R1- Reviewer UXgD

Con1:

Lacks analysis on the differentiation between the new proposed tasks and the similar task proposed in TPG[25].

Response-to-Con1:

The research task in TPG and our task are highly related. In our work, based on the observations and analyses from real-world datasets, we formally define the Time-Specific Next POI Recommendation (TS-NPR). In [25], a Temporal Prompt-based and Geography-aware (TPG) framework is developed. In the TPG [25], the research task is not formally defined. TPG performs the next location recommendation and interval predictions. The research problems of our work and TPG are similar. However, the techniques are distinct. It proposes a temporal prompt-based decoder, using timestamps as prompts and queries for the decoder. The temporal information is incorporated via the traditional concatenation approach. We also conduct extensive experiments to evaluate and compare its performance, which demonstrates the advantages of our solution.

Con2:

The advantage of the T2R technique in mining periodic patterns is not clearly compared with existing approaches[5,10,40,51].

Response-to-Con2:

Thanks for the suggestions. In fact, periodic patterns and temporal information are widely used for the next POI recommendation. There are extensive research studies, including [5, 10, 40, 51], that have considered this factor. However, existing studies do not explicitly incorporate the target time when predicting the next POIs. They are developed for the conventional next-POI recommendation task. Additionally, [5, 10, 40, 51] were published 3-6 years ago, which are not the latest methods. Consequently, we do not compare them in our work. Instead, we compare our model with the more recent and stronger baselines in this paper.

To address the reviewer's concern, we have conducted experiments on three datasets to compare with these mentioned methods. Please refer to the results in the Response-to-Q5.

Con3:

The paper claims that studying temporal patterns can help solve the TS-NPR problem, but there is no comparison with methods utilizing temporal patterns in the experiments.

Response-to-Con3:

The temporal information is widely used in the POI recommendation task. Most recent methods have considered temporal patterns. In fact, the baseline models (STRNN, STGN, PLSPL, STAN, GETNext, CLSPRec, AGRAN, and TPG) compared in Section 5.1.2 have utilized various temporal patterns. For example, TPG [25] uses temporal information as prompts and GETNext [49] concatenates time embeddings into the input of the sequence modeling method (i.e., Transformer). The major differences lie in using temporal patterns for what task and how they are exploited. Most existing methods do not consider temporal patterns for the time-specific next POI recommendation problem. In addition, we propose a novel strategy to incorporate the temporal patterns.

Q1:

In Section 2.2, it is mentioned that similar work TPG can generate POI recommendations for a specific target time, but the analysis only focuses on methodological differences. It is unclear how the problem proposed in TPG differs from the one addressed in this paper, which raises doubts about the main contribution stated in the introduction - proposing a new POI recommendation task.

Response-to-Q1:

The problem proposed in TPG is similar to our task. Based on the data observations on real-world datasets, we formally defined the time-specific next-POI recommendation problem in our work. We find the asymmetric temporal influence and different temporal distribution of users and POIs. Then we design a novel Time2Rotation technique to capture temporal information. Please refer to the Response-to-Con1.

Q2:

T2R utilizes the concept of rotation to preserve embedding distribution. However, the impact of distribution changes due to temporal information encoding through concatenation or addition in existing work on recommendation performance is not analyzed or experimentally demonstrated.

Response-to-Q2:

In Table 3 (Section 5.3), we have presented the results of ablation studies. The variant of "(2) w/0 T2R" exploits the concatenation to replace the Time2Rotation technique in our framework, which is widely used in previous methods (e.g., TPG[25]). The concatenation of time embedding would increase the number of dimensions of the learned representations, which alters the space of learned representations. Moreover, by comparing the "Original" and "(2) w/0 T2R", we can observe that the performance of rotation is much better than the concatenation.

Concatenation, addition, and rotation are three methods of utilizing time embeddings. We further investigate these methods on the datasets, and the results are shown in the following table. According to the results, we can observe that Rotation outperforms the traditional methods (concatenation and addition), which demonstrates the benefits of rotation techniques for temporal information.

Table1. The results of different methods of incorporating temporal information.

	Models	Acc@1	Acc@5	Acc@10	MRR
NYC	Concatenation	0.2562	0.4927	0.5881	0.3642
	Addition	0.2872	0.4833	0.5566	0.3792
	Rotation	0.3115	0.5259	0.6085	0.4105
TKY	Concatenation	0.2326	0.4607	0.5599	0.3402
	Addition	0.2292	0.4614	0.5492	0.3363
	Rotation	0.2493	0.4631	0.5421	0.3504
CA	Concatenation	0.1851	0.3724	0.4467	0.2750
	Addition	0.1807	0.3634	0.4444	0.2705
	Rotation	0.2173	0.3707	0.4411	0.2921

Q3:

In Section 4.2, the authors mention the construction of a collaborative POI-POI transition graph without providing details on its components, such as the representation of nodes and edges. The relationship between the quadruplet and the POI-POI graph is also not explained. It is suggested to provide an illustration within Figure 4 to clarify this aspect.

Response-to-Q3:

Thanks for your suggestion. Due to the space limit, we don't present the details of the POI-POI transition graph in this manuscript. We have introduced the main idea of the collaborative POI-POI transition graph in Section 4.2, which has been used in previous studies [43, 49, 50]. The POI-POI transition relations (e.g., $p_i \to p_{i+1}$) are extracted from the POI trajectory. Different from existing methods, we additionally consider the temporal information (t_i, t_{i+1}) for each transition (e.g., $p_i \to p_{i+1}$). In this way, each quadruplet denotes a sequential transition relation in the POI-POI graph, shown in

Equation 2. As illustrated on the left side of Figure 4, based on the given user check-in trajectory, three quadruplets can be extracted. After that, we can learn node embeddings and timeslots' rotations. Note that to capture the asymmetric POI-POI transition relations, we utilize source rotation and target rotation for the temporal information. Overall, the process is well-defined, but details are not explained due to the space limit. We will provide more explanations and enhance the illustrations within Figure 4.

Q4:

The experimental setup fails to discuss how the next POI prediction method without using the target time is applicable to the problem proposed in the paper.

Response-to-Q4:

The proposed TS-NPR problem is essentially a variant of traditional next POI prediction. Our experimental setup is the same as the conventional next POI recommendation, except for the inclusion of target time information. It incorporates the target time as input when making recommendations. TS-NPR thus combines the next POI prediction with target time modeling, allowing methods designed for the next POI prediction to be applicable in this paper's setup.

In Table 3 (Section 5.3), we present the results of ablation studies. The variant "(3) w/o Tgt" denotes that target time is not used, representing the same setting as the traditional next POI recommendation task. By comparing "Original" with "(2) w/o Tgt", we observe a significant performance decrease upon eliminating target time information, highlighting its pivotal role in the next POI recommendation task.

To further examine performance without using target time, we provide additional experimental results. Here, we remove the target time and evaluate our model in the next POI prediction setting. The results are shown in the following tables. Based on these tables, we observe that even without target time information, our proposed ROTAN method still achieves remarkable performance, outperforming various next-POI recommendation methods. Notably, the task in TPG is highly similar to ours, representing a recent and strong method. We compare its performance (either with or without target time) to ROTAN's performance. The experimental results indicate the benefits of the proposed ROTAN method.

Table2. The results of without using the target time on NYC.

Models	**Acc@1**	**Acc@5**	**Acc@10**	**MRR**
STAN	0.2231	0.4582	0.5734	0.3253
GETNext	0.2406	0.4815	0.5811	0.3528
CLSPRec	0.1784	0.3830	0.4591	0.2691
AGRAN	0.2121	0.4519	0.5529	0.3179
TPG(w/o Target Time)	0.2592	0.4928	0.5854	0.3635

ROTAN (w/o Target Time)	0.2499	0.5007	0.5943	0.3634
TPG	0.2555	0.5005	0.5932	0.3669
ROTAN	0.3106	0.5281	0.6131	0.4104

Table3. The results of without using the target time on TKY.

Models	**Acc@1**	**Acc@5**	**Acc@10**	**MRR**
STAN	0.1963	0.3798	0.4464	0.2852
GETNext	0.1829	0.4045	0.4961	0.2853
CLSPRec	0.1453	0.3394	0.4106	0.2340
AGRAN	0.1428	0.3737	0.4605	0.2471
TPG(w/o Target Time)	0.1770	0.3915	0.4748	0.2767
ROTAN (w/o Target Time)	0.2291	0.4531	0.5469	0.3345
TPG	0.1420	0.3631	0.4492	0.2436
ROTAN	0.2458	0.4626	0.5392	0.3475

Table4. The results of without using the target time on CA.

Models	**Acc@1**	**Acc@5**	**Acc@10**	**MRR**
STAN	0.1104	0.2348	0.3018	0.1869
GETNext	0.1526	0.3278	0.3946	0.2364
CLSPRec	0.0891	0.1815	0.2013	0.1302
AGRAN	0.1199	0.3148	0.4017	0.2140
TPG(w/o Target Time)	0.1661	0.3366	0.4019	0.2456
ROTAN (w/o	0.1685	0.3523	0.4381	0.2535

Target Time)				
TPG	0.1749	0.3285	0.3860	0.2479
ROTAN	0.2199	0.3718	0.4334	0.2931

Q5:

While the paper argues for the importance of temporal patterns in solving the TS-NPR problem, the comparison methods do not utilize periodic pattern methods, such as [5,10,40,51] in experiments.

Response-to-Q5:

Thank you for your comment. As mentioned in Response-to-Con2, the papers [5,10,40,51] were published 3-6 years ago and do not represent the latest methods. Instead, we employ more recent and robust baselines in our experiments. All evaluated baseline methods in our study incorporate temporal information, which is commonly used for POI recommendation.

However, to address the reviewer's concern, we made efforts to evaluate the performance of [5,10,40,51]. These methods do not explicitly consider the target time when predicting the next locations. Their experimental results on three datasets are reported as follows. Based on the results, we observe that our proposed ROTAN (with or without target time) outperforms these methods, demonstrating the superiority of the ROTAN method.

Table5. The results of the above four baselines and ROTAN on NYC.

	NYC			
	Acc@1	**Acc@5**	**Acc@10**	**MRR**
[5] (CIKM-21)	0.2477	0.4709	0.5525	0.3449
[10] (WWW-18)	0.1499	0.3661	0.4262	0.2433
[40] (ICWS-21)	0.1678	0.3581	0.4218	0.2539
[51] (WWW journal-19)	0.1996	0.4018	0.4738	0.2924
ROTAN (W/o Target Time)	0.2499	0.5007	0.5943	0.3634
ROTAN	0.3106	0.5281	0.6131	0.4104

Table6. The results of the above four baselines and ROTAN on TKY.

	TKY			
	Acc@1	**Acc@5**	**Acc@10**	**MRR**

[5]（CIKM-21）	0.1972	0.4230	0.5139	0.3034
[10] (WWW-18)	0.1168	0.2939	0.3813	0.2032
[40] (ICWS-21)	0.1649	0.3405	0.4248	0.2502
[51] (WWW journal-19)	0.1832	0.3698	0.4422	0.2707
ROTAN (W/o Target Time)	0.2291	0.4531	0.5469	0.3345
ROTAN	0.2458	0.4626	0.5392	0.3475

Table7. The results of the above four baselines and ROTAN on CA.

	CA			
	Acc@1	**Acc@5**	**Acc@10**	**MRR**
[5]（CIKM-21）	0.1654	0.3161	0.3913	0.2411
[10] (WWW-18)	0.1115	0.2336	0.2798	0.1708
[40] (ICWS-21)	0.1119	0.2472	0.2884	0.1763
[51] (WWW journal-19)	0.1292	0.2771	0.3469	0.2034
ROTAN (W/o Target Time)	0.1685	0.3523	0.4381	0.2535
ROTAN	0.2199	0.3718	0.4334	0.2931