasets have been employed, the most widely used are the NYC and Tokyo Dataset [57] (often abbreviated as FSQ-NYC and FSQ-TKY) and the Global-scale Check-in Dataset (GSCD) [55, 56], curated by the same authors. Other LBSN sources occasionally used include Gowalla [4], Brightkite [4], and Weeplaces [26].

Saturated to Two Cities and Old Timespan Due to the widespread use of FSQ-NYC and FSQ-TKY [57], the majority of POI recommendation studies are disproportionately focused on these two cities, as illustrated in Fig. 1. While there is nothing inherently problematic about studying NYC and Tokyo, there has been growing interest in expanding research to a broader range of cities, particularly those that are underexplored or considered low-resource [63], as cultural and regional differences influence collective mobility behaviors. For instance, in some urban contexts, residents tend to commute to central business districts in the morning, whereas in others, nightlife activities such as visiting bars after work are more common [55]. Ensuring diverse geographic coverage is increasingly important, especially as LLMs are adopted for POI recommendation tasks. LLMs are known to exhibit geographical biases, often underperforming in regions with lower socioeconomic conditions [27]. It remains an open question whether LLM-based POI recommendation models can effectively generalize across diverse urban environments.

In addition, because many studies rely on the FSQ-NYC and FSQ-TKY, they are often constrained to the timespan it covers: check-in data from 2012 to 2013. However, POI data is inherently dynamic: venues may have closed, relocated, or changed in category over time. [61] underscores the importance of validating the temporal quality of POI datasets by recording whether and when a venue's information has been updated to reflect real-world changes. This is particularly critical, as recommender systems should avoid suggesting POIs that no longer exist or have undergone substantial changes (e.g., a former bookstore converted into a coworking space) and behave dynamically over longitudinal periods [53]. Moreover, behavioral patterns captured over a decade ago may no longer align with modern user preferences and routines. For example, the opening of a new train station may significantly shift commuting patterns and the popularity of surrounding POIs.

Low Data Quality: Erroneous Entries More recently, researchers have begun leveraging the broader Global-scale Check-in Dataset (GSCD) [55, 56], which spans 415 cities across 77 countries. Despite its wider geographic coverage, GSCD is temporally limited to the same 2012-2013 period as FSQ-NYC and FSQ-TKY, and thus suffers from similar issues of temporal quality. More critically, [29] demonstrated that GSCD suffers from significant data quality issues, with over 14 million check-ins (about 44%) of the dataset flagged as erroneous due to anomalous user behavior. These include (1) repeated check-ins at the same venue, (2) check-ins occurring within implausibly short time intervals (less than one minute), and (3) transitions between venues that would require travel speeds exceeding Mach 1, which are physically unreasonable.

To address these limitations, [29] introduced the Semantic Trails Dataset (STD), which applies systematic filtering procedures to enhance data quality. STD comprises two subsets: a cleaned version of GSCD covering 2012-2013 (STD 2013), and a newer collection of check-ins from 2017-2018 (STD 2018), sourced from Foursquare Swarm. STD 2018 also spans a wider range of cities, making it valuable for capturing globally distributed user behavior, in contrast to GSCD's focus on densely populated urban centers. Both subsets follow the same rigorous filtering criteria, resulting in a higher-quality check-in dataset for POI recommendation tasks. Given these improvements, we adopted STD as the source for our check-in dataset.

Poor Reproducibility Another persistent challenge in POI recommendation research is the lack of reproducibility in dataset preprocessing. While some recent studies utilize datasets like GSCD to cover a wide range of cities, they often omit important details needed for replicating their data filtering processes. For example, AgentMove [7] conducted city-level filtering based on a minimum distance between each trajectory and the city center, but they did not specify how the city center was defined or what distance threshold was used. Generally, city filtering can be done in two ways: (1) by selecting points within a fixed radius from a central coordinate, or (2) by applying precise administrative boundaries, such as those from OpenStreetMap. The radius-based approach is less reliable, as it assumes a circular city shape and requires a subjective definition of the city's center. In contrast, the boundary-based method is more robust and reproducible, and is the approach we adopted in this work. Without standardized, transparent filtering criteria and publicly available datasets, it remains difficult to ensure fair comparisons across POI recommendation methods.

2.2 Understanding Urban Features and POI Recommendation

POI recommendation studies that evaluate models across multiple city-level datasets often include analyses to assess how well their methods generalize across different urban contexts. It is well understood that POI recommendation accuracy metrics (e.g., Acc@k, NDCG@k) can vary substantially between cities and can be interpreted as a proxy for how easy or difficult a city is to model. The assumption is that higher performance reflects more predictable or structured mobility patterns. This viewpoint is consistent with prior work highlighting the role of cultural and urban-specific factors in shaping mobility behaviors [55, 34].

Several studies have proposed hypotheses connecting specific urban features to modeling difficulty. For example, GETNext [60] hypothesized that cities with fewer check-ins and higher spatial sparsity of POIs are harder to model. STHGCN [54] suggested that a larger number of user trajectories improves predictive accuracy by providing richer collaborative signals, whose architecture is designed to leverage. LLM4POI [22] proposed that cities with a greater variety of POI categories are easier to model due to LLMs' contextual reasoning capabilities, whereas cities covering a broader geographic area tend to be more difficult to model. In the zero-shot POI recommendation setting, AgentMove [7]

Table 2: **Summary statistics** of the 12 Massive-STEPS subsets, including the number of users, trajectories, POI locations, total check-ins, and train, validation, and test sample counts. For comparison, we also include statistics from existing Foursquare-based [57] and Gowalla-based [4] datasets. †Due to variations in dataset preprocessing across studies, we report the version used in [54].

City	Users	Trajectories	POIs	Check-ins	#train	#val	#test
NYC and Tokyo Check-in Dataset† [57]							
New York	1,048	14,130	4,981	103,941	72,206	1,400	1,347
Tokyo	2,282	65,499	7,833	405,000	274,597	6,868	7,038
Gowalla† [4, 62]							
California	3,957	45,123	9,690	238,369	154,253	3,529	2,780
Massive-STEPS							
Beijing	56	573	1,127	1,470	400	58	115
Istanbul	23,700	216,411	53,812	544,471	151,487	21,641	43,283
Jakarta	8,336	137,396	76,116	412,100	96,176	13,740	27,480
Kuwait City	9,628	91,658	17,180	232,706	64,160	9,166	18,332
Melbourne	646	7,864	7,699	22,050	5,504	787	1,573
Moscow	3,993	39,485	17,822	105,620	27,639	3,949	7,897
New York	6,929	92,041	49,218	272,368	64,428	9,204	18,409
Petaling Jaya	14,308	180,410	60,158	506,430	126,287	18,041	36,082
São Paulo	5,822	89,689	38,377	256,824	62,782	8,969	17,938
Shanghai	296	3,636	4,462	10,491	2,544	364	728
Sydney	740	10,148	8,986	29,900	7,103	1,015	2,030
Tokyo	764	5,482	4,725	13,839	3,836	549	1,097

reported two key findings: (1) geospatial biases inherent in LLMs can hinder prediction quality across cities, and (2) LLMs are influenced by city-specific mobility patterns.

Building on these insights, we used Massive-STEPS to explore how urban features affect POI recommendations. Its diverse set of 12 cities allows for a comprehensive analysis across different cultural and urban contexts. We analyzed the correlation between urban features and model accuracy, and based on the results, proposed a new hypothesis that contrasts previous findings in the literature.

3 Dataset

3.1 Creation Process

Massive-STEPS is derived from the two subsets of STD [29], incorporating check-ins from both the 2013 and 2018 subsets. We utilize two additional components from STD: (1) the **cities** metadata file, which provides the latitude and longitude of administrative regions (e.g., towns, suburbs) along with their corresponding country codes obtained from GeoNames; and (2) the POI **category** mapping, which links each Foursquare Category ID to its descriptive name (e.g., "Restaurant"). Based on this metadata, each POI is thus associated with several attributes: Foursquare Place ID, Foursquare Category ID, category name, latitude/longitude of the administrative region, the administrative region name, and the country code. For anonymization purposes and model training compatibility, we apply ordinal encoding to the Place IDs and Category IDs, assigning each a unique integer index.

3.1.1 Preprocessing

Trajectory Grouping Most POI recommendation models operate on sequences of check-ins, commonly referred to as trajectories. The model is tasked with predicting the next POIs a user is likely to visit, given the current trajectory. STD conveniently provides pre-grouped trajectories (trails) by applying a time interval-based grouping: for each user, check-ins that occur within a time interval of $\delta_\tau = 8$ hours are grouped into the same trajectory.

Matching Trajectories to Target Cities To obtain city-specific datasets, we matched trajectories to the target cities. For each city, we obtain geographic boundaries from OpenStreetMap and retrieve its GeoJSON file via the Overpass API. The GeoJSON file contains a polygon defining the city's boundary in latitude and longitude. Using this boundary, we filter check-ins by comparing the

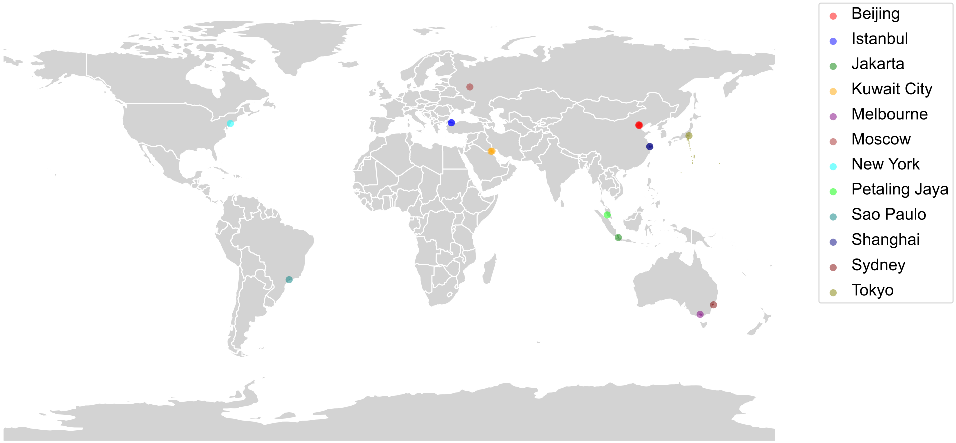

Figure 2: **World map highlighting the cities included in the Massive-STEPS dataset**.

latitude/longitude of each POI's administrative region and retain only those that are within the city's polygon. This ensures that all retained trajectories are spatially grounded within the designated city.

Filtering Short Trajectories and Inactive Users To ensure data quality, we apply an additional filtering step by removing trajectories with fewer than two check-ins and excluding users with fewer than three trajectories. This prevents the model from learning from overly sparse or irrelevant data.

Train, Validation, and Test Splits We split trajectories into training, validation, and test sets in a ratio of 7:1:2, following [7]. We ensure that all users in the test set appear at least once in the training or validation set, a common practice in prior studies [60, 54].

3.1.2 POI Enrichment via Foursquare OS Places

Since the POIs in STD include their corresponding Foursquare Place IDs, we matched them directly with entries in the Foursquare OS Places dataset using these IDs as the key. This one-to-one ID correspondence allows for a straightforward join operation, enriching each POI with additional metadata such as its precise latitude and longitude, name (e.g., of a restaurant or subway station), and address. However, not all POIs in the Foursquare OS Places dataset include the full metadata, particularly those categorized as private residences, which are excluded due to privacy restrictions.

3.2 Description and Addressing Literature Gaps

Massive Semantic Trajectories for Understanding POI Check-ins (Massive-STEPS) dataset is a city-level POI check-in dataset derived from Semantic Trails [29], comprising user check-in trajectories from 12 cities: Beijing, Istanbul, Jakarta, Kuwait City, Melbourne, Moscow, New York, Petaling Jaya, São Paulo, Shanghai, Sydney, and Tokyo. It features anonymized POI check-ins enriched with geographical metadata to support spatiotemporal and sequential modeling tasks. City-level statistics, along with comparisons to existing datasets, are presented in Table 2. Fig. 2 shows a world map highlighting the locations of all cities included in the Massive-STEPS dataset. Table 6 shows the available fields in the dataset and provides an example for each field.

Massive-STEPS offers a more comprehensive and diverse representation of urban mobility compared to typical POI check-in datasets. As shown in Table 2, datasets like FSQ-NYC and FSQ-TKY [57] contain fewer than 10,000 candidate POI locations. In contrast, cities in Massive-STEPS cover significantly more POIs: Massive-STEPS New York has over 49,000 POIs, while Massive-STEPS Jakarta exceeds 76,000. Massive-STEPS Istanbul, one of the largest subsets, features a large user base of 23,700, offering a broad range of user behaviors. Although some Massive-STEPS subsets are smaller than their FSQ counterparts (e.g., Tokyo), we attribute this to the strict filtering procedures applied by STD to remove erroneous entries, as explained in Section 2.1. This scale introduces

Table 3: **Benchmark results on POI recommendation task**. The metric reported is Acc@1. Full results, including other metrics, are available in Section C.3. **Bold** indicates the best performance for each city, while underline indicates the second-best.

Model	Beijing	Istanbul	Jakarta	Kuwait City	Melbourne	Moscow	New York	Petaling Jaya	São Paulo	Shanghai	Sydney	Tokyo
FPMC	0.000	0.026	0.029	0.021	0.062	0.059	0.032	0.026	0.030	0.084	0.075	0.176
RNN	0.085	0.077	0.049	0.087	0.059	0.075	0.061	0.064	0.097	0.055	0.080	0.133
LSTPM	0.127	0.142	0.099	0.180	0.091	0.151	0.099	0.099	0.158	0.099	0.141	0.225
DeepMove	0.106	0.150	0.103	0.179	0.083	0.143	0.097	0.112	0.160	0.085	0.129	0.201
GETNext	0.433	0.146	0.155	0.175	0.100	0.175	0.134	0.139	0.202	0.115	0.181	0.180
STHGCN	**0.453**	**0.241**	**0.197**	**0.225**	**0.168**	**0.223**	**0.146**	**0.174**	**0.250**	**0.193**	**0.227**	**0.250**

additional computational challenges. Models that rely on dense POI-to-POI adjacency matrices, for instance, may require more efficient implementations to avoid excessive memory consumption.

Beyond scale, Massive-STEPS addresses the oversaturation of FSQ-NYC and FSQ-TKY in POI recommendation research. Notably, Massive-STEPS includes low-resource and previously under-explored cities in human mobility studies, such as Petaling Jaya and Kuwait City, both of which are among the cities with the highest number of check-ins from STD. This broader coverage opens new research opportunities for studying location-based behaviors across diverse cultural and geographic contexts. Furthermore, since Massive-STEPS is based on STD, it benefits from the carefully filtered, high-quality check-ins and a longer, more recent timespan. These characteristics make Massive-STEPS a more relevant and reliable resource for modeling human mobility patterns.

Massive-STEPS is designed to be easily extended to other geographical regions. Since the data processing code is open-source and fully reproducible, adding a new city only requires its geographic boundaries from OpenStreetMap. Moreover, Massive-STEPS is scalable to higher levels of geographic granularity, enabling the creation of provincial, state, and country-level POI check-in datasets, which support collective mobility studies at broader geographic scales.

4 Benchmark

4.1 POI Recommendation

This benchmark covers the common task of POI recommendation, where the goal is to predict where a user will go next based on their previous check-ins. The input to the model is a trajectory, which is a sequence of places the user has visited. The model is expected to suggest a set of K POIs that the user might visit next. This task can also be framed as re-ranking a set of N candidate POIs in the city based on the user's recent behavior. This task reflects a typical real-world use case in POI recommendation systems and human mobility modeling. It is a **supervised** task as the model is trained using all available historical trajectories of the user, allowing it to learn personalized patterns of movement over time. Appendix C provides the details on problem formulation, hyperparameters, experimental setups, and the full results with all evaluation metrics.

Dataset Preparation By design, our dataset is structured to support consistency and reproducibility, making it straightforward to use for supervised POI recommendation tasks. We adopted the predefined trajectories from the original STD, which has grouped sequences of check-ins into trajectories based on a fixed time interval (see Section 3.1.1). Since all input features in our dataset have been numerically encoded to facilitate model training, we simply used them across all experiments.

For this task, models typically use four kinds of features: (1) social features: user ID; (2) spatial features: POI ID, geographic coordinates; (3) temporal features: check-in timestamp; and (4) categorical features: POI category. Since not all POIs have exact geographic coordinates (see Section 3.1.2), we use the geographic coordinates of their administrative region as a proxy for all POIs.

Models We evaluated three kinds of models: (1) Markov-based methods, (2) classical deep learning models, and (3) Transformer-based graph neural networks:

- **FPMC** [32]: A classical baseline that combines first-order Markov chains with matrix factorization to model personalized next-location predictions.

- **RNN** [41], **LSTPM** [35], and **DeepMove** [8]: Recurrent neural networks designed to capture sequential dependencies, with varying mechanisms to incorporate spatio-temporal context.
- **GETNext** [60] and **STHGCN** [54]: Transformer-based graph neural networks to model social, spatial, and temporal dependencies.

Evaluation Metrics We used two popular metrics in POI recommender systems: Acc@k, which checks if the true POI appears in the top-k predicted results, and NDCG@k, which measures the ranking quality of the suggested results.

Results As shown in Table 3, STHGCN consistently achieves the highest accuracy across all cities, highlighting the effectiveness of Transformer-based GNNs. GETNext often ranks second, performing well in most cities, and older RNN-based models such as LSTPM and DeepMove also remain competitive in a few cities. The best-performing model achieves an average Acc@1 of 22.9%, which is comparable to results from previous studies using datasets of a similar size [7].

We investigated which urban features affect POI recommendation accuracy by computing Spearman correlations between various city features and model performance. We found that **category entropy**, based on Shannon entropy, strongly correlates with recommendation accuracy ($r = -0.736$), as shown in Fig. 6. Namely, cities with more evenly distributed POI categories and no dominant POI category tend to have lower accuracy and are thus harder to predict. This finding is consistent with the results of prior work on other datasets. Further details are provided in Appendix D.

4.2 Zero-shot POI Recommendation

An increasingly popular approach in POI recommendation leverages the zero-shot capabilities of LLMs, allowing models to perform zero-shot POI recommendation without any additional training. This setting challenges LLMs to generalize to any target city and personalize recommendations for any user. The task mirrors the supervised counterpart: given a user's trajectory, the model predicts the user's next destination by ranking a set of K POIs. Appendix E provides the details on problem formulation, prompts, experimental setups, and the full results with all evaluation metrics.

Dataset Preparation Since LLMs are central for this task, trajectories must be transformed into textual prompts [52, 51]. We adapted the prompts used in [7], which implemented the three LLM methods evaluated in our study. Notably, because LLMs can effectively leverage contextual information, not all input features need to be numerically encoded. The evaluated methods utilize only a subset of features: the timestamp, POI category name, and POI ID.

Methods and Models We evaluated three LLM-based prompting methods:

- **LLM-Mob** [42]: One of the earliest methods to use LLMs for next POI prediction, prompting LLMs with both historical and current (contextual) trajectories.
- **LLM-ZS** [1]: A simplified version of LLM-Mob that retains the use of historical and contextual trajectories but simplifies its prompt design.
- **LLM-Move** [10]: Extends previous prompting methods by introducing a RAG-like approach, retrieving nearby POIs as candidates, and ranking them by geographic distance to the user's most recent visit.

To ensure a more robust evaluation, we tested each method using four different LLMs: one closed-source API (Gemini 2.0 Flash [36]) and three open-source models (Qwen 2.5 7B [38], Llama 3.1 8B [12], and Gemma 2 9B [37]). All open-source models are instruction-tuned variants, quantized to INT4 using AWQ [25], and served through vLLM [21].

Evaluation Metrics We used the same metrics as in the supervised setting, Acc@k and NDCG@k, for the same reasons: to assess predictive accuracy and to evaluate the quality of the ranking.

Results As shown in Table 4, LLM-Move [10] performed the best among the three methods, likely due to its well-crafted prompts that supply potential candidate POIs, rather than relying solely on historical or contextual trajectories like LLM-Mob and LLM-ZS. This also supports the use of

Table 4: **Benchmark results on zero-shot POI recommendation task**. The metric reported is Acc@1. Full results, including other metrics, are available in Section E.3. **Bold** indicates the best performance for each city, while underline indicates the second-best.

Method	LLM	Beijing	Istanbul	Jakarta	Kuwait City	Melbourne	Moscow	New York	Petaling Jaya	São Paulo	Shanghai	Sydney	Tokyo
LLM-Mob	**Gemini 2 Flash**	0.115	0.080	0.100	0.095	0.060	0.130	0.095	0.090	0.130	0.055	0.060	0.140
	Qwen 2.5 7B	0.058	0.035	0.105	0.080	0.030	0.090	0.070	0.030	0.090	0.040	0.035	0.110
	Llama 3.1 8B	0.000	0.020	0.055	0.030	0.010	0.030	0.025	0.010	0.030	0.005	0.020	0.005
	Gemma 2 9B	0.115	0.075	0.105	0.080	0.055	0.100	0.070	0.055	0.085	0.050	0.030	0.145
LLM-ZS	**Gemini 2 Flash**	0.058	0.090	0.110	0.080	0.065	0.125	0.080	0.110	0.150	0.065	0.060	0.160
	Qwen 2.5 7B	0.038	0.040	0.065	0.050	0.040	0.080	0.050	0.045	0.095	0.045	0.045	0.120
	Llama 3.1 8B	0.077	0.040	0.045	0.060	0.040	0.080	0.055	0.030	0.030	0.060	0.040	0.110
	Gemma 2 9B	0.096	0.045	0.105	0.070	0.050	0.080	0.075	0.065	0.075	0.050	0.045	0.110
LLM-Move	**Gemini 2 Flash**	0.096	**0.205**	**0.295**	**0.220**	**0.225**	0.220	**0.235**	**0.210**	**0.285**	**0.170**	**0.230**	**0.250**
	Qwen 2.5 7B	**0.192**	0.175	0.115	0.160	0.110	**0.230**	0.120	0.135	0.155	0.095	0.125	**0.250**
	Llama 3.1 8B	0.058	0.015	0.015	0.010	0.040	0.005	0.035	0.040	0.045	0.020	0.055	0.030
	Gemma 2 9B	0.096	0.100	0.235	0.120	0.115	0.110	0.115	0.175	0.195	0.105	0.125	0.130

administrative region coordinates as a proxy when exact POI coordinates are unavailable (e.g., due to privacy issues). Across different LLMs, Gemini 2.0 Flash achieved the highest accuracy across all three prompting strategies, with Qwen 2.5 7B and Gemma 2 9B following closely as strong open-source alternatives. In contrast, we found that Llama 3.1 8B often struggled to follow prompt instructions and frequently produced irrelevant predictions, especially when using the prompts of LLM-Mob and LLM-Move.

Notably, these zero-shot methods outperformed, matched, or came close to the performance of supervised baselines in several cities (e.g., Jakarta, Kuwait City, Moscow), demonstrating their effectiveness even without additional fine-tuning. These results indicate that LLMs can effectively leverage the contextual information included in trajectory prompts to guide their predictions. Since LLMs are pre-trained, they do not require additional training, which reduces both computation time and cost. While inference may require more powerful hardware, it can still be faster overall than training supervised models from scratch.

5 Limitations and Future Work

Firstly, Massive-STEPS is derived from the Semantic Trails dataset and thus inherits its biases and potential errors, which may propagate through downstream tasks. Additionally, the dataset is sparse in several cities, which can impact model training quality and limit cross-city generalization. Secondly, Massive-STEPS focuses solely on trajectories and POI metadata, without including user demographic or social information (e.g., age, social connections). This restricts its applicability for personalized or socially-aware POI recommendation tasks. Thirdly, while our benchmarking covers a wide range of models and cities to emphasize replicability and geographic breadth, we did not perform extensive hyperparameter tuning, which may affect the peak performance of the evaluated models.

While the current version of Massive-STEPS already surpasses existing POI check-in datasets in scale and diversity, we envision expanding it further to include even more cities worldwide. Our dataset creation pipeline is designed to be easily extensible, allowing researchers to integrate additional cities with minimal effort. This allows Massive-STEPS to evolve into a truly global POI check-in dataset.

6 Conclusion

In this paper, we presented the Massive-STEPS dataset to address longstanding limitations in POI recommendation research, particularly the reliance on older, geographically saturated, and non-reproducible check-in datasets. Massive-STEPS offers a large-scale, semantically enriched resource spanning 12 cities across diverse global regions and two time periods, supporting both longitudinal and cross-city analyses. The dataset includes rich semantic information such as venue name, address, category, and coordinates. We also provide benchmark results for both supervised and zero-shot POI recommendation methods, illustrating the dataset's utility across model types and urban contexts. By releasing Massive-STEPS and our evaluation pipeline publicly, we aim to advance open, reproducible, and globally inclusive research in human mobility and POI recommendation systems. We released our dataset under the Apache 2.0 license.

Acknowledgments and Disclosure of Funding

We would like to thank the support of the National Computational Infrastructure and the ARC Center of Excellence for Automated Decision Making and Society (CE200100005). Computational facilities were provided by the School of Computer Science and Engineering at UNSW Sydney through the Wolfpack computational cluster. Additionally, we express our gratitude to the NVIDIA Academic Grant Program for providing access to A100 GPUs on Saturn Cloud. We further thank the Google Cloud Research Credits program for API access to Gemini models.

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A Existing POI Recommendation Datasets

To examine the trend of the usage of POI recommendation datasets, we filtered the comprehensive survey by [68] to extract studies that explicitly mention the cities used in their experiments. The resulting distribution is summarized in Table 5, which shows a strong concentration of studies focused on New York and Tokyo. Additionally, Fig. 1 visualizes the same data, highlighting the uneven distribution of city choices across studies. We also include information on the LBSN platforms used, revealing that Foursquare remains the predominant data source in the field. These findings underscore the need for broader, more inclusive datasets that support evaluation across a wider range of global cities.

B Data Visualization

We present several visualizations highlighting Massive-STEPS' scale and diversity to complement our dataset description.

In Fig. 3, we show the top 10 most frequent POI categories for each city. The distribution reflects the local culture and lifestyle across different urban areas. For example, Beijing and Shanghai have a high number of Chinese restaurants, while Melbourne and Sydney show a strong presence of cafes. In Tokyo, convenience stores and ramen shops dominate. These patterns illustrate the diversity of local culture and user interests.

Fig. 4 plots the distribution of trajectory lengths (i.e., number of check-ins per trajectory). The distribution is long-tailed, with most trajectories being relatively short, similar to the original Semantic Trails dataset. This indicates that users often make only a few check-ins per outing.

Finally, we show the distribution of user activity levels, measured by the number of trajectories per user in Fig. 5. Most users exhibit cold-start behavior, contributing only a small number of trajectories. This highlights the importance of models that are robust to sparse and short user histories.

Table 5: **Overview of POI Recommendation Studies by City and LBSN Platform**. This table is adapted from Table IV in the survey by [68] and presents a filtered list of POI recommendation studies that explicitly mention city names and their associated LBSN platforms.

Study	Cities	LBSN
SSTPMF [5]	New York, Tokyo	Foursquare, Gowalla
ST-LSTM [69]	California, Singapore	Brightkite, Foursquare, Gowalla
LSMA [43]	New York, San Fransisco, Tokyo	Foursquare, Weeplaces
DLAN [46]	New York, Tokyo	Foursquare
TLR-M [13]	New York, Tokyo	Foursquare
GETNext [60]	New York, Tokyo, California	Foursquare, Gowalla
CARAN [17]	New York, Tokyo	Foursquare, Gowalla
JANICP [70]	New York, Tokyo	Foursquare, Weeplaces
Li et al. [23]	New York, Tokyo	Foursquare
AMACF [58]	New York, Tokyo	Foursquare, Weeplaces
CHA [64]	New York, Tokyo	Foursquare
HAT [47]	Beijing, Shanghai	Yelp, others
STAR-HiT [49]	New York	Foursquare, Gowalla
CAFPR [14]	Tokyo, California, Budapest, Melbourne	Foursquare
TGAT [19]	New York, Tokyo	Foursquare
MobGT [50]	New York	Foursquare, Gowalla
POIBERT [16]	Budapest, Delhi, Edinburgh, Glasgow, Osaka, Perth, Toronto	Flickr
AutoMTN [30]	New York, Tokyo	Foursquare
CCDSA [40]	New York, Tokyo, San Fransisco	Foursquare, Weeplaces
TDGCN [2]	Tokyo, California	Foursquare, Gowalla, Weeplaces
BayMAN [48]	New York	Foursquare, Gowalla
ROTAN [11]	New York, Tokyo, California	Foursquare, Gowalla
STGCN [15]	Boston, Chicago, London	Gowalla, others
ADQ-GNN [44]	New York, Tokyo	Foursquare, Gowalla
HS-GAT [67]	Boston, Chicago, London	Yelp, others
HKGNN [66]	New York, Jakarta, Kuala Lumpur, Sao Paulo	Foursquare
S2GRec [24]	New York, Tokyo	Foursquare, Gowalla
GSBPL [39]	New York, Tokyo	Foursquare, Gowalla
LSPSL [18]	New York, Tokyo	Foursquare
SCL [3]	Florence, Rome, Pisa, Edinburgh, Toronto	Flickr
LLM-Move [10]	New York, Tokyo	Foursquare
LLM4POI [22]	New York, Tokyo, California	Foursquare, Gowalla
DiffPOI [31]	Singapore, New York, Tokyo	Foursquare, Gowalla
DSDRec [45]	New York, Tokyo	Foursquare
Diff-DGMN [72]	Istanbul, Jakarta, Sao Paulo, New York, Los Angeles	Foursquare

Table 6: **Fields available in the Massive-STEPS dataset**, including user, POI, geographic/spatial, and temporal details, along with example data for each field.

Field	Description	Example
`trail_id`	Numeric identifier of trajectory	`2013_2866`
`user_id`	Numeric identifier of user	`90`
`venue_id`	Numeric identifier of POI venue	`185`
`latitude`	Latitude of POI venue	`-33.87301862604473`
`longitude`	Longitude of POI venue	`151.20668402700997`
`name`	POI name	`Sydney Town Hall`
`address`	Street address of POI venue	`483 George St`
`venue_category`	POI category name	`City Hall`
`venue_category_id`	Foursquare Category ID	`4bf58dd8d48988d129941735`
`venue_category_id_code`	Numeric identifier of POI category	`72`
`venue_city`	Administrative region name	`Sydney`
`venue_city_latitude`	Latitude of administrative region	`-33.86785`
`venue_city_longitude`	Longitude of administrative region	`151.20732`
`venue_country`	Country code	`AU`
`timestamp`	Check-in timestamp	`2012-04-22 08:20:00`

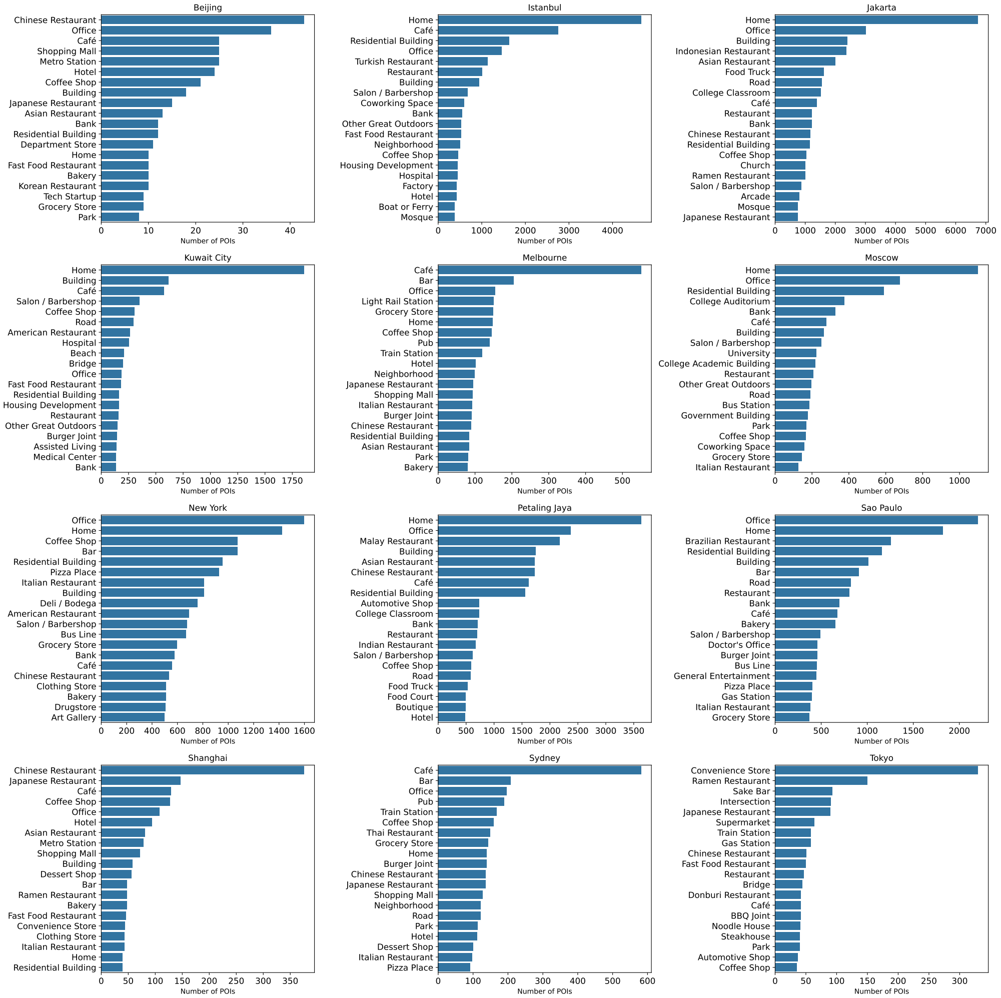

Figure 3: **Top 10 most frequent POI categories in each city**, highlighting local cultural and urban preferences.

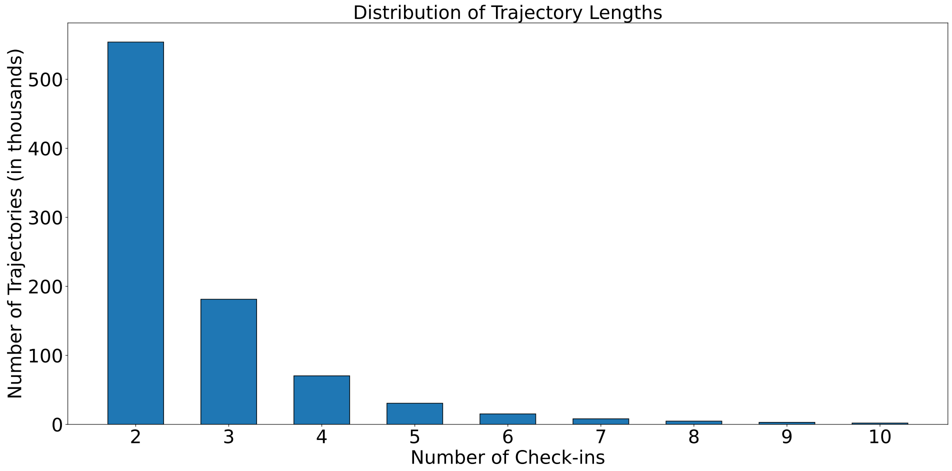

Figure 4: **Distribution of trail lengths**, showing a long-tailed pattern with most trajectories consisting of a few check-ins.

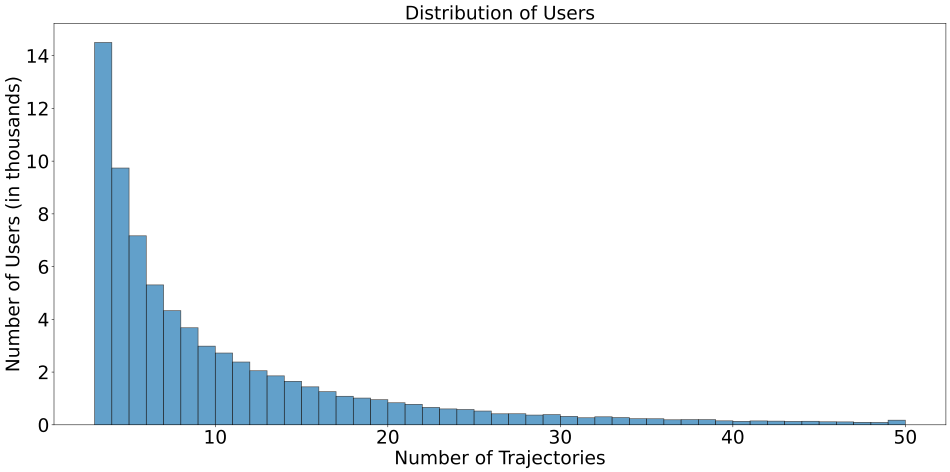

Figure 5: **Distribution of user activity** based on the number of trajectories per user, indicating a cold-start-heavy dataset.

C POI Recommendation: Task Details

We adopt the conventional problem formulation used in prior POI recommendation studies [68, 60, 54], which defines the task as learning user preferences and routines from historical check-ins to recommend future POIs.

C.1 Problem Formulation

Let $\mathcal{U} = \{u_1, u_2, \ldots, u_M\}$ denote the set of users, $\mathcal{P} = \{p_1, p_2, \ldots, p_N\}$ the set of Points of Interest (POIs), and $\mathcal{T} = \{t_1, t_2, \ldots, t_K\}$ the set of timestamps, where $M, N, K \in \mathbb{N}$.

POI Definition Each POI $p \in \mathcal{P}$ is represented as a tuple:

$$p = \langle \phi, \lambda, \kappa, \alpha, \beta, \gamma \rangle,$$

where:

- ϕ and λ are the latitude and longitude,
- κ is the POI category (e.g., *restaurant*, *park*),
- α is the unique POI identifier,
- β is the textual address, and
- γ is the POI name.

Check-in Definition A check-in is a tuple $c = \langle u, p, t \rangle \in \mathcal{U} \times \mathcal{P} \times \mathcal{T}$, indicating that user u visited POI p at timestamp t.

Trajectory Definition A trajectory for user u is defined as a temporally ordered sequence of check-ins within a fixed time interval $\delta\tau = 8$ hours. Each trajectory $T_u^i(t)$ up to timestamp t is defined as:

$$T_u^i(t) = \{(p_1, t_1), (p_2, t_2), \ldots, (p_k, t_k)\}$$

such that $t_1 < t_2 < \ldots < t_k = t$ and $t_k - t_{k-1} \leq \delta\tau$. Given a set of historical trajectories

$$\mathcal{T}_u = \{T_u^1, T_u^2, \ldots, T_u^L\}$$

for user u, where L is the number of such **historical** trajectories, the goal is to recommend the POIs that u is most likely to visit next after the current **contextual** trajectory $T_u'(t)$.

POI Recommendation Task Definition Given a current contextual trajectory $T'_u(t)$ of user u up to time t, along with their historical trajectories $\mathcal{T}_u$, the task of next POI recommendation is to rank all candidate POIs $p_i \in \mathcal{P}$ according to the model's predicted probability that user u will visit each POI next.

Formally, the model learns a ranking function:

$$f : (T'_u(t), \mathcal{T}_u) \rightarrow \{\hat{y}_i\}_{i=1}^{|\mathcal{P}|}$$

where $\hat{y}_i$ denotes the predicted likelihood that user u will visit POI p_i next. Based on these scores, a ranked list of POIs is returned as recommendations.

This formulation enables POI recommendation, where the goal is to suggest a set of likely POIs that a user may visit next, based on their historical check-ins and inferred preferences. Our evaluation metrics, Acc@k and NDCG@k, assess whether the ground-truth POI appears among the top-k ranked candidates, reflecting the quality of the recommended set. In particular, Acc@1 captures the stricter task of *immediate* next POI prediction, measuring whether the top-ranked POI matches the user's actual next visit.

C.2 Experiment and Implementation Details

For training and evaluation, we used the LibCity[1] library [41], which provides implementations of classical baselines including FPMC [32], RNN [41], LSTPM [35], and DeepMove [8]. The training hyperparameters are listed in Table 7 and, unless otherwise noted, follow the default configurations provided by LibCity.

For GETNext[2] [60] and STHGCN[3] [54], we adapted the original source code released by the respective authors. Due to variations in dataset sizes and training costs across cities, we applied different hyperparameters for some cities, as detailed in Table 8.

Table 7: **Hyperparameters for Markov-based methods and recurrent networks baselines**.

Hyperparameter	FPMC	RNN	LSTPM	DeepMove
Batch Size	20	20	20	20
Learning Rate	5e-4	1e-3	1e-4	1e-3
Max Epoch	1	30	40	30
Location Embedding Size	64	500	500	500
Hidden Embedding Size	N/A	500	500	500
Dropout	N/A	0.3	0.8	0.5

Table 8: **Hyperparameters for Transformer-based graph neural networks**.

Model	Cities	Batch Size	LR	Epochs
GETNext	Beijing, Melbourne, Moscow, Shanghai, Sydney, Tokyo	16	1e-3	200
	Istanbul, Kuwait City, New York, Petaling Jaya, São Paulo	16	1e-4	20
	Jakarta	16	5e-5	20
STHGCN	Beijing, Melbourne, Shanghai, Sydney, Tokyo	16	1e-4	20
	Istanbul, Jakarta, Kuwait City, Moscow, New York, Petaling Jaya, São Paulo	64	1e-4	20

All modified code implementations are available as submodules in our main dataset repository. Experiments were conducted using GPUs provided by the School of Computer Science and Engineering at UNSW Sydney via the Wolfpack computational cluster, which includes NVIDIA L4, L40S, and H100 GPUs.

C.3 Supplementary Results

We report the full results of our supervised POI recommendation baselines in Table 9 and 10, using three evaluation metrics: Acc@1, Acc@5, and NDCG@5.

[1] `https://github.com/libcity/bigscity-libcity-datasets/`

[2] `https://github.com/songyangme/GETNext`

[3] `https://github.com/alipay/Spatio-Temporal-Hypergraph-Model`

Table 9: **Performance of supervised POI recommendation baselines across 6 cities**: Beijing, Istanbul, Jakarta, Kuwait City, Melbourne, and Moscow. We report three metrics: Acc@1 (A@1), Acc@5 (A@5), and NDCG@5 (N@5).

Model	**Beijing**			**Istanbul**			**Jakarta**			**Kuwait City**			**Melbourne**			**Moscow**		
	A@1	**A@5**	**N@5**	**A@1**	**A@5**	**N@5**	**A@1**	**A@5**	**N@5**	**A@1**	**A@5**	**N@5**	**A@1**	**A@5**	**N@5**	**A@1**	**A@5**	**N@5**
FPMC	0.000	0.021	0.009	0.026	0.074	0.050	0.029	0.085	0.058	0.021	0.089	0.054	0.062	0.147	0.107	0.059	0.129	0.094
RNN	0.085	0.183	0.134	0.077	0.178	0.130	0.049	0.115	0.083	0.087	0.203	0.146	0.059	0.105	0.083	0.075	0.164	0.122
LSTPM	0.127	0.211	0.169	0.142	0.286	0.217	0.099	0.210	0.157	0.180	0.362	0.275	0.091	0.204	0.150	0.151	0.300	0.229
DeepMove	0.106	0.261	0.190	0.150	0.298	0.228	0.103	0.212	0.160	0.179	0.360	0.274	0.083	0.179	0.134	0.143	0.283	0.217
GETNext	0.433	0.527	0.486	0.146	0.268	0.210	0.155	0.257	0.209	0.175	0.322	0.251	0.100	0.250	0.179	0.175	0.335	0.260
STHGCN	0.453	0.640	0.552	0.241	0.385	0.318	0.197	0.334	0.270	0.225	0.394	0.314	0.168	0.318	0.247	0.223	0.382	0.308

Table 10: **Performance of supervised POI recommendation baselines across 6 cities**: New York, Petaling Jaya, São Paulo, Shanghai, Sydney, and Tokyo. We report three metrics: Acc@1 (A@1), Acc@5 (A@5), and NDCG@5 (N@5).

Model	**New York**			**Petaling Jaya**			**São Paulo**			**Shanghai**			**Sydney**			**Tokyo**		
	A@1	**A@5**	**N@5**	**A@1**	**A@5**	**N@5**	**A@1**	**A@5**	**N@5**	**A@1**	**A@5**	**N@5**	**A@1**	**A@5**	**N@5**	**A@1**	**A@5**	**N@5**
FPMC	0.032	0.090	0.061	0.026	0.084	0.057	0.030	0.079	0.055	0.084	0.154	0.120	0.075	0.180	0.131	0.176	0.291	0.239
RNN	0.061	0.119	0.092	0.064	0.148	0.107	0.097	0.191	0.147	0.055	0.120	0.090	0.080	0.164	0.125	0.133	0.254	0.197
LSTPM	0.099	0.206	0.155	0.099	0.222	0.163	0.158	0.319	0.243	0.099	0.195	0.149	0.141	0.265	0.206	0.225	0.394	0.315
DeepMove	0.097	0.195	0.149	0.112	0.234	0.175	0.160	0.310	0.240	0.085	0.168	0.128	0.129	0.240	0.188	0.201	0.362	0.288
GETNext	0.134	0.263	0.202	0.139	0.254	0.200	0.202	0.360	0.286	0.115	0.230	0.177	0.181	0.347	0.266	0.180	0.361	0.275
STHGCN	0.146	0.259	0.207	0.174	0.301	0.241	0.250	0.425	0.344	0.193	0.329	0.264	0.227	0.378	0.307	0.250	0.432	0.350

D Analyzing Urban Features and POI Recommendation Performance

As discussed in Section 2.2, several hypotheses have been proposed to explain why POI recommendation models perform better in certain cities than others. These hypotheses aim to uncover how various urban features affect model performance. For example, Gowalla-CA [4, 62] often yields lower accuracy compared to FSQ-NYC and FSQ-TKY [57], suggesting that some cities may be inherently harder to model. In this analysis, we focus on supervised models only.

Prior studies [60, 54, 22] have suggested several features as potential explanatory variables, including:

- Number of unique check-ins,
- Number of unique trajectories,
- Number of unique POI categories,
- Geographical area (larger areas are assumed to be harder to model), and
- POI density or spatial sparsity (i.e., unique POIs per unit area).

We also propose several additional features for consideration:

- Number of unique POIs,
- Check-in density (unique check-ins per area),
- Trajectory density (unique trajectories per area), and
- Category entropy, our proposed feature capturing category diversity.

Category entropy, based on Shannon entropy, measures how evenly POI categories are distributed in a city. A higher entropy suggests that check-ins are spread across a wide variety of categories, while a lower entropy indicates a concentration in fewer types. The formula for Shannon entropy is:

$$H = -\sum_{i=1}^{N} p_i \log(p_i) \tag{1}$$

where p_i is the proportion of venues in category i, and N is the total number of POI categories. The proportion p_i is defined as:

$$p_i = \frac{c_i}{\sum_{j=1}^{N} c_j} \tag{2}$$

where c_i is the count of venues in category i. In other words, p_i represents the fraction of all venues that belong to category i.

Moreover, previous studies have primarily focused on only three datasets: FSQ-NYC, FSQ-TKY, and Gowalla-CA. In contrast, Massive-STEPS provides broader coverage across 12 cities, enabling a more comprehensive and robust analysis. To examine the relationship between urban features and model performance, we averaged the three evaluation metrics across six supervised baselines for each city and computed the Spearman correlation with each candidate feature. To further support our findings, we also included the results of GETNext [60] and STHGCN [54] on FSQ-NYC, FSQ-TKY, and Gowalla-CA, calculated their corresponding urban features, and averaged the reported metrics of each city. Fig. 6 presents the correlations between all nine features and the average performance metric.

Among all features, **category entropy** shows the strongest correlation with model performance, with a Spearman correlation of $r = -0.736$ ($p = 0.002$). This suggests that cities with more evenly distributed POI categories *tend* to yield lower prediction accuracy. Intuitively, when no single category dominates (a city has roughly equal proportions of restaurants, cafes, homes, and other POIs), it becomes more difficult for models to predict a user's next destination. In these cases, user behavior is more varied and less predictable. On the other hand, cities with more skewed category distributions (e.g., mostly food places or mostly residential areas) tend to have more consistent patterns of movement, making them easier for models to learn and predict. Interestingly, our finding contradicts the hypothesis proposed by LLM4POI [22], which suggests that FSQ-NYC is easier to model than Gowalla-CA due to the former's vast number of POI categories, which were supposed to provide richer contextual signals for the model. Our results indicate that it is not the number of categories that matters, but rather how these categories are distributed.

E Zero-shot POI Recommendation: Task Details

E.1 Problem Formulation

The zero-shot POI recommendation task follows the same problem formulation as its supervised counterpart (see Section C.1). The key difference is that in this setting, the model parameters remain frozen and the models are pre-trained, rather than trained from randomly initialized weights.

E.2 Experiment and Implementation Details

Preprocessing We adopted the AgentMove[4] library [7], which provides implementations of three LLM methods: LLM-Mob [42], LLM-ZS [1], and LLM-Move [10]. The preprocessing steps used by AgentMove are as follows.

First, we selected 200 random users from the test set and sampled one random trajectory for each user. This trajectory serves as the **context stays**, representing the current trajectory to be predicted. The **historical stays** are composed of the most recent 15 trajectories from the same user, drawn from the training set. Each check-in is described by four attributes: the hour (in 12-hour format), the day of the week, the POI ID, and the POI category name.

Second, the LLMs are set to return outputs in JSON format, generating the top 5 predicted POI IDs along with an explanation of their reasoning. Following the AgentMove setup and to ensure replicability, we set the generation parameters as follows: a temperature of 0.0, a maximum output length of 1000 tokens, and an input context window capped at 2000 tokens.

Prompting Prompt templates for each method, LLM-Mob, LLM-ZS, and LLM-Move, are presented in Listing 1, 2, and 3, respectively.

```
Your task is to predict a user's next location based on his/her
    activity pattern.
```

[4] `https://github.com/tsinghua-fib-lab/agentmove/`

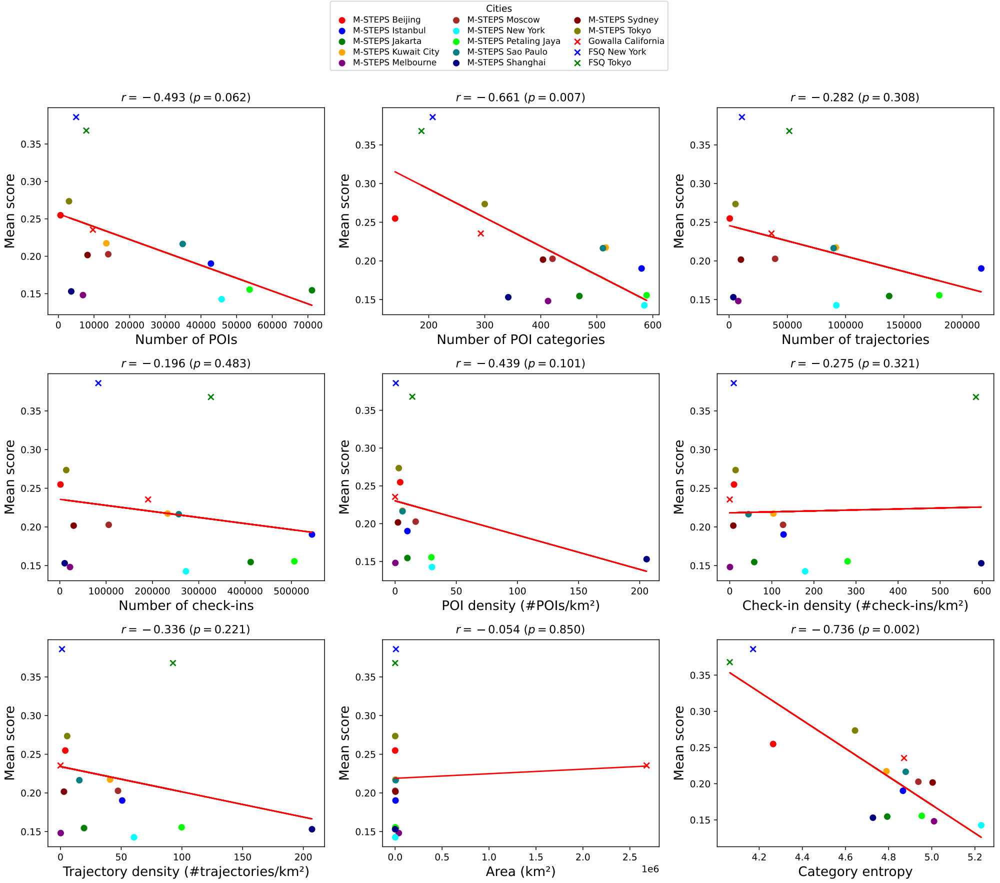

Figure 6: **Spearman correlation between nine candidate urban features and the mean score of POI recommendation models** across 15 cities, including Massive-STEPS (ours), FSQ [57], and Gowalla [4, 62].

```
You will be provided with <history> which is a list containing this user's historical stays, then <context> which provide contextual information
about where and when this user has been to recently. Stays in both <history> and <context> are in chronological order.
Each stay takes on such form as (start_time, day_of_week, duration, place_id). The detailed explanation of each element is as follows:
start_time: the start time of the stay in 12h clock format.
day_of_week: indicating the day of the week.
duration: an integer indicating the duration (in minute) of each stay. Note that this will be None in the <target_stay> introduced later.
place_id: an integer representing the unique place ID, which indicates where the stay is.

Then you need to do next location prediction on <target_stay> which is the prediction target with unknown place ID denoted as <next_place_id> and
unknown duration denoted as None, while temporal information is provided.

Please infer what the <next_place_id> might be (please output the 10 most likely places which are ranked in descending order in terms of probability), considering the following aspects:
```

```
1. the activity pattern of this user that you learned from <history>, e.g., repeated visits to certain places during certain times;
2. the context stays in <context>, which provide more recent activities of this user;
3. the temporal information (i.e., start_time and day_of_week) of target stay, which is important because people's activity varies during different time (e.g., nighttime versus daytime)
and on different days (e.g., weekday versus weekend).

Please organize your answer in a JSON object containing following keys:
"prediction" (the ID of the five most probable places in descending order of probability) and "reason" (a concise explanation that supports your prediction). Do not include line breaks in your output.

The data are as follows:
<history>: {historical_stays}
<context>: {context_stays}
<target_stay>: {target_time, target_day_of_week}
```

Listing 1: Prompt for LLM-Mob

```
Your task is to predict <next_place_id> in <target_stay>, a location with an unknown ID, while temporal data is available.

Predict <next_place_id> by considering:
1. The user's activity trends gleaned from <historical_stays> and the current activities from  <context_stays>.
2. Temporal details (start_time and day_of_week) of the target stay, crucial for understanding activity variations.

Present your answer in a JSON object with:
"prediction" (IDs of the five most probable places, ranked by probability) and "reason" (a concise justification for your prediction).

The data:
<historical_stays>: {historical_stays}
<context_stays>: {context_stays}
<target_stay>: {target_time, target_day_of_week}
```

Listing 2: Prompt for LLM-ZS

```
<long-term check-ins> [Format: (POIID, Category)]: {historical_stays}
<recent check-ins> [Format: (POIID, Category)]: {context_stays}
<candidate set> [Format: (POIID, Distance, Category)]: {candidates}
Your task is to recommend a user's next point-of-interest (POI) from <candidate set> based on his/her trajectory information.
The trajectory information is made of a sequence of the user's <long-term check-ins> and a sequence of the user's <recent check-ins> in chronological order.
Now I explain the elements in the format. "POIID" refers to the unique id of the POI, "Distance" indicates the distance (kilometers) between the user and the POI, and "Category" shows the semantic information of the POI.

Requirements:
1. Consider the long-term check-ins to extract users' long-term preferences since people tend to revisit their frequent visits.
2. Consider the recent check-ins to extract users' current perferences.
3. Consider the "Distance" since people tend to visit nearby pois.
4. Consider which "Category" the user would go next for long-term check-ins indicates sequential transitions the user prefer.
```

```

Please organize your answer in a JSON object containing following keys
    :
"prediction" (10 distinct POIIDs of the ten most probable places in <
    candidate set> in descending order of probability), and "reason" (
    a concise explanation that supports your recommendation according
    to the requirements). Do not include line breaks in your output.
```

Listing 3: Prompt for LLM-Move

Models and Implementations We use the following LLMs in our experiments:

- Gemini 2.0 Flash (`gemini-2.0-flash`),
- Qwen 2.5 7B Instruct (`Qwen2.5-7B-Instruct-AWQ`)[5],
- Llama 3.1 8B Instruct (`Meta-Llama-3.1-8B-Instruct-AWQ-INT4`)[6],
- Gemma 2 9B Instruct (`gemma-2-9b-it-AWQ-INT4`)[7].

All open-source models are quantized using AWQ [25] and served via vLLM [21]. Inference of open-source models was conducted on NVIDIA A100 GPUs provided by SaturnCloud[8] through the NVIDIA Academic Grant Program. We accessed Gemini via the official API and through the Google Cloud Research Credits program. All modified code implementations are publicly available in our main dataset repository.

E.3 Supplementary Results

We provide the full results of our zero-shot POI recommendation results in Table 11 and 12, providing three metrics: Acc@1, Acc@5, and NDCG@5.

Table 11: **Performance of zero-shot POI recommendation baselines across 6 cities**: Beijing, Istanbul, Jakarta, Kuwait City, Melbourne, and Moscow. We report three metrics: Acc@1 (A@1), Acc@5 (A@5), and NDCG@5 (N@5).

Method	Model	Beijing			Istanbul			Jakarta			Kuwait City			Melbourne			Moscow		
		A@1	A@5	N@5	A@1	A@5	N@5	A@1	A@5	N@5	A@1	A@5	N@5	A@1	A@5	N@5	A@1	A@5	N@5
LLM-Mob	Gemini 2 Flash	0.115	0.308	0.226	0.080	0.225	0.160	0.100	0.245	0.174	0.095	0.270	0.185	0.060	0.150	0.108	0.130	0.245	0.187
	Qwen 2.5 7B	0.058	0.385	0.218	0.035	0.240	0.148	0.105	0.245	0.179	0.080	0.220	0.155	0.030	0.130	0.083	0.090	0.270	0.185
	Llama 3.1 8B	0.000	0.000	0.000	0.020	0.110	0.065	0.055	0.150	0.104	0.030	0.100	0.066	0.010	0.065	0.040	0.030	0.100	0.068
	Gemma 2 9B	0.115	0.288	0.206	0.075	0.200	0.146	0.105	0.240	0.178	0.080	0.210	0.150	0.055	0.150	0.108	0.100	0.240	0.176
LLM-ZS	Gemini 2 Flash	0.058	0.385	0.246	0.090	0.235	0.166	0.110	0.250	0.188	0.080	0.245	0.167	0.065	0.160	0.115	0.125	0.300	0.217
	Qwen 2.5 7B	0.038	0.404	0.237	0.040	0.235	0.141	0.065	0.250	0.161	0.050	0.220	0.140	0.040	0.155	0.100	0.080	0.260	0.176
	Llama 3.1 8B	0.077	0.346	0.221	0.040	0.225	0.137	0.045	0.200	0.126	0.060	0.210	0.137	0.040	0.155	0.101	0.080	0.270	0.183
	Gemma 2 9B	0.096	0.308	0.217	0.045	0.225	0.141	0.105	0.250	0.180	0.070	0.230	0.153	0.050	0.140	0.100	0.080	0.290	0.194
LLM-Move	Gemini 2 Flash	0.096	0.346	0.218	0.205	0.385	0.289	0.295	0.405	0.350	0.220	0.380	0.295	0.225	0.325	0.275	0.220	0.400	0.316
	Qwen 2.5 7B	0.192	0.346	0.280	0.175	0.270	0.226	0.115	0.225	0.169	0.160	0.285	0.227	0.110	0.220	0.165	0.230	0.310	0.274
	Llama 3.1 8B	0.058	0.135	0.100	0.015	0.055	0.036	0.015	0.025	0.021	0.010	0.035	0.023	0.040	0.195	0.123	0.005	0.065	0.031
	Gemma 2 9B	0.096	0.365	0.229	0.100	0.200	0.155	0.235	0.290	0.266	0.120	0.275	0.202	0.115	0.275	0.199	0.110	0.245	0.185

F License and Data Usage

Our work **does not** involve the collection of new data. Instead, we derive our resulting dataset by combining and aligning two publicly available datasets, both of which are distributed under permissive licenses. We did not scrape data from the internet or use proprietary APIs to construct this dataset.

We accessed the Semantic Trails Dataset [29] via Figshare: `https://doi.org/10.6084/m9.figshare.7429076.v2`. The dataset is licensed under the Creative Commons CC0 1.0 license

[5] `https://huggingface.co/qwen/qwen2.5-7b-instruct-awq`

[6] `https://huggingface.co/hugging-quants/Meta-Llama-3.1-8B-Instruct-AWQ-INT4`

[7] `https://huggingface.co/hugging-quants/gemma-2-9b-it-AWQ-INT4`

[8] `https://saturncloud.io/`

Table 12: **Performance of zero-shot POI recommendation baselines across 6 cities**: New York, Petaling Jaya, São Paulo, Shanghai, Sydney, and Tokyo. We report three metrics: Acc@1 (A@1), Acc@5 (A@5), and NDCG@5 (N@5).

Method	Model	New York			Petaling Jaya			São Paulo			Shanghai			Sydney			Tokyo		
		A@1	A@5	N@5	A@1	A@5	N@5	A@1	A@5	N@5	A@1	A@5	N@5	A@1	A@5	N@5	A@1	A@5	N@5
LLM-Mob	Gemini 2 Flash	0.095	0.175	0.136	0.090	0.220	0.160	0.130	0.305	0.223	0.055	0.160	0.111	0.060	0.160	0.112	0.140	0.320	0.238
	Qwen 2.5 7B	0.070	0.185	0.131	0.030	0.195	0.116	0.090	0.290	0.188	0.040	0.170	0.108	0.035	0.145	0.091	0.110	0.350	0.243
	Llama 3.1 8B	0.025	0.090	0.061	0.010	0.090	0.050	0.030	0.165	0.098	0.005	0.020	0.013	0.020	0.085	0.053	0.005	0.045	0.025
	Gemma 2 9B	0.070	0.175	0.124	0.055	0.185	0.122	0.085	0.230	0.162	0.050	0.150	0.104	0.030	0.130	0.086	0.145	0.345	0.255
LLM-ZS	Gemini 2 Flash	0.080	0.170	0.129	0.110	0.210	0.164	0.150	0.315	0.235	0.065	0.160	0.113	0.060	0.155	0.111	0.160	0.380	0.278
	Qwen 2.5 7B	0.050	0.180	0.116	0.045	0.175	0.111	0.095	0.290	0.198	0.045	0.155	0.103	0.045	0.170	0.109	0.120	0.365	0.257
	Llama 3.1 8B	0.055	0.160	0.111	0.030	0.205	0.123	0.030	0.280	0.159	0.060	0.165	0.116	0.040	0.185	0.110	0.110	0.415	0.269
	Gemma 2 9B	0.075	0.185	0.129	0.065	0.185	0.126	0.075	0.300	0.192	0.050	0.165	0.112	0.045	0.155	0.103	0.110	0.395	0.263
LLM-Move	Gemini 2 Flash	0.235	0.415	0.325	0.210	0.335	0.273	0.285	0.415	0.350	0.170	0.270	0.221	0.230	0.420	0.331	0.250	0.470	0.368
	Qwen 2.5 7B	0.120	0.255	0.188	0.135	0.175	0.155	0.155	0.235	0.199	0.095	0.165	0.133	0.125	0.280	0.205	0.250	0.360	0.312
	Llama 3.1 8B	0.035	0.130	0.084	0.040	0.060	0.049	0.045	0.045	0.045	0.020	0.040	0.030	0.055	0.220	0.141	0.030	0.060	0.046
	Gemma 2 9B	0.115	0.245	0.183	0.175	0.235	0.208	0.195	0.300	0.252	0.105	0.150	0.128	0.125	0.370	0.254	0.130	0.305	0.225

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We accessed the Foursquare Open Source Places dataset via Hugging Face: `https://huggingface.co/datasets/foursquare/fsq-os-places`. Foursquare Open Source Places is licensed under the Apache License, Version 2.0:

More details are available in Foursquare's documentation: `https://docs.foursquare.com/data-products/docs/access-fsq-os-places`.

We released our Massive-STEPS dataset under the same Apache Version 2.0 License, and have included Foursquare Open Source Places' license in our hosted dataset's README file.

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