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# Large Language Models are Zero-Shot Next Location Predictors

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## Abstract

Predicting the locations an individual will visit in the future is crucial for solving many societal issues like disease diffusion and reduction of pollution among many others. The models designed to tackle next-location prediction, however, require a significant amount of individual-level information to be trained effectively. Such data may be scarce or even unavailable in some geographic regions or peculiar scenarios (e.g., cold-start in recommendation systems). Moreover, the design of a next-location predictor able to generalize or geographically transfer knowledge is still an open research challenge. Recent advances in natural language processing have led to a rapid diffusion of Large Language Models (LLMs) which have shown good generalization and reasoning capabilities. These insights, coupled with the recent findings that LLMs are rich in geographical knowledge, allowed us to believe that these models can act as zero-shot next-location predictors. This paper evaluates the capabilities of many popular LLMs in this role, specifically Llama2, Llama2 Chat, GPT-3.5 and Mistral 7B. After designing a proper prompt, we tested the models on three real-world mobility datasets. The results show that LLMs can obtain accuracies up to 32.4%, a significant relative improvement of over 600% when compared to sophisticated deep learning models specifically designed for human mobility. Moreover, we show that other LLMs are unable to perform the task properly. To prevent positively biased results, we also propose a framework inspired by other studies to test data contamination (e.g., public datasets already observed during training). Finally, we explored the possibility of using LLMs as text-based explainers for next-location prediction showing that, regardless of the model size, LLMs can effectively provide an explanation for their decision. Notably, 7B models provide more generic, but still reliable, explanations compared to larger counterparts. The code is available at [github.com/ssai-trento/LLM-zero-shot-NL](https://github.com/ssai-trento/LLM-zero-shot-NL)

## 1 Introduction

Next-location prediction (NL) consists of predicting an individual’s future whereabouts based on their historical visits to locations. NL is crucial for addressing various societal challenges, including traffic management and optimization, control of disease diffusion, and disaster response management (Barbosa et al., 2018; Yabe et al., 2023). NL has been tackled employing Markov models (Gambs

et al., 2012; Bontorin et al., 2024), pattern-based approaches (Comito, 2017; Trasarti et al., 2017) and, more recently, Deep Learning (DL) techniques (Liu et al., 2016; Feng et al., 2018; Sun et al., 2020; Luo et al., 2021; Xue et al., 2021). However, such approaches are not geographically transferable (Luca et al., 2021). Thus, once these models are trained on a geographic area, they face a severe performance drop if deployed in different geographic regions (Luca et al., 2021). Although efforts have been made to improve geographic transferability, advancements mainly relate to collective mobility patterns, and zero-shot geographic independence remains unresolved (Simini et al., 2021; McArthur et al., 2011; Luca et al., 2021). Recent progress in DL has led to the proliferation of foundation models (Zhou et al., 2023), which are now used in various domains including time-series forecasting, finance, healthcare, and mobility forecasting (Jin et al., 2024; Zhou et al., 2024; Gruver et al., 2024; Zhang et al., 2023; Li et al., 2024; Jiang et al., 2023; Xue et al., 2024; Mizuno et al., 2022; Zhao et al., 2023). In addition, it has been shown that LLMs embed spatial and geographic knowledge and that this knowledge can be effectively extracted (Manvi et al., 2024; Tan et al., 2023).

All this evidence led us to explore the usage of LLMs as zero-shot next-location predictors. More specifically, we assessed the performance of four LLMs: Llama2 (Touvron et al., 2023), Llama2 Chat (Touvron et al., 2023), GPT-3.5 (AI, 2022), and Mistral (Team, 2023), while discussing some limitations regarding other LLMs like Phi-1.5 (Li et al., 2023), Phi-2 (Microsoft, 2023), Phi-3 (Microsoft, 2024), Gemma (et al, 2024), GPT-J (Wang and Komatsuzaki, 2021), Dolly (Databricks, 2023).

After showing the geographic transferability issues of some selected DL models commonly used as baselines for NL, we tested LLM’s capabilities to act as zero-shot next-location predictors. We found that LLMs can effectively operate as zero-shot NLs, achieving accuracies up to 32.4%.

We also explored the role of in-context learning (ICL) testing the LLMs with examples of input and expected output (Brown et al., 2020; Liu et al., 2023; Wei et al., 2022). In particular, we systematically analyzed the impact of zero-shot, one-shot and few-shot prompting on LLMs’ performances, finding that one-shot and few-shot prompts do not imply better performances. Further, we examined the influence of prompted historical information, such as the number of past location visits of a user and the context of the current trajectory. We observed that lowering the available information can have severe performance drops (up to -47.72%). On the other hand, providing additional historical visits can improve performances up to 16.69% in terms of relative improvement.

Finally, we tested the models for data contamination (Sainz et al., 2023). As LLMs are trained on a vast amount of publicly available data, there is the risk of obtaining positively biased results because data were observed during training. To avoid issues related to data contamination, (i) we tested the models for it, and (ii) we ran all the experiments using two publicly available datasets (Yang et al., 2014) and a private dataset (). As a result data contamination was not an issue, and the performances obtained using public datasets were comparable to the ones obtained using our private dataset. In addition to all the previous experiments, we also explored the possibility of using LLMs as text-based explainers for NL, showing that LLMs can effectively provide a text-based explanation on why a specific location was shortlisted as a potential next-location.

**Contributions.** In a nutshell, this work contributed to highlighting that LLMs can effectively be used as zero-shot next-location predictors and we assessed the impact of different prompting strategies (zero-shot, one-shot, and few-shot) as well as the role of contextual and historical data in enhancing the predictive accuracy of LLMs. Finally, we tested LLMs for potential data contamination issues, and we analyzed the possibility of using LLMs as text-based explainers for NL.

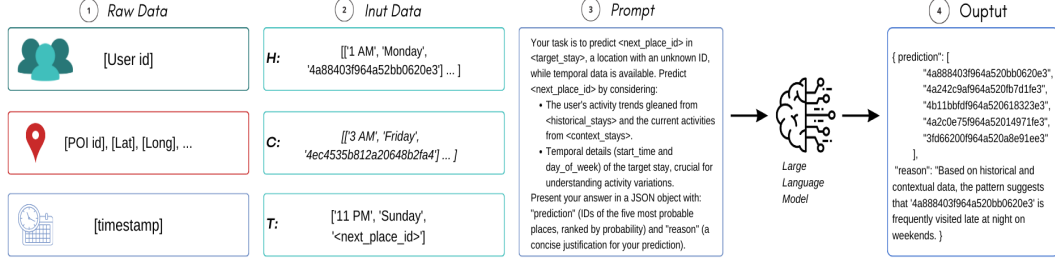


Figure 1: Graphical representation of the proposed framework. We start with the preprocessing of raw data and trajectory segmentation (1). Then, each visit in the trajectory is classified as historical visit ( $\mathcal{H}$ ), contextual visit ( $\mathcal{C}$ ) or target location ( $\mathcal{T}$ ) (2). After, we use the extracted information to craft a prompt (3) that is passed to the LLM to predict the next-location and explain the choice (4). Examples of prompts and relative outputs can be found in Appendix C

## 2 Related Work

Next-location prediction has been faced using pattern-based (Trasarti et al., 2017; Comito, 2017), Markov-based (Gambs et al., 2012; Bontorin et al., 2024) and, DL-based approaches (Feng et al., 2018; Luca et al., 2021; Liu et al., 2016; Sun et al., 2020; Luo et al., 2021; Xue et al., 2021). Following the evolution of DL techniques, researchers shifted from solutions based on recurrent networks (Liu et al., 2016; Feng et al., 2018) to more sophisticated transformer-like architectures (Xue et al., 2021). With these models, we can effectively predict individuals’ future whereabouts in most circumstances. However, there are scenarios in which even sophisticated DL models fail to perform NL. Examples are out-of-routine mobility (Luca et al., 2023) and data-scarce geographical areas where transferable models or zero-shot learners are needed (Luca et al., 2021). Concerning the latter, researchers have designed datasets (Yabe et al., 2023) and geographically transferable algorithms (Simini et al., 2021; McArthur et al., 2011) to overcome known limitations. However, the most prominent results have been obtained for collective mobility models as they depend on population density and distances between locations, thus are less geographically dependent by design (Simini et al., 2021; McArthur et al., 2011).

Recent advances in DL have brought rapid diffusion and easier accessibility to many LLMs. Consequently, researchers started to investigate performing language-based forecasting in various domains (Zhou et al., 2024; Zhang et al., 2023; Li et al., 2024; Zhao et al., 2023). Concerning the field of human mobility, LLMs have been successfully used to generate individual-level trajectories (Mizuno et al., 2022) and predict mobility demand at a point-of-interest (POI) level (Xue et al., 2022, 2024). Very recently, researchers also started to tackle NL (Wang et al., 2023). However, in Wang et al. (2023), the authors used a single LLM - namely GPT-3.5 - and the analysis was limited to performance evaluations. While the authors have shown LLMs could be used to perform NL, the role of prompting, predictive scenario (i.e., zero-shot, one-show, few-shot), data availability, parroting and benchmarking of multiple models were out of the scope of the paper. Furthermore, as discussed later, at least one of the datasets used in Wang et al. (2023) is publicly available and has been observed during the training phase of the selected LLMs, thus the performances may be positively biased.

## 3 Preliminaries

### 3.1 Task Definition

Next-location prediction is commonly defined as the problem of predicting the next location an individual will visit given their historical movements, typically represented as spatio-temporal trajectories (Luca et al., 2021).

**Definition 1 (Trajectory)** A spatio-temporal point  $p = (t, l)$  is a tuple where  $t$  indicates a timestamp and  $l$  a geographic location. A trajectory  $P = p_1, p_2, \dots, p_n$  is a time-ordered sequence of  $n$  spatio-temporal points visited by an individual, who may have several trajectories,  $P_1, \dots, P_k$ , where all the locations in  $P_i$  are visited before locations in  $P_{i+1}$ .

We further filtered trajectories following the methodology proposed in DeepMove (Feng et al., 2018). This involves filtering out users with fewer than 10 records. Also, we selected a 72-hour interval as the threshold for distinguishing between separate trajectories. Subsequently, any user with fewer than five trajectories is excluded from the analysis.

Each trajectory  $P$  of a user is composed of Historical and Contextual visits. We identified Historical visits  $\mathcal{H}$  and Contextual visits  $\mathcal{C}$  as follows.

**Definition 2 (Historical visits)** *Historical visits  $\mathcal{H} = \{h_1, h_2, \dots, h_n\}$  are the  $n$  spatio-temporal points that represent the user’s long-term mobility patterns and are visited immediately before the Contextual visits  $\mathcal{C}$ . Formally,*

$$\mathcal{H} = \{h_i \mid h_i \in P_k \text{ and } h_i \prec c_1\}$$

where  $c_1 = \min(\mathcal{C})$  represents the earliest point in the Contextual visits.

**Definition 3 (Contextual visits)** *Contextual visits  $\mathcal{C} = \{c_1, c_2, \dots, c_m\}$  are the  $m$  spatio-temporal points that capture the user’s short-term mobility patterns. The last point of the Contextual visits,  $c_m$ , is the same as the last point of the current trajectory,  $c_m = p_n$ . Thus, these set of points are visited immediately before the target point  $p_{n+1}$ . Formally,*

$$\mathcal{C} = \{c_j \mid c_j \in P_k \text{ and } c_j \prec p_{n+1}\}$$

We formalize the problem of next-location prediction as follows:

**Problem 1 (Next-location prediction)** *Given:*

- The current trajectory of an individual  $P_k = \{p_1, p_2, \dots, p_n\}$ , with at least two points;
- The historical trajectories of the individual  $\mathcal{L} = \{P_1, P_2, \dots, P_{k-1}\}$ ;

*Next-location prediction is the problem of forecasting the next location point  $p_{n+1} \in P_k$ .*

*In other words, a next-location predictor (NL) is a function*

$$\mathcal{M} : (\mathcal{H}, \mathcal{C}) \rightarrow p_{n+1}$$

*where  $\mathcal{H}$  are the Historical visits formed by filtering the earlier parts of  $P_k$  and possibly earlier trajectories  $P_1, \dots, P_{k-1}$  and  $\mathcal{C}$  are the Contextual visits defined as the last few points of  $P_k$  leading up to  $p_n$ .*

### 3.2 Datasets

We leveraged two datasets collected on Foursquare, a location-based social network where users can check-in at POIs. Data were collected in New York City (NYC) and Tokyo (Yang et al., 2014). Each entry consists of a user identifier, a location identifier, geographical coordinates, a timestamp, and a venue’s category. In NYC, we have 4,390 users and 13,960 unique POIs, corresponding to 12,519 distinct trajectories. In Tokyo, we have 935 users, 21,394 unique POIs, and 34,662 trajectories.

We also employed a private dataset to mitigate potential data contamination issues. It consists of GPS trajectories produced by cyclists in Ferrara, Italy (Bucchiarone et al., 2023). We divided the city into 200 x 200 square meters and ended up with 2,488 unique locations. We then computed the stop locations (Aslak and Alessandretti, 2020) (see Appendix A). We randomly selected 500 trajectories belonging to 32 users. Table 1 provides a concise summary of key statistics for all the datasets.

Table 1: Number of users, unique locations, and trajectories for each dataset.

		Users	Locations	Trajectories	Time Span
FSQ NYC	(Yang et al., 2014)	4,390	13,960	12,519	8 Months
FSQ Tokyo	(Yang et al., 2014)	935	21,394	34,662	8 Months
Our Dataset	(Bucchiarone et al., 2023)	32	2,488	500	3 Months

### 3.3 Evaluation Metrics

We employed the  $k$ -accuracy ( $\text{ACC}@k$ ) metric, a standard in the field of NL (Luca et al., 2021). This metric quantitatively measures the frequency with which the actual next location a person visits appears within the top  $k$  predictions provided by a model. In our analyses, we primarily focused on  $\text{ACC}@1$ ,  $\text{ACC}@3$  and  $\text{ACC}@5$ .

$$\text{ACC}@k = \frac{1}{N} \sum_{i=1}^N \mathbf{1}(\text{rank}(p_{n+1}) \leq k)$$

### 3.4 Baselines

Our first goal is to show that current SOTA models are not zero-shot predictors and are not geographically transferable. To do so, we selected the following widely adopted models as baselines: **RNNs** are widely used as building blocks of NLs to capture spatial and temporal patterns in the trajectories; **ST-RNNs** (Liu et al., 2016) add to standard RNNs time-specific and space-specific transition matrices; **DeepMove** (Feng et al., 2018) leverages attention mechanisms to capture spatio-temporal patterns in individual-level historical trajectories; **LSTPM** (Sun et al., 2020) combines long- and short-term sequential models, where long-term patterns are modelled using a non-local network (Wang et al., 2018), while short-term preferences are captured using a geographic-augmented version of the concept of dilated RNNs (Chang et al., 2017); **STAN** (Luo et al., 2021) captures spatio-temporal data by employing a multi-modal embedding to depict trajectories and a spatio-temporal attention mechanism to discern patterns within the data; and finally **MobTCast** (Xue et al., 2021) incorporates a transformer encoder-based structure to predict the next point of interest (POI), taking into account temporal, semantic, social, and geographical contexts. Baselines are available in LibCity Wang et al. (2021) and MobTCast in <https://github.com/xuehaouwa/POI-TForecast>

### 3.5 Large Language Models

Concerning LLMs, we extensively evaluated the following models. **Llama2** (7B,13B,70B) and relative Chat versions (Touvron et al., 2023). Llama2 is a decoder-only transformer-like model trained on 2 trillion tokens. We tested Llama2 and its chat version using Replicate APIs<sup>1</sup>. We also extensively tested **GPT-3.5** (AI, 2022), by querying the model with OpenAI APIs<sup>2</sup>. GPT-3.5 is the successor of GPT-3, a decoder-only model with 175B parameters (Brown et al., 2020). GPT-3.5 is known for containing a significant amount of knowledge (Bian et al., 2023). We also evaluated **Mistral 7B** (Team, 2023), a 7 billion parameter model able to perform better than bigger models (e.g., Llama2 13B) on many benchmarks. We also tested other models like Phi-1.5, Phi-2 (Microsoft, 2023), Phi-3 (Microsoft, 2024), Gemma 2B (et al, 2024), GPT-J (Wang and Komatsuzaki, 2021), Dolly (3B, 7B, 12B) (Databricks, 2023). The outputs from these models, however, were empty or contained text not representing locations, location identifiers or reasoning about possible next locations. Examples of prompts with relative outputs are provided in Appendix C.

## 4 Results

### 4.1 Next-Location Predictors are not Geographically Transferable

Once models are trained in a city, the deployment in different areas (e.g., another city) leads to severe performance drops. In addition, NLs are known to have limited generalization capabilities (Luca et al., 2023; Bontorin et al., 2024). In this section, we highlight such issues, underlining the need for a zero-shot geographically transferable NL. We first split each dataset into a training set (70%), a validation set (10%), and a test set (20%). The split has been done following the user-based approach proposed in Feng et al. (2018) and is widely used for training and evaluating mobility models (Luca et al., 2021). This implies that after segmenting the raw dataset into trajectories, for each user, we select their first 70% of trajectories as training, the following 10% as validation and the last 20% as the test ones. For this experiment we are using only the two datasets collected with

<sup>1</sup><https://replicate.com/>

<sup>2</sup><https://platform.openai.com/docs/api-reference/chat>

Foursquare as different data sources may lead to different self-selection biases and spatial granularity and thus, results may be less interpretable (Luca et al., 2021; Barbosa et al., 2018). We trained the models using the training set partitions from both Foursquare NYC and Foursquare Tokyo using the hyperparameters listed in Appendix B. Subsequently, we evaluated the performance of each trained model on the test set of the alternate city. Results in terms of ACC@5 are reported in Table 2.

Table 2: ACC@5 of traditional models when trained using Foursquare NYC / Tokyo and tested on Foursquare Tokyo / NYC. MobTCast is the best-performing model in both cases.

	<b>Train: FSQ NYC</b> <b>Test: FSQ TKY</b>	<b>Train: FSQ TKY</b> <b>Test: FSQ NYC</b>
RNN	0.028	0.029
ST-RNN	0.031	0.038
DeepMove	0.031	0.046
LSTPM	0.030	0.046
STAN	0.038	0.048
MobTCast	<b>0.042</b>	<b>0.049</b>

As we can see, MobTCast obtained the best results with a 4.2% ACC@5 when trained in NYC and tested in Tokyo. When trained on Tokyo, and tested on NYC, MobTCast reached an ACC@5 of 4.9%. In this scenario, LSTPM, DeepMove and STAN reached comparable ACC@5 of 4.6%, 4.6% and 4.8%, respectively. Such results highlight severe limitations regarding generalization power and geographic transferability of SOTA DL models (Luca et al., 2023, 2021). Such limitations also prevent us from using SOTA NLs as zero-shot predictors effectively. Designing a zero-shot NL remains an open challenge, and in this paper, we test whether LLMs can represent a solution for language-based zero-shot next-location predictions.

## 4.2 Language-Based Zero-Shot Next Location Predictors

We designed a structured prompt tailored to provide LLMs with the same information commonly provided to NLs (Luca et al., 2021). Specifically, we prompted the LLMs with data on individuals’ historical and contextual visits, extracted according to the definitions in Section 3.1 and we asked the LLMs to predict the top five possible next locations an individual will visit. Moreover, to enhance the comparability among the LLMs we choose to use the same prompt for all the models, which can be observed in Figure 1 and in Appendix C. We started by specifying the task, data and desired output and then, we provided a list of spatio-temporal historical points and contextual visits.

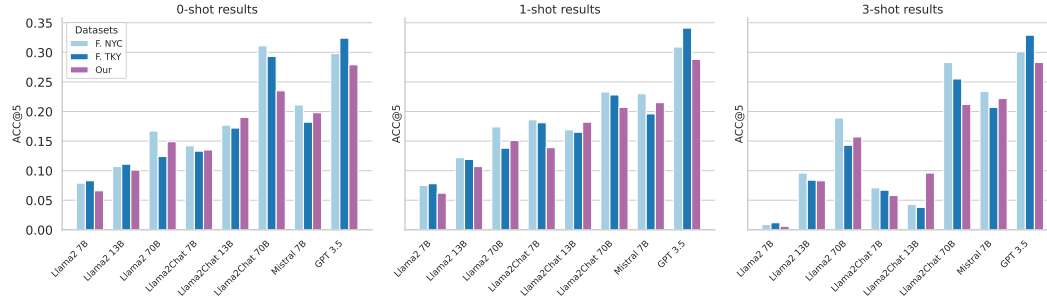


Figure 2: ACC@5 of selected LLMs prompted to perform zero-shot (left), one-shot (middle) and 3-shot (right) next location prediction. GPT-3.5 was the best performing model and the prompt providing the best result was the one-shot prompt. Llama2 13B and Llama2 Chat 7B obtained their best performances using a one-shot prompt. There were cases in which models performed better with 0-shot prompts - Llama2 7B, Llama2 Chat 13B, Llama2 Chat 70B - or with few-shots prompts - Mistral 7B.

In Table 36 (left panel) of the Appendix, we report the results regarding ACC@5 of the LLMs over the three datasets. GPT-3.5 is the best performing across all datasets, reaching an ACC@5 of 0.298, 0.324 and 0.279 on the datasets of Foursquare NYC, Foursquare Tokyo and our private dataset, respectively. In Table 36 of the Appendix we found that bigger models perform better than the smaller ones in zero-shot scenarios (Kaplan et al., 2020). Interestingly, the only exception is Mistral 7B, which consistently outperforms 13B models despite having fewer parameters. In Appendix E and F,

we also report the results for ACC@1 and ACC@3, showing that the insights obtained are consistent across all the evaluation metrics. Remarkably, we also observed that LLMs performed significantly better than DL SOTA next-location predictors when tested in a setting which is as close as possible to zero-shot NL. In particular, using GPT-3.5, using zero-shot prompts, we have a relative improvement of 601% in NYC and 561% in Tokyo.

In addition to zero-shot prompting, we also tested one and few-shot prompting as performances may vary.

### 4.3 In-Context Learning with One-Shot and Few-Shot Performance Evaluation

In-Context Learning (ICL) consist of providing LLMs with examples of input and expected outputs so that models may be facilitated to understand the task. In this sense, one-shot and few-shot prompting consist of providing the LLMs with a prompt that includes one or few examples of pairs of input and expected output instead of directly asking the models to solve a task (zero-shot prompting).

Here we explored how different predictive prompting strategies affect the accuracy of the selected models. Results are reported in Table 36 of the Appendix, central and right panels. GPT-3.5 is the model that achieved the best performance regardless of the dataset and prompting technique. Also, it reached higher accuracies using one-shot prompts. Likewise, Llama2 13B and Llama2 Chat 7B obtained the best performances with a one-shot prompting strategy. There are cases (Llama2 7B, Llama2 Chat 13B, 70B) where zero-shot prompts lead to the best performances. Finally, Mistral 7B gives its best with few-shot prompts. The role of prompting techniques is fundamental and there are instances (e.g., Llama2 Chat 13B) in which the performance relative drop between the different prompts can be higher than 75%.

### 4.4 The Role of Contextual and Historical Visits

In our prompts, we provided LLMs with 15 historical visits and 6 contextual visits. We modified these numbers of historical visits ( $H$ ) and contextual visits ( $C$ ) to carry out an ablation study. We analyzed how accuracies change by halving and doubling the number of  $C$  and  $H$ . Also, we explored how performances are impacted when no  $C$  or  $H$  are provided.

As we can see in Figure 3, increasing the number of visits in  $C$  or  $H$  leads to an improvement in terms of ACC@5 regardless of the model. With the default prompt ( $C = 6$ ;  $H = 12$ ), ACC@5 varies between 0.079 (NYC), 0.083 (TKY), 0.066 (our) obtained by Llama2 7B and 0.311 (NYC), 0.293 (TKY), 0.235 (our) obtained by Llama2 Chat 70B. The average ACC@5 was 0.183 with NYC, 0.181 using the TKY dataset and 0.163 with our dataset. When we double contextual information ( $C = 12$ ), the new ACC@5 varies between 0.085-0.319 (NYC), 0.090-0.302 (TKY), 0.071-0.248 (our) with an average performance of 0.196 (NYC), 0.195 (TKY), 0.178 (our) corresponding to an average relative improvement of 7.21% (NYC), 7.67% (TKY), 5.17% (our). When we double the number of historical visits ( $H = 30$ ), ACC@5 ranges between 0.092-0.326 (NYC), 0.099-0.317 (TKY) and 0.087-0.239 (our) with an average performance of 0.213 (NYC), 0.217 (TKY), 0.184 (our) in terms of ACC@5 and an average relative improvement of 16.79% (NYC), 19.59% (TKY) and 8.74% (our). We also tested prompts with a reduced number of visits (i.e.,  $C = 3$  or  $H = 7$ ) or with no contextual ( $C = 0$ ) or historical ( $H = 0$ ) information at all. When we use half of the contextual information ( $C = 3$ ), we experienced a reduction of the ACC@5 ranges between 0.062-0.266 (NYC), 0.065-0.263 (TKY), 0.058-0.225 (our) with an average ACC@5 of 0.159 (NYC), 0.162 (TKY), 0.150 (our) and relative improvement of -12.82% (NYC), -10.81 (TKY), -11.60 (our). Concerning the reduction of historical information ( $H = 7$ ), the average performance is 0.174 (NYC), 0.169 (TKY), 0.162 (our) with accuracies varying between 0.066-0.288 in NYC, 0.073-0.254 in Tokyo and 0.062-0.231 in our dataset corresponding to an average relative improvement of -4.75%, -6.73% and -4.43 % respectively. The extreme case in which we completely remove contextual or historical information leads to severe drops in performances. With  $C = 0$ , relative improvements are of -23.43% for NYC, -24.24% for Tokyo and -26.38% in our dataset. Also, by setting  $H = 0$  we obtained an average ACC@5 of 0.096, 0.089 and 0.101 for NYC, Tokyo and our dataset respectively.

We also tried to quantify the importance of  $C$  and  $H$  in the standard prompt (i.e.,  $C = 6$ ;  $H = 15$ ). Given all the correctly predicted next-locations, we look at the number of instances in which the next location was part of  $H$  and the percentage of times in which the prediction was based on  $C$ . We found that, for the dataset of Foursquare NYC, in the 56.92% (49.26% in Foursquare Tokyo, 64.21

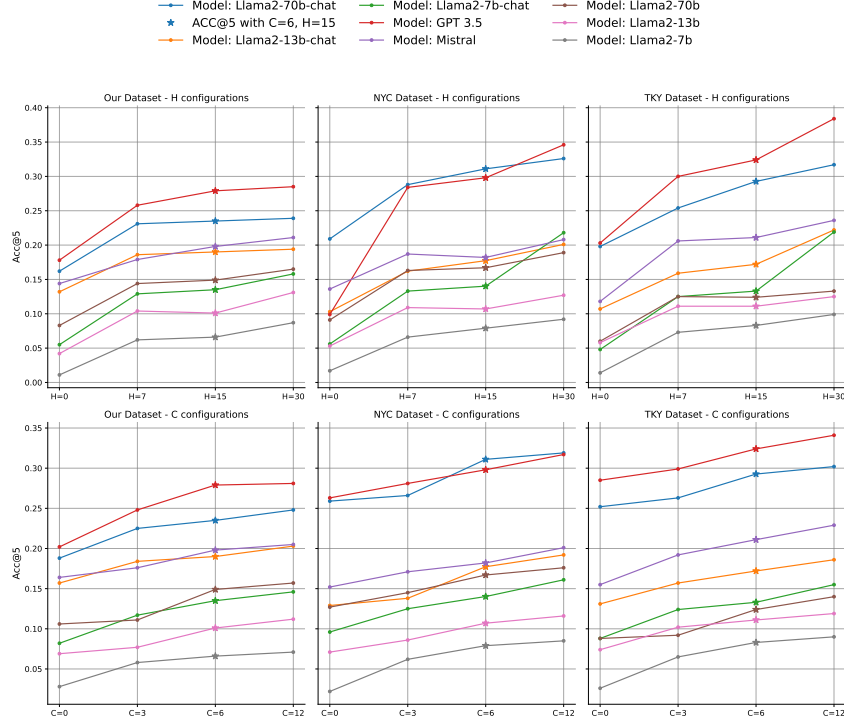


Figure 3: Acc@5 for various models on multiple datasets, comparing H configurations (top row) and C configurations (bottom row), with a highlighted performance at standard configuration (stars)

in Our dataset) of the cases it was possible to find the next location mentioned both in  $C$  and  $H$ . In 30.64% (38.71% in Foursquare Tokyo, 22.29% in Our dataset) of the cases, the next location was only available in historical visits  $H$  and in just 12.44% (12.03% in Foursquare Tokyo, 13.50% in our dataset) of the cases, the actual next-location was only present in  $C$ . This analysis suggests why changing the number of historical visits  $H$  is more impactful than contextual visits in  $C$ .

#### 4.5 Searching for Data Contamination

An important analysis when it comes to LLMs is to understand how much the results and accuracies obtained are biased as open datasets may have already been observed during training. Foursquare NYC and Foursquare Tokyo datasets are publicly available with many instances on websites and repositories (e.g., GitHub codes). Thus, we must be sure that the good zero-shot performances presented in Section 4.2 do not depend on potential data contamination issues. To mitigate this problem, we have done the following three actions.

**Test on a private dataset.** As a first counteraction, we analyzed the performances also on a private dataset which we are sure was not used to train any LLM. Results are presented in Table 2 and Table 3. The performances we obtained are similar to the ones on other publicly available datasets. Thus, LLMs can be effectively used as zero-shot NLs even on datasets that we can guarantee have not been observed in any way during the training phase.

**Carry out a data contamination analysis (Sainz et al., 2023).** We designed a quiz (following Golchin and Surdeanu (2023)) where we provided the LLMs with precise questions about the content (e.g., rows) of the datasets and four possible answers. Only one of the answers consists of entries coming from the same dataset, while the other options were designed following the suggestions in Golchin and Surdeanu (2023). All the models could not select the correct option further highlighting that the results obtained are not biased by data contamination. Examples of the quiz questions are provided in Appendix I

**Analyze unusual outputs.** As a last analysis, we also carefully examined specific outputs of the models. What we found is that the models provided three types of outputs: *i*) empty outputs and no



next-location; *ii*) correct predictions; *iii*) hallucinated location identifiers. Concerning the latter, we selected all the answers with a location identifier that was not included in the historical or contextual visits and we checked the outputs. We found that the structure of the identifiers was similar to real Foursquare location identifiers (e.g., comparable numbers of characters) but none of them correspond to existing locations. The Appendix 25 gives an example of this hallucinated output.

#### 4.6 Large Language Models as Explainer for Next Location Predictors

We designed our prompts also to obtain an explanation about what drove the LLMs outputting a specific next-location. In Table 3, we report an example of an explanation provided by GPT-3.5. We noticed that the level of detail of the explanation mainly depends on the number of parameters of the models with larger models (e.g., GPT-3.5, Llama2 70B) being able to refer to specific locations identifiers and smaller models (e.g., Llama2 7B) that are capable of providing reasonable but more general explanations. An example of an explanation for each model is provided in Appendix D. Remarkably, regardless of models’ sizes, the explanations focus on locations visited in similar circumstances (e.g., weekends versus weekdays, similar hours). In accordance with multiple studies about NL (Luca et al., 2021; Schneider et al., 2013; Song et al., 2010), focusing on previously visited locations may represent an effective way to perform zero-shot next location prediction and it may justify the good performances obtained by LLMs when used as zero-shot NLs.

Table 3: Explanation provided by a large model (GPT-3.5)

Explanation GPT-3.5:
Based on the historical locations, the user has frequently visited places '4d48864b551db1f722e9a330', '4a5dd98ef964a520c2bd1fe3', '3fd66200f964a520def11ee3', '42ec1480f964a5209e261fe3', and '4a3d735cf964a5204ba21fe3'. Additionally, the context locations provide recent activities at places '4a5dd98ef964a520c2bd1fe3', '3fd66200f964a520def11ee3', and '4a3d735cf964a5204ba21fe3'. Based on the temporal information (3 PM, Thursday), it is likely that the user will visit one of these places again.

## 5 Discussion and Conclusions

In this paper, we tested the capabilities of GPT-3.5, Llama2 and Mistral 7B to act as zero-shot next-location predictors. The task consists in predicting the next location an individual will visit given a set of historical and contextual visits. While there are many sophisticated deep learning models specifically designed to solve this task, having models that are geographically transferable and that can effectively predict future whereabouts in data-scarce scenarios remains an open challenge. In our work, we show that, indeed, LLMs can act as zero-shot location predictors obtaining remarkable results (i.e., up 0.324 - ACC@5) corresponding to relative improvements up to 601% with respect to DL-based next-location predictors when tested in a scenario as close as possible to the zero-shot. We also tested Gemma, Phi-1.5, Phi-2, Phi-3, GPT-J and Dolly (3B,7B,12B) but we found that, differently from other LLMs, such models tend to misunderstand the task providing empty or unusable answers. We also explore the role of in-context learning and how it affects performances showing that the number of examples of input/output pairs provided to the models have mixed effects on performances with some models obtaining their best performances with few-shot prompts and others with one- or zero-shot prompts. Moreover, we explored the role of the amount of available historical and contextual information. We found that performances may vary between -26.38% and 56.92% (relative improvements) with data-richer prompts leading to better performances. Finally, we investigated the possibility of using LLMs as text-based explainers for next-location prediction. We showed that LLMs can explain why the model selected that particular location.

**Limitations.** In our study, we tested a limited yet significant number of LLMs using a single prompt to ensure comparable results across the different models. However, each LLM comes with model-specific knowledge and prompt formulations. To maximize an LLM’s performance, prompts should be tailored to each model. However, beyond ensuring comparability, using a single prompt helped us manage costs. Indeed, testing LLMs incurred nearly 1,000 USD in API call expenses and running the experiments on local machines may lead to similar or higher management costs. We also found that not all the tested LLMs could understand the task and provide meaningful answers. Also, the working ones could hallucinate outputs (i.e., generate plausible but non-existent location

identifiers). It would be interesting to investigate if allowing LLMs to access external resources (e.g., list of location identifiers, business type) can improve performances and reduce hallucinations. Also, improving performances may allow policymakers to deploy LLMs in real-world use cases. While an improvement of more than 600% in terms of ACC@5 is remarkable, an ACC@5 of 34% may not be sufficiently reliable for critical use cases (e.g., natural disasters).

**Broader impact.** From a societal perspective, the use of LLMs in predicting human mobility can significantly impact urban planning and public policy. Accurate predictions can help to improve public services like transportation and infrastructure development. They can also enhance responses to emergencies and disasters by optimizing evacuation routes and resource allocation. In this sense, LLMs’ capabilities to effectively perform next-location prediction in zero-shot and with a small amount of information may be a critical factor. On the other hand, the use of LLMs also raises important ethical and societal concerns. A critical ethical issue is the potential for bias in the models (Manvi et al., 2024). LLMs trained on large datasets may inherit biases present in their training data, which could generate predictions based on demographic or geographical factors, leading to discriminatory and unfair outcomes. Different demographic groups may have varying mobility patterns that are not equally represented in the training datasets, thus less accurate predictions for underrepresented groups, amplifying existing inequalities.

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## A Stop Location Computation

Given a dense trajectory, to compute the stop locations we identified each temporal sequence of GPS coordinates within a 65-meter radius, where a user stayed for a minimum of 5 minutes (Hariharan and Toyama, 2004). Subsequently, we applied the DBSCAN algorithm (Ester et al., 1996) to identify dense clusters of points within a distance of  $\epsilon = \Delta_s - 5$ . We define these dense clusters as stop locations.

## B Models' Hyperparameters

Table 4: Hyperparameters used for the baselines

	Foursquare NYC	Foursquare Tokyo	Our
RNN	lr: 0.005 epochs: 200 batch: 32	lr: 0.005 epochs: 200 batch: 32	lr: 0.05 epochs: 75 batch: 16
ST-RNN	lr: 0.001 epochs: 200 batch: 32	lr: 0.001 epochs: 200 batch: 32	lr: 0.05 epochs: 75 batch: 16
DeepMove	lr: 0.001 epochs: 200 batch: 32	lr: 0.001 epochs: 200 batch: 32	lr: 0.05 epochs: 75 batch: 16
LSTPM	lr: 0.0001 epochs: 200 batch: 32	lr: 0.0001 epochs: 200 batch: 32	lr: 0.05 epochs: 75 batch: 16
STAN	lr: 0.0001 epochs: 200 batch: 32	lr: 0.0001 epochs: 200 batch: 32	lr: 0.05 epochs: 75 batch: 16
MobTCast	lr: 0.0001 epochs: 220 batch: 32	lr: 0.0001 epochs: 220 batch: 32	lr: 0.005 epochs: 75 batch: 16

Table 5: Hyperparameters used for LLMs

<b>Model</b>	<b>Hyperparameters (All Datasets)</b>
<b>GPT-3.5</b>	temperature: 0.01 max_new_tokens: 100 max_tokens: 1000
<b>Llama2 Chat</b>	temperature: 0.01 max_new_tokens: 200
<b>Llama2</b>	temperature: 0.01 max_new_tokens: 200 top_p: 0.95 top_k: 250 length_penalty: 1 presence_penalty: 0
<b>Mistral 7B</b>	temperature: 0.01 max_new_tokens: 128 top_p: 0.95 top_k: 50 length_penalty: 1 presence_penalty: 0
<b>Gemma</b>	temperature: 0.01 max_new_tokens: 200
<b>Phi 1.5</b>	temperature: 0.01 max_length: 500
<b>Phi 2</b>	temperature: 0.01 max_length: 500
<b>Phi 3</b>	temperature: 0.01 max_length: 500
<b>GPT-J</b>	temperature: 0.01 max_new_tokens: 200
<b>Dolly</b>	temperature: 0.01 max_new_tokens: 200

## C Prompt Example

Table 6: Zero-shot prompt for next location prediction used for all the LLMs

Prompt Zero-Shot
<p>Your task is to predict &lt;next_place_id&gt; in &lt;target_stay&gt;, a location with an unknown ID, while temporal data is available.</p> <p>Predict &lt;next_place_id&gt; by considering:</p> <ol style="list-style-type: none"> <li>1. The user's activity trends gleaned from &lt;historical_stays&gt; and the current activities from &lt;context_stays&gt;.</li> <li>2. Temporal details (start_time and day_of_week) of the target stay, crucial for understanding activity variations.</li> </ol> <p>Present your answer in a JSON object with:</p> <p>"prediction" (IDs of the five most probable places, ranked by probability) and "reason" (a concise justification for your prediction).</p> <p>The data:</p> <p>&lt;historical_stays&gt;:</p> <pre>{['6 PM', 'Sunday', '42ec1480f964a5209e261fe3'], ['1 PM', 'Monday', '4d48864b551db1f722e9a330'], ['1 PM', 'Wednesday', '4d48864b551db1f722e9a330'], ['4 PM', 'Wednesday', '4cdf0650ffcf37041bd71682'], ['5 PM', 'Wednesday', '4b705cd2f964a52052152de3'], ['5 PM', 'Wednesday', '4d531225f1b4a09039dee672'], ['5 PM', 'Wednesday', '4ada106af964a520ed1d21e3'], ['6 PM', 'Wednesday', '4c176109f693b7139f0f5f54'], ['2 AM', 'Friday', '4c498ca56f1420a1c019c155'], ['1 AM', 'Saturday', '4b7c698af964a520bc912fe3'], ['2 PM', 'Saturday', '41102700f964a520d60b1fe3'], ['8 PM', 'Saturday', '4be5dfe9910020a13ea2d314'], ['8 PM', 'Saturday', '4a43c0aef964a520c6a61fe3'], ['4 PM', 'Sunday', '41102700f964a520d60b1fe3'], ['5 PM', 'Monday', '4ba7ef65f964a520fabf39e3']}</pre> <p>&lt;context_stays&gt;:</p> <pre>{['5 PM', 'Wednesday', '4531059cf964a520683b1fe3'], ['6 PM', 'Wednesday', '50a430bfe4b0f010d751e3a5'], ['7 PM', 'Wednesday', '4a871b30f964a5209a0220e3'], ['3 PM', 'Thursday', '4b8f50d9f964a520365133e3'], ['11 PM', 'Thursday', '4e7bb781887742fc66380d56'], ['7 PM', 'Friday', '4b7ecc2cf964a520420030e3']}</pre> <p>&lt;target_stay&gt;:</p> <pre>{['6 AM', 'Saturday', '\next_place_id']}</pre>

Table 7: One-shot prompt for next location prediction used for all the LLMs

Prompt One-Shot
<p>Original Prompt:</p> <p>Your task is to predict &lt;next_place_id&gt; in &lt;target_stay&gt;, a location with an unknown ID, while temporal data is available.</p> <p>Predict &lt;next_place_id&gt; by considering:</p> <ol style="list-style-type: none"> <li>1. The user’s activity trends gleaned from &lt;historical_stays&gt; and the current activities from &lt;context_stays&gt;.</li> <li>2. Temporal details (start_time and day_of_week) of the target stay, crucial for understanding activity variations.</li> </ol> <p>Present your answer in a JSON object with:</p> <p>"prediction" (IDs of the five most probable places, ranked by probability) and "reason" (a concise justification for your prediction).</p> <p>The data:</p> <p>&lt;historical_stays&gt;:</p> <pre>{['6 PM', 'Sunday', '42ec1480f964a5209e261fe3'], ['1 PM', 'Monday', '4d48864b551db1f722e9a330'], ['1 PM', 'Wednesday', '4d48864b551db1f722e9a330'], ['4 PM', 'Wednesday', '4cdf0650ffcf37041bd71682'], ['5 PM', 'Wednesday', '4b705cd2f964a52052152de3'], ['5 PM', 'Wednesday', '4d531225f1b4a09039dee672'], ['5 PM', 'Wednesday', '4ada106af964a520ed1d21e3'], ['6 PM', 'Wednesday', '4c176109f693b7139f0f5f54'], ['2 AM', 'Friday', '4c498ca56f1420a1c019c155'], ['1 AM', 'Saturday', '4b7c698af964a520bc912fe3'], ['2 PM', 'Saturday', '41102700f964a520d60b1fe3'], ['8 PM', 'Saturday', '4be5dfe9910020a13ea2d314'], ['8 PM', 'Saturday', '4a43c0aef964a520c6a61fe3'], ['4 PM', 'Sunday', '41102700f964a520d60b1fe3'], ['5 PM', 'Monday', '4ba7ef65f964a520fabf39e3']}</pre> <p>&lt;context_stays&gt;:</p> <pre>{['5 PM', 'Wednesday', '4531059cf964a520683b1fe3'], ['6 PM', 'Wednesday', '50a430bfe4b0f010d751e3a5'], ['7 PM', 'Wednesday', '4a871b30f964a5209a0220e3'], ['3 PM', 'Thursday', '4b8f50d9f964a520365133e3'], ['11 PM', 'Thursday', '4e7bb781887742fc66380d56'], ['7 PM', 'Friday', '4b7ecc2cf964a520420030e3']}</pre> <p>&lt;target_stay&gt;:</p> <pre>{['6 AM', 'Saturday', 'next_place_id']}</pre>



```

prediction:
[{'4b80bafef964a520ee8830e3',
'4b558306f964a5201be627e3',
'4b7e3467f964a520fde52fe3',
'4c182e2c6a21c9b6f2bbc897',
'4dff7dd51495f702193690bf'}],
reason:
'User has repeatedly visited places in the evening and at night, especially on weekdays. The
most recent context stays are also at nighttime.'

Original prompt:
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>:
[{'6 PM', 'Sunday', '42ec1480f964a5209e261fe3'},
{'1 PM', 'Monday', '4d48864b551db1f722e9a330'},
{'1 PM', 'Wednesday', '4d48864b551db1f722e9a330'},
{'4 PM', 'Wednesday', '4cdf0650ffcf37041bd71682'},
{'5 PM', 'Wednesday', '4b705cd2f964a52052152de3'},
{'5 PM', 'Wednesday', '4d531225f1b4a09039dee672'},
{'5 PM', 'Wednesday', '4ada106af964a520ed1d21e3'},
{'6 PM', 'Wednesday', '4c176109f693b7139f0f5f54'},
{'2 AM', 'Friday', '4c498ca56f1420a1c019c155'},
{'1 AM', 'Saturday', '4b7c698af964a520bc912fe3'},
{'2 PM', 'Saturday', '41102700f964a520d60b1fe3'},
{'8 PM', 'Saturday', '4be5dfe9910020a13ea2d314'},
{'8 PM', 'Saturday', '4a43c0aef964a520c6a61fe3'},
{'4 PM', 'Sunday', '41102700f964a520d60b1fe3'},
{'5 PM', 'Monday', '4ba7ef65f964a520fabf39e3'}]
<context_stays>:
[{'3 AM', 'Friday', '44166f04f964a52003311fe3'},
{'11 PM', 'Friday', '4b55f1eef964a52002f827e3'},
{'7 PM', 'Saturday', '4c537ec4fd2ea5936ffe8328'}]
<target_stay>:
[{'8 PM', 'Saturday', 'next_place_id'}]

```

Table 8: Few-Shot prompt for next location prediction used for all the LLMs

Prompt Few-Shot
<p>Your task is to predict &lt;next_place_id&gt; in &lt;target_stay&gt;, a location with an unknown ID, while temporal data is available. Predict &lt;next_place_id&gt; by considering:</p> <ol style="list-style-type: none"> <li>1. The user's activity trends gleaned from &lt;historical_stays&gt; and the current activities from &lt;context_stays&gt;.</li> <li>2. Temporal details (start_time and day_of_week) of the target stay, crucial for understanding activity variations.</li> </ol> <p>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). Consider the following examples to understand the user's patterns:</p> <p>Example 1:</p> <p><b>historical_stays:</b> {['10:49 PM', 'Sunday', '4b80bafef964a520ee8830e3'], ['03:16 AM', 'Monday', '4c182e2c6a21c9b6f2bbc897'], ['08:57 AM', 'Monday', '4b8ef710f964a5209c4133e3'], ['02:46 PM', 'Monday', '4b80bafef964a520ee8830e3'], ['03:13 PM', 'Wednesday', '4b80bafef964a520ee8830e3'], ['02:10 AM', 'Thursday', '4bb365f54019a593e6d937b8'], ['11:29 PM', 'Sunday', '4b80bafef964a520ee8830e3'], ['12:32 AM', 'Monday', '4bb365f54019a593e6d937b8'], ['12:59 AM', 'Monday', '4b7e3467f964a520fde52fe3'], ['02:22 PM', 'Thursday', '4b5d54a2f964a5200e5a29e3'], ['01:40 PM', 'Friday', '4cdbe66e22bd721e4302f847'], ['02:03 PM', 'Saturday', '4e13debb4cd473c968b5afc'], ['12:17 AM', 'Friday', '4bf5d425004ed13aa27541a0'], ['11:04 AM', 'Friday', '4c2c8fd677cfe21e2029b6f1'], ['08:58 AM', 'Thursday', '4b7e3467f964a520fde52fe3'], ['07:26 AM', 'Friday', '4dff7dd51495f702193690bf'], ['07:32 AM', 'Friday', '4bb365f54019a593e6d937b8'], ['07:33 AM', 'Friday', '4b7e3467f964a520fde52fe3'], ['12:19 AM', 'Tuesday', '4bf5d425004ed13aa27541a0']}</p> <p><b>context_stays:</b> {['12:09 AM', 'Wednesday', '4dff7dd51495f702193690bf'], ['10:44 AM', 'Wednesday', '4b8da54ef964a5202e0633e3'], ['11:04 AM', 'Wednesday', '4dff7dd51495f702193690bf'], ['11:12 AM', 'Wednesday', '4b7e3467f964a520fde52fe3'], ['02:24 PM', 'Wednesday', '4b22e836f964a520185024e3']}</p> <p><b>target_stay:</b> {'prediction': ['4b80bafef964a520ee8830e3', '4b558306f964a5201be627e3', '4b7e3467f964a520fde52fe3', '4c182e2c6a21c9b6f2bbc897', '4dff7dd51495f702193690bf']}</p> <p>Example 2:</p> <p><b>historical_stays:</b> {['03:47 AM', 'Monday', '4b7e3467f964a520fde52fe3'], ['10:45 PM', 'Tuesday', '4b80bafef964a520ee8830e3'], ['11:39 PM', 'Tuesday', '4dff7dd51495f702193690bf'], ['11:45 PM', 'Tuesday', '4bb365f54019a593e6d937b8'], ['03:01 PM', 'Thursday', '4b22e836f964a520185024e3']}</p> <p><b>context_stays:</b> {['12:09 AM', 'Wednesday', '4dff7dd51495f702193690bf'], ['10:44 AM', 'Wednesday', '4b8da54ef964a5202e0633e3'], ['11:04 AM', 'Wednesday', '4dff7dd51495f702193690bf'], ['11:12 AM', 'Wednesday', '4b7e3467f964a520fde52fe3'], ['02:24 PM', 'Wednesday', '4b22e836f964a520185024e3']}</p> <p><b>target_stay:</b> {'prediction': ['4b6ba709f964a52059142ce3', '4c182e2c6a21c9b6f2bbc897', '4b8ef710f964a5209c4133e3', '4bea89ca415e20a1af16e5bb', '4dff7dd51495f702193690bf']}</p> <p>Consider the user's activity patterns, historical stays, and recent context stays when making your prediction. Consider also the temporal information of the target stay. Provide the 5 most likely places (place_id) ranked in descending order of probability. Ensure that your output does not include line breaks.</p> <p>The data are as follows:</p>

```

<historical_stays>: {[ '9 AM', 'Tuesday', '50e8ed15e4b07ff4593e1bf4'],
[ '10 AM', 'Wednesday', '4dd2d4bc81dcfc9dc2c2124f'], [ '10 AM', 'Wednesday',
'4df8089a1f6e448ec28e6fe0'], [ '12 PM', 'Wednesday', '4d22782eb69c6dcbf7be8295'],
[ '12 PM', 'Wednesday', '4da61b1ea86ecc5168c8828c'], [ '2 PM', 'Wednesday',
'4bf804ee8d30d13a1feaff17'], [ '8 AM', 'Thursday', '4bae676cf964a520c6ad3be3'], [ '9 AM',
'Thursday', '4eba3331722edc0eaf1762bb'], [ '4 AM', 'Friday', '4bd1af9b41b9ef3bca54fce5'],
[ '5 AM', 'Friday', '4b5d272ef964a520c15429e3'], [ '7 AM', 'Monday',
'4c7f04be7fd4ef3b108394a1'], [ '0 AM', 'Tuesday', '4d9fa1d483f0b1f7ea8c9ec7'], [ '1 AM',
'Tuesday', '4c4b52ce9e6dbe9acbd4e10b'], [ '8 AM', 'Tuesday', '4c7f04be7fd4ef3b108394a1'],
[ '12 PM', 'Tuesday', '4b06d110f964a520c3f022e3']}
<context_stays>: {[ '7 PM', 'Saturday', '510c9f9de4b0ec5cc005fc87'], [ '8 PM', 'Saturday',
'4bae0e67f964a520487f3be3'], [ '8 PM', 'Saturday', '4be9e20e6295c9b61acb8508'], [ '9 PM',
'Saturday', '4d1fdddf5c4ca1cdb4a49c3d'], [ '0 AM', 'Sunday', '4cc744c0a32bb1f75758a7a8'],
[ '0 AM', 'Sunday', '4abd30e1f964a520ed8820e3'], [ '2 AM', 'Sunday',
'4b60b7e5f964a520b7f529e3'], [ '4 AM', 'Sunday', '4bea19226295c9b6b61e8608'], [ '5 AM',
'Sunday', '4cc184d3f82ebfb75c417091'], [ '6 PM', 'Monday', '4eba3331722edc0eaf1762bb'],
[ '2 AM', 'Tuesday', '4c65b90018b676b084a0ad0e'], [ '4 AM', 'Tuesday',
'501b374ce4b06c31c5001715'], [ '6 AM', 'Tuesday', '4cfeed7c202e224bc2a7ab2a'], [ '8 AM',
'Tuesday', '4c7f04be7fd4ef3b108394a1'], [ '9 AM', 'Tuesday', '4b0737c3f964a520e4f922e3'],
[ '10 AM', 'Tuesday', '4dd3fa5e6365c27b0dbeec7d'], [ '11 AM', 'Tuesday',
'4a257482f964a520557e1fe3'], [ '12 PM', 'Tuesday', '4cd78a30a42b236ad848fb08']}
<target_stay>: {[ '6 AM', 'Saturday', 'next_place_id']}

```

## C.1 Output Examples

Table 9: GPT-3.5 output example

GPT-3.5 Output
<pre>{   "prediction": [     "4b7ecc2cf964a520420030e3",     "41102700f964a520d60b1fe3",     "4d531225f1b4a09039dee672",     "4b705cd2f964a52052152de3",     "4c176109f693b7139f0f5f54"   ],   "reason": "Based on the historical stays, the user has frequently visited the places with place IDs 4b7ecc2cf964a520420030e3, 41102700f964a520d60b1fe3, 4d531225f1b4a09039dee672, 4b705cd2f964a52052152de3, and 4c176109f693b7139f0f5f54. These places have been visited during different times of the day and on different days of the week. Considering the current context stays and the temporal information of the target stay, it is likely that the user will visit one of these places as his/her next location." }</pre>

Table 10: Llama2 Chat 70B output example

Llama2 Chat 70B Output
<pre>{   "prediction": [     "4be5dfe9910020a13ea2d314",     "4ada106af964a520ed1d21e3",     "4cdf0650ffcf37041bd71682",     "4c176109f693b7139f0f5f54",     "4ba7ef65f964a520fabf39e3"   ],   "reason": "Based on the user's historical stays, it is likely that they will visit a place they have been to before, especially during the same time of day and day of the week. The top five predicted places are all locations that the user has previously visited on Wednesdays between 4-6 PM, which suggests a pattern of regular activity at these times" }</pre>

Table 11: Llama2 Chat 13B output example

Llama2 Chat 13B Output
<pre>{   " Sure, I'd be happy to help! Based on the provided data, here is     my prediction for the next location of the user:"prediction":     ["4c176109f693b7139f0f5f54","4d48864b551db1f722e9a330","4     ada106af964a520ed1d21e3","4ba7ef65f964a520fabf39e3","4     be5dfe9910020a13ea2d314"],"reason": "Based on the user's     historical stays, it is likely that they will visit places with     high repeat visits and proximity to their recent context stays     . The target"   } }</pre>

Table 12: Llama2 Chat 7B output example

Llama2 Chat 7B Output
<pre>{   " Based on the provided data, I have predicted the next location     of the user as follows:"prediction": ["4af5a46af964a520b5fa21e3     ", "4b0a9290f964a520352523e3", "4ad507bff964a520660121e3", "4     c881d60a0ffb60ccda81fc5"],"reason": "Based on the user's     historical stays and contextual information, it is likely that     the user will visit a place that is similar to their previous     destinations. The target stay has a start time of 0 AM on     Saturday, which is a weekend day. The user has previously     visited places during weekends, such as on Friday night (4     af5a46"  } }</pre>

Table 13: Llama2 70B output example

Llama2 70B Output
<pre>["4c498ca56f1420a1c019c155","4d531225f1b4a09039dee672","4   b7c698af964a520bc912fe3","4d531225f1b4a09039dee672","4   b7c698af964a520bc912fe3"] Based on the user's historical stays,   it is likely that they will visit places with high repeat   visits"</pre>

Table 14: Llama2 13B output example

Llama2 13B Output
<pre>["41102700f964a520d60b1fe3","41102700f964a520d60b1fe3","4   ada106af964a520ed1d21e3","4d531225f1b4a09039dee672","4   d531225f1b4a09039dee672"] User will likely visit places with   high repeat visits"</pre>

Table 15: Llama2 7B output example

Llama2 7B Output
<pre>[ "4b7ecc2cf964a520420030e3", "4b7ecc2cf964a520420030e3", "4 b7ecc2cf964a520420030e3", "4b7ecc2cf964a520420030e3", "4 b7ecc2cf964a520420030e3"] User will likely visit places with high repeat visits</pre>

Table 16: Mistral 7B output example

Mistral 7B Output
<pre>The user frequently visits ['4be5dfe9910020a13ea2d314', '4 a5dd98ef964a520c2bd1fe3', '4a43c0aef964a520c6a61fe3', '4a3d735cf964a5204ba21fe3', '4a3d735cf964a5204ba21fe3 ']. The user will likely visit one of these places again.</pre>

## C.2 Failed Models

Table 17: Dolly 3B output example

Dolly 3B Output
<pre>{"prediction": "Your response will contain the following keys: " prediction" and "reason" The JSON will contain the following key/value pair: "prediction": ["14687", "Night Life"] " reason": "According to our stay history, the probability that the place 14687 is the next location is high." The output will be as follows: {"prediction": ["14687", "Night Life"]} Note that the location 14687 is merely an example. In reality, it might contain more than 10 possible locations where this user may go next. Please see the following example for more details on how to choose the most probable place. { prediction": ["14687", "Night Life"], "reason": " According to our stay history, the probability that the place 14687 is the next location is high." } That's it! PS. This answer was submitted in about 1 min 36 secs, using JSON formatted data provided.", "reason": null}</pre>

Table 18: Dolly 7B output example

Dolly 7B Output	
<pre>{   "prediction": [     "11:52 PM",     "07:26 AM",     "06:51 PM",     "10:15 PM",     "07:35 AM",     "11:24 PM",     "01:11 AM",     "12:30 AM",     "07:02 AM",     "08:17 AM",     "04:54 AM",     "12:09 AM",     "12:15 AM",     "01:40 AM",     "05:31 PM",     "11:55 PM",     "06:46 AM",     "06:02 AM",     "07:12 PM",     "10:49 PM",     "02:13 AM",     "03:39 AM",     "03:21 AM",     "02:33 AM",     "09:08 PM",     "11:55 PM",     "07:02 PM",     "05:45 PM",     "06:42 AM",     "reason": null] }</pre>	

Table 19: Dolly 12B output example

Dolly 12B Output	
<pre>" prediction ": "10:29 PM " , " reason ": " most likely " } , { " prediction ": "12:43 AM " , " reason ": " most likely " } , { " prediction ": "12:44 AM " , " reason ": " most likely " } ] The most probable next location is "12:43 AM " for this user , since " historical_stays " show this as their most recent activity and there are three historical stay with an overlap of 11:06 PM to 12:43 AM . This can also be explained with the temporal data in the " target_stay " as this is the only stay with an overlap of 11:06 PM to 12:43 AM . This supports the users most recent activity of "11:06 PM " for the following reasons : 1 . This is the most recent activity of a " Tuesday " and this is the most recent activity of any day .2 . This is also the most recent activity of a " Wednesday " and this is the most recent activity of any day .3 . This is also the most " , " reason ": null</pre>	

Table 20: GPT-J output example

GPT-J Output	
<pre>The following code snippet shows this data parsing.```python# Importing required librariesimport jsonimport timeimport randomimport numpy as npimport pandas as pd# Read JSON datawith open('data.json', 'r') as json_input:    json_data = json.load (json_input)# Transform data into Pandas DataFrame formatdata = pd.DataFrame.from_dict(json_data['historical_stays'])# The following two lines are for testing only#data = pd.DataFrame ([[[] for k in range(data.shape[0])])#data['reason'] = {k:[[] for k in range(data.shape[0])]}# Defining variablespredicted_idx = random.sample(range(1, 11), 10)data = data.iloc[predicted_idx ,: ]# Extract unique place IDs from each stayplace_ids = [data[' place_id'].apply(lambda x:" , "reason": null}]</pre>	

Table 21: Phi 1.5 output example

Phi 1.5 Output
<pre>Your task is to predict a user's next location based on his/her activity pattern.                                You will be provided with a JSON containing &lt;historical_stays&gt; which contain this user's historical stays, then &lt;context_stays&gt; which provide contextual information</pre>

Table 22: Phi 2 output example

Phi 2 Output
<pre>{[place]}\</pre>

Table 23: Phi 3 output example

Phi 3 Output
<pre>prediction \</pre>

Table 24: Dolly 2B output example

Dolly 2B Output
<pre>**Output:**  '''json {"prediction": 2, "reason": "People tend to visit the same places at similar times throughout the week, so the next most probable place would be somewhere within that vicinity."} '''</pre>



### C.3 Hallucinated output example

Table 25: This table illustrates an example of hallucinated output generated by GPT-3.5. The output appears coherent and includes location IDs similar to the Foursquare dataset. However, these IDs do not match the input data, the original dataset, or any valid Foursquare POIs.

Hallucinated Output
<pre> <input": "="" ",="" "4a3f1f6af964a52095a11fe3",="" "4e81a1509adf897ae2fbed4f"="" "4e81e4b65c5cb93d42acb10f",="" "4f451eff19836ed001be34fe",="" "4fd93beeb634312a5bc2ca50",="" "based="" "output":="" "prediction":="" "reason":="" &lt;context_stays&gt;.="" &lt;context_stays&gt;:="" &lt;historical_stays&gt;="" &lt;historical_stays&gt;:="" &lt;next_place_id&gt;="" &lt;target_stay&gt;,="" &lt;target_stay&gt;:="" '&lt;next_place_id&gt;']="" '3fd66200f964a52005eb1ee3'],="" '3fd66200f964a5203de71ee3'],="" '3fd66200f964a520cce51ee3'],="" '43a26468f964a520322c1fe3'],="" '44ddb091f964a520bf361fe3'],="" '45699170f964a520e73d1fe3'],="" '46c77917f964a5201a4a1fe3'],="" '46c77917f964a5201a4a1fe3']]="" '4a47de2df964a52036aa1fe3'],="" '4a5e4a0df964a52050be1fe3'],="" '4aa48305f964a520004720e3'],="" '4b00383ff964a5209f3b22e3'],="" '4b9ee138f964a5200d0837e3']]="" '4ce08a08ffcf370469b12082'],="" '4e055891fa767637fd1db8e7'],="" '4f900989e4b0324e976f087b'],="" '50036b8ee4b04c8e75c1945f'],="" 'friday',="" 'monday',="" 'prediction'="" 'reason'="" 'saturday',="" 'sunday',="" 'thursday',="" 'tuesday',="" 'wednesday',="" (a="" (ids="" (start_time="" 1.="" 2.="" <="" [="" ['0="" ['1="" ['11="" ['2="" ['3="" ['5="" ['6="" ['8="" [['0="" [['5="" ],="" a="" activities="" activity="" additionally,="" align="" am',="" an="" and="" answer="" are="" as="" at="" available.="" been="" by="" can="" certain="" concise="" considering="" considering:="" context="" crucial="" current="" data="" data:="" day_of_week)="" days="" details="" during="" five="" for="" frequently="" from="" gleaned="" have="" historical="" id,="" in="" indicated="" information="" is="" it="" json="" justification="" likely="" location="" most="" next="" object="" observe="" of="" on="" ones="" patterns.="" periods="" places="" places,="" pm',="" pre="" predict="" predicted="" prediction).="" present="" previous="" probability)="" probable="" provided="" ranked="" similar="" specific="" stay,="" stays="" stays,="" stays."="" target="" task="" temporal="" that="" the="" their="" therefore,="" time="" times.="" to="" trends="" understanding="" unknown="" user="" user's="" variations.="" visit="" visited="" visits="" we="" week="" while="" will="" with="" with:="" your="" {="" }=""> </input":></pre>

## D LLMs Explaination Examples

Table 26: Explanation provided by GPT-3.5

---

**Explanation GPT-3.5:**

Based on the historical locations, the user has frequently visited places '4d48864b551db1f722e9a330', '4a5dd98ef964a520c2bd1fe3', '3fd66200f964a520def11ee3', '42ec1480f964a5209e261fe3', and '4a3d735cf964a5204ba21fe3'. Additionally, the context locations provide recent activities at places '4a5dd98ef964a520c2bd1fe3', '3fd66200f964a520def11ee3', and '4a3d735cf964a5204ba21fe3'. Based on the temporal information (3 PM, Thursday), it is likely that the user will visit one of these places again..

---

Table 27: Explanation provided by Llama2 Chat 70B

---

**Explanation Llama2 Chat 70B:**

Based on the user's historical stays, it is likely that they will visit one of the places they have previously been to during the same time frame (4 PM on a Saturday). The top five predicted places are all locations that the user has visited before at around the same time.

---

Table 28: Explanation provided by Llama2 Chat 13B

---

**Explanation Llama2 Chat 13B:**

The predicted places are based on the user's historical stays, contextual information from recent stays, and temporal information. The top three predictions are all locations that the user has visited before

---

Table 29: Explanation provided by Llama2 Chat 7B

---

**Explanation Llama2 Chat 7B:**

The user's activity pattern and recent contextual information suggest that they are likely to visit places that are similar to their previous locations. For example, they have repeatedly visited a coffee shop near their workplace during lunchtime.

---

Table 30: Explanation provided by Llama2 70B

---

**Explanation Llama2 70B:**

Based on the user 's historical stays , it is likely that they will visit places with high repeat visits

---

Table 31: Explanation provided by Llama2 13B

---

**Explanation Llama2 13B:**

User will likely visit places with high repeat visits

---

Table 32: Explanation provided by Llama2 7B

---

**Explanation Llama2 7B:**

User will likely visit places with high repeat visits

---

Table 33: Explanation provided by Mistral 7B

---

**Explanation Mistral 7B:**

The user will likely visit one of these places again

---

## E ACC@1 of LLMs

Table 34: ACC@1 of selected LLMs prompted to perform zero-shot, one-shot, and few-shot next location prediction across all the datasets. The table highlights the highest accuracy scores in each column. GPT-3.5 achieves the best overall performance in several settings, demonstrating its robustness and versatility. Llama2 Chat 70B also shows strong performance, particularly in the F. TKY dataset. Interestingly, Mistral 7B outperforms some larger models, indicating that model architecture and training methodology can significantly impact accuracy.

	F. NYC			F. TKY			Our		
	zero-shot	one-shot	few-shot	zero-shot	one-shot	few-shot	zero-shot	one-shot	few-shot
Llama2 7B	.054	.062	.007	.063	.046	.009	.036	.040	.004
Llama2 13B	.080	.078	.074	.090	.096	.050	.078	.081	.050
Llama2 70B	.112	.105	.158	.098	.086	.087	.121	.106	.116
Llama2 Chat 7B	.110	.159	.051	.084	.123	.045	.085	.090	.034
Llama2 Chat 13B	.100	.119	.036	.103	.116	.031	.112	.153	.069
Llama2 Chat 70B	.168	.128	.214	<b>.211</b>	.178	.199	.144	.149	.146
Mistral 7B	.137	.143	.174	.130	.119	.125	.127	<b>.176</b>	.147
GPT-3.5	<b>.184</b>	<b>.194</b>	<b>.260</b>	.193	<b>.227</b>	<b>.217</b>	<b>.163</b>	.165	<b>.176</b>

## F ACC@3 of LLMs

Table 35: ACC@3 of selected LLMs prompted to perform zero-shot, one-shot, and few-shot next location prediction. GPT-3.5 and Llama2 Chat 70B achieve the best overall performance, demonstrating the effectiveness of instruction-based models and large-scale architectures. Interestingly, Mistral 7B outperforms some larger models, indicating the importance of architecture and training methodology.

	F. NYC			F. TKY			Our		
	zero-shot	one-shot	few-shot	zero-shot	one-shot	few-shot	zero-shot	one-shot	few-shot
Llama2 7B	.077	.070	.009	.078	.075	.012	.062	.057	.006
Llama2 13B	.103	.114	.092	.106	.114	.078	.094	.102	.077
Llama2 70B	.158	.167	.177	.115	.129	.136	.142	.143	.147
Llama2 Chat 7B	.132	.175	.069	.128	.170	.064	.128	.130	.054
Llama2 Chat 13B	.163	.163	.041	.161	.156	.037	.180	.172	.089
Llama2 Chat 70B	<b>.298</b>	.224	.269	.283	.213	.237	.228	.197	.204
Mistral 7B	.202	.214	.216	.175	.184	.197	.192	.201	.213
GPT-3.5	.281	<b>.299</b>	<b>.290</b>	<b>.308</b>	<b>.330</b>	<b>.317</b>	<b>.259</b>	<b>.276</b>	<b>.270</b>

## G ACC@5 of LLMs

Table 36: ACC@5 of selected LLMs prompted to perform zero-shot, one-shot and 3-shot next location prediction. Instruction-based models tend to be the ones obtaining the best performances and, as expected, the number of parameters has a significant impact on the accuracy. An exception is Mistral 7B whose performances are consistently higher than 13B selected models. Regardless the dataset and prompting technique, GPT-3.5 is the best-performing model and the prompt providing the best result is the one-shot prompt. Likewise, Llama2 13B and Llama2 Chat 7B obtain their best performances using a one-shot prompt. However, there are cases in which models perform better with 0-shot prompts - Llama2 7B, Llama2 Chat 13B, Llama2 Chat 70B - or with few-shots prompts - Mistral 7B.

	F. NYC			F. TKY			Our		
	zero-shot	one-shot	few-shot	zero-shot	one-shot	few-shot	zero-shot	one-shot	few-shot
Llama2 7B	.079	.075	.009	.083	.078	.012	.066	.062	.006
Llama2 13B	.107	.122	.096	.111	.119	.084	.101	.107	.083
Llama2 70B	.167	.174	.189	.124	.138	.143	.149	.151	.157
Llama2 Chat 7B	.142	.186	.071	.133	.181	.067	.135	.139	.058
Llama2 Chat 13B	.177	.169	.043	.172	.165	.038	.190	.182	.096
Llama2 Chat 70B	<b>.311</b>	.233	.283	.293	.228	.255	.235	.207	.212
Mistral 7B	.211	.230	.234	.182	.196	.207	.198	.215	.222
GPT-3.5	.298	<b>.309</b>	<b>.301</b>	<b>.324</b>	<b>.341</b>	<b>.329</b>	<b>.279</b>	<b>.288</b>	<b>.283</b>

## H Context and Historical Role

Table 37: ACC@5 of selected LLMs evaluated on different datasets (Our, NYC, TKY) under varying configurations of context (C) and historical stays (H). The standard configuration (C=6, H=15) is shown in the first column for reference.

Model Name	Dataset	C=6; H=15	C=0	C=3	C=12	H=0	H=7	H=30
Llama2 Chat 70B	Our	0.2350	0.188	0.225	0.248	0.162	0.231	0.239
Llama2 Chat 70B	NYC	0.3110	0.259	0.266	0.319	0.209	0.288	0.326
Llama2 Chat 70B	TKY	0.2927	0.252	0.263	0.302	0.198	0.254	0.317
Llama2 Chat 13B	Our	0.1900	0.157	0.184	0.203	0.132	0.186	0.194
Llama2 Chat 13B	NYC	0.1773	0.129	0.138	0.192	0.103	0.162	0.201
Llama2 Chat 13B	TKY	0.1720	0.131	0.157	0.186	0.107	0.159	0.222
Llama2 Chat 7B	Our	0.1350	0.082	0.117	0.146	0.055	0.129	0.158
Llama2 Chat 7B	NYC	0.1402	0.096	0.125	0.161	0.056	0.133	0.218
Llama2 Chat 7B	TKY	0.1330	0.088	0.124	0.155	0.048	0.125	0.219
GPT-3.5	Our	0.2790	0.202	0.248	0.281	0.178	0.258	0.285
GPT-3.5	NYC	0.2980	0.263	0.281	0.317	0.099	0.284	0.346
GPT-3.5	TKY	0.3240	0.285	0.299	0.341	0.203	0.300	0.384
Mistral	Our	0.1980	0.164	0.176	0.205	0.144	0.179	0.211
Mistral	NYC	0.1820	0.152	0.171	0.201	0.136	0.187	0.208
Mistral	TKY	0.2110	0.155	0.192	0.229	0.118	0.206	0.236
Llama2 70B	Our	0.1490	0.106	0.111	0.157	0.083	0.144	0.165
Llama2 70B	NYC	0.1670	0.127	0.145	0.176	0.091	0.163	0.189
Llama2 70B	TKY	0.1240	0.088	0.092	0.140	0.060	0.125	0.133
Llama2 13B	Our	0.1010	0.069	0.077	0.112	0.042	0.104	0.131
Llama2 13B	NYC	0.1070	0.071	0.086	0.116	0.053	0.109	0.127
Llama2 13B	TKY	0.1110	0.074	0.102	0.119	0.058	0.111	0.125
Llama2 7B	Our	0.0660	0.028	0.058	0.071	0.011	0.062	0.087
Llama2 7B	NYC	0.0790	0.022	0.062	0.085	0.017	0.066	0.092
Llama2 7B	TKY	0.0830	0.026	0.065	0.090	0.014	0.073	0.099

## I Quiz for Data Contamination

An example of the quiz to test data contamination inspired by Golchin and Surdeanu (2023). To construct the questions, we extracted a random row from the original dataset and we assigned to it a random letter between A, B, C and D. All the other options are slightly modified to provide the model with realistic but non-existing entries of the dataset. For example, we change the user identifier (first value), the category of the location or, the last few characters of the location identifier. The LLMs were supposed to select the correct option given their potential knowledge of the dataset. It turned out that any of the LLMs were consistently selecting the right options. For instance, GPT-3.5 selected the right option 9 times over 50 quizzes and represented the best-performing model.

**Instruction:** You are provided with a four-choice quiz. Your task is to correctly select the option that exactly corresponds to an instance from the Foursquare NYC ("dataset\_TSMC2014\_NYC.txt") dataset.

When selecting the option, you must ensure that you follow the following rules:

1. You must ensure that you only generate a single option letter as your answer.
2. If you do not know the dataset or the correct answer, you must select option "E) None of the provided options."

*Hint: While all the following options seem similar, there is only one option that reflects an exact match with respect to the original instance.*

**Options:**

- A) 390 4bcde547511f95210d62b5c7 4bf58dd8d48988d124941735 Office  
40.750945522488436 -74.00563392176072 -240 Tue Apr 03 18:15:07 +0000 2012
- B) 390 44af9feef964a5202b351fe3 4bf58dd8d48988d1c1941735 Mexican Restaurant  
40.747738169430534 -73.98519814526952 -192 Tue Apr 03 18:15:33 +0000 2012
- C) 390 44af9feef964a5202b351fe3 4bf58dd8d48988d1c1910101 Mexican Restaurant  
40.747738169430534 -73.98519814526952 -192 Tue Apr 03 18:15:33 +0000 2012
- D) 390 44af9feef964a5202b351fe3 4bf58cc8d48988d1c1941735 Office  
40.747738169430534 -73.98519814526952 -192 Tue Apr 03 18:15:33 +0000 2012
- E) None of the provided options.