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wPOI: Weather-Aware POI Recommendation Engine

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Abstract. Weather is an integral part of the decision-making process for travelers and, in particular, certain locations or events will not even be recommended during unsafe poor weather. In this article, we introduce a weather assistant framework called wPOI, which calculates weather forecasts in places of interest (POI) that can be suggested. We demonstrate that experience of climatic patterns at a POI and previous insights about how visitors rank their destinations in many different weather situations can be useful in improving the reliability of the choosing. The findings of our research indicate the significantly greater validity of the recommendations and greater comfort with the suggested solution.

Keywords. POI, tourism, itinerary.

1 Introduction

The decision to buy a tourist item or to visit a POI is the result of a difficult decision-making procedure [24]. So many considerations influence tourist decision, a few of them are "internal" to tourists, for example, psychological or experiences of prior experiences, some are "external" (for example, suggestions or feedback, item knowledge, or climate) [17, 20]. Environment and weather are particularly significant considerations in judgment in tourists and affect tourism business' efficient operations [17]. Although visitors can quickly forecast common weather patterns, they are going to face the real weather while they visit a location that can vary between various situations.

In this article, we are focusing on applications and methods which can help forecast POI rankings for tourists and provide the most relevant suggestions for tourists keeping in mind tourist interest, tour popularity and traveling cost.

We are aiming for this purpose by considering the effect of the weather at a particular POI on the tourist assessment of the location in the framework recommended system.

2 Related Work

Recently, the POI recommendation becomes a popular field of study [3, 21, 22]. Several applications [6, 14, 26, 29] have also been built to deliver awesome, peaceful, pleasant tours [19] and random walk [16].

2.1 Background on the Orienteering Problem

In the case of orienteering problems, the various control spots with the associated scores are placed at many places [23]. Competition members strive to maximize their overall performance in the shortest time achievable by reaching as many controls as possible. The most important thing is to reach the highest rating despite the short lifespan [8, 28].

2.2 Tour Recommendation based on Orienteering Problem and its Variants

Lim et al. [11] changed the tourism orienteering problems according to the importance of the POI tour guidance model. Vansteenwegen et al. [27] proposed an approach for adapting the tour schedule so that it would improve the overall balance between the defined degree of involvement from the starting and end, such as expenditure and all POIs. Lim and al. [12] have identified places of importance and reputation in the form of the minimum queuing time.

Tours that satisfy the different levels of tourist interest within the group have been developed in such a manner as the concept of orienteering problem [2, 13].

2.3 Different Tourism Related Work

The time concerned measurement technique that considers tourist visitation at an attraction was proposed by Ying et al. [30]. Furthermore, over a while, the result was shown to make this technique complicated. Aliannejadi et al. [1] developed a possible model to assess the connection between the tourist comments label and a similar attraction. The findings were measuring in combination with studying to rank techniques from different LBSN tools. Given the considerable time, Zhao et al. [31] proposed a latent spatial time model to propose optimal subsequent destinations.

Li et al. [10] recommended that all information from spatial and temporal inspections be stored using the Time-aware Factorizing Personalized Markov Chain (TA-FPMC). The study analyzed the time-decay factor by comparing the gap across two concurrent experiments. Both calculations were built on both check-in experiences and the design was highly complex. The authors also consider the customer as an extra layer that is not necessary for this work. Consequently, if included in the recommended framework, the productivity of a future customer will decrease.

Our suggested model differs significantly from the current POI and tour recommendation scheme: Our algorithms categorize the interests of visitors dynamically depending on time and popularity with geo-tagged images. The POI tourist costs and local distance between the past POI of the initial path and the initial POI of the subsequent path are also reduced in consideration.

If a tourist goes to a new geographical area without a history of his experience, the suggested methodology can offer a suggestion. While some of the solutions suggested have a similar viewpoint, those only have one route in unexplored locations, depending on the kind of POI he/she has experienced The existing approach discovers the connection between a familiar and an unfamiliar location.

The proposed approach recommends several POIs and the associated POIs are also coordinated.

3 Background and Problem Definition

$\mathcal{P} = \{\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3, ...\mathcal{P}_n\}$ is being used to describe the series of POIs in a given city. A POI is graded as Class $\mathbb{C}$ if it meets those requirements, like music, movies, or a park. The cumulative exterior distance between $\mathcal{P}_{\dot{x}}$ and $\mathcal{P}_{\dot{x}+1}$, as well as the distance, traveled at each POI, define the distance covered by a person.

The sum of the distances between both POIs $\mathcal{P}_1$ and $\mathcal{P}_2$ is used to measure the distance among them. According to [14], we used a traveling speed of 4 km/hour. In this study, we recognize 2 different categories of tourists.

3.1 Average POI Visit Duration for Local and Global Users

Every tourists $\mathbb{U}$ are aware of the tour's past information. In a specific POI, Eqn. 1 can be used to measure the duration:

$$\Xi(\mathcal{P}) = \frac{\sum_{\dot{u}=1}^{\dot{k}'} \sum_{\jmath=1}^{\dot{m}} (t_\jmath^d - t_\jmath^a)\delta(\mathcal{P}_j = \mathcal{P})}{\sum_{\dot{u}=1}^{\dot{k}'} \nabla_u \, \delta(\mathcal{P}_j = \mathcal{P})} \forall \mathcal{P} \in P, \tag{1}$$

where $\jmath = \{1, 2, ..., \dot{m}\}$, $u = \{1, 2, ..., k'\}$ and ∇ and denotes the number of travels to a given POI by $\delta(\mathcal{P}_j = \mathcal{P}) = \{^{1 \; if \; (\mathcal{P}_j = \mathcal{P})}_{0, \; otherwise}$. In the case of all tourists, $\Xi(\mathcal{P})$ is often employed [4, 7].

3.2 Time-based user interest for local and global users

$\mathbb{C}_\mathcal{P}$ represents POI group $\mathcal{P}$, as shown in the prior section. Eqn. 2 helps to register the interest of a particular tourist $\dot{u}$ in POI group $\dot{c}$:

$$\overline{Int}_{u_\mathcal{P}} \dot{c} = \sum_{\jmath=1}^{\dot{m}} \frac{(t_{\mathcal{P}_\jmath}^d - t_{\mathcal{P}_\jmath}^a)}{\Xi(\mathbb{P}_\jmath)} \delta(\mathcal{C}_{\mathcal{P}_\jmath} = \dot{c}) \; \forall \dot{c} \in \mathcal{C}, \tag{2}$$

where $\delta(\mathcal{C}_{\mathcal{P}_\jmath}) = \{^{1 \; if \; \mathcal{C}_{\mathcal{P}_\jmath} = \dot{c}}_{0, \; otherwise}$.

The tourist interest for the POI group $\dot{c}$ is measured by Eqn. 2 as per the spending time on the POI group $\dot{c}$ based on the total spending time by all the tourists. It seems obvious that the tourist will devote most of his or her time at that POI.

3.3 Similarity of Local and Global Users

The identity of local and global tourists are computed based on the Cosine Similarity measure based on the interest of a given destination for both local and global tourists and which is computed utilizing Eqn. 3:

$$\mathbb{S}(\dot{u}_{\dot{x}}, \dot{u}_{\dot{y}}) = \frac{\overline{Int}_{\dot{u}_{\dot{x}}} \cdot \overline{Int}_{\dot{u}_{\dot{y}}}}{||\overline{Int}_{\dot{u}_{\dot{x}}}|| \cdot ||\overline{Int}_{\dot{u}_{\dot{y}}}||}, \tag{3}$$

where $\dot{u}_{\dot{x}}$ and $\dot{u}_{\dot{y}}$ are the 2 distinct tourists.

3.4 Itinerary from Travel History

The traveling reports have been defined for a particular tourist $\dot{u} \in \mathbb{U}$, based on the sequence $\dot{n}$ travel POIs $\mathbb{S}_{\dot{u}} = ((\mathcal{P}_1, t^a_{\mathcal{P}_1}, t^d_{\mathcal{P}_1}), ..., (\mathcal{P}_{\dot{n}}, t^a_{\mathcal{P}_{\dot{n}}}, t^d_{\mathcal{P}_{\dot{n}}}))$, wherein a triplet $(\mathcal{P}_{\dot{y}}, t^a_{\mathcal{P}_{\dot{y}}}, t^d_{\mathcal{P}_{\dot{y}}})$, where $\mathcal{P}_{\dot{y}}$ is the tourist's traveled POI, $t^a_{\mathcal{P}_{\dot{y}}}$ and $t^d_{\mathcal{P}_{\dot{y}}}$ are the time of entry and exit.

The difference between the time of entry and exit indicates the duration of the POI $\mathcal{P}_{\dot{y}}$. Here, $Su = ((\mathcal{P}_1, t^a_{\mathcal{P}_1}, t^d_{\mathcal{P}_1}), ..., (\mathcal{P}_{\dot{n}}, t^a_{\mathcal{P}_{\dot{n}}}, t^d_{\mathcal{P}_{\dot{n}}}))$ could be re-written as $\mathbb{S}_{\dot{u}} = (\mathcal{P}_1, ..., \mathcal{P}_{\dot{n}})$.

3.5 Time-based user Interest of a POI

The POI interest $\mathcal{P}_{\dot{y}}$ is a part of $\mathbb{S}_{\dot{u}}$ and could be calculated with the help of Eqn. 4:

$$\mathcal{P}_{\dot{y}}(int) = \sum_{\jmath=1}^{\dot{k}} \frac{(t^a_{\mathcal{P}_\jmath} - t^d_{\mathcal{P}_\jmath})}{\Xi(\mathcal{P}_\jmath)}. \tag{4}$$

3.6 Popularity of a POI Category

The POI popularity is measured by using Eqn. 5 as per the overall number of tourists visiting on the POI with respect to to the number of tourists visits to every POI:

$$\mathbb{C}(\overline{pop}) = \sum_{\jmath=1}^{\dot{k}} \frac{\overline{pop}_{\mathcal{P}_\jmath}}{\varphi(\mathcal{P}_\jmath)}, \tag{5}$$

where the $\mathbb{C}(\overline{pop})$ represents category $\mathbb{C}$ of popularity and $\varphi(\mathcal{P})$ represents the number of instances of all tourists visiting a specific POI.

3.7 Traveling Cost

The cost of travel is determined using the actual path the traveler travels through. While a few previous studies have taken into account the full length of the trip, distances are a relevant consideration for the tourist recommendation that the costs trigger when a tourist selects a long-distance pattern to visit different POIs.

We will minimize traveling time by utilizing quicker modes of transportation. If the gap between the two POIs increases and in that situation traveling costs will therefore arise, a quicker form of travel is necessary. We however intended to minimize the length of the tour. The transportation costs are calculated by Eqn.6:

$$\Gamma^{cost}(\dot{x}) = \sum_{\dot{y}=1}^{\dot{n}} \sum_{\jmath=2}^{\dot{y}} \gamma^{intr}(\mathcal{P}_{\dot{y}}^{\mathcal{P}_{\jmath-1,\jmath}}) + \sum_{\dot{y}=1}^{\dot{n}} \gamma^{extr}(\mathcal{P}_{\dot{y}}^{\mathcal{P}_n}, \mathcal{P}_{\dot{y}+1}^{\mathcal{P}_1}). \tag{6}$$

The first portion of Eqn. 6 consists of the inner length of all POIs in the pac plan. The inner length of the POI $\mathcal{P}_{\dot{y}}$ is calculated by the total length of all POIs. The second portion of Eqn. 6 reflects the consecutive real length among $\mathcal{P}_{\dot{y}}$ and $\mathcal{P}_{\dot{y}+1}$ POIs, which could be calculated by taking account of the length between the two consecutive POIs.

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3.8 Problem Definition

This portion deals with the problem of different POIs for one person. Our main objective is to maximize the interest and popularity of visitors and to reduce expenditures. A type of orienteering issue [12] could be used to resolve this issue:

$$\mathbb{O}_{\dot{y}} = \frac{\big(\Theta\mathcal{P}_{\dot{y}}(\overline{int}) + (1-\Theta)\mathcal{P}_{\dot{y}}(\overline{pop})\big) + W(inte)}{Cost(\mathcal{P}_{\dot{y}})}. \quad (7)$$

Our aim here is to propose an itinerary focused on tourist interest for specific POI , tour popularity and weather interest. The weight parameter can be adjusted as needed. The key goal of this arch is to propose an itinerary to increase the interest, popularity of visitors, weather interest and minimize travel expenses. The user's interest in various weather conditions, such as winter, summer, and so on, is used to quantify the weather interest, which is denoted by $W(inte)$. For eg, if a visitor prefers to visit a location in the winter, this indicates that the atmosphere is appealing to him.

The aim is to find an itinerary tour plan I= $(\mathcal{P}_1, \mathcal{P}_2 ..., \mathcal{P}_{\dot{n}}$) that:

$$Max(\frac{\big(\Theta\mathcal{P}_{\dot{y}}(\overline{int}) + (1-\Theta)\mathcal{P}_{\dot{y}}(\overline{pop})\big) + W(inte)}{Cost(\mathcal{P}_{\dot{y}})}). \quad (8)$$

Let $T_{\mathcal{P},\mathcal{P}'} = 1$, if the traveler has explored the POIs $\mathcal{P}$ and $\mathcal{P}'$ sequentially. That means a tourist can travel from $\mathcal{P}$ to a $\mathcal{P}'$. $T_{\mathcal{P},\mathcal{P}'} = 0$, otherwise [11]. Then Eqn. 8 could be overcome with 19-22 restrictions:

$$\sum_{\mathcal{P}'=2}^{\mathbb{N}} T_{1,\mathcal{P}'} = \sum_{\mathcal{P}=1}^{\mathbb{N}-1} T_{\mathcal{P},\mathbb{N}} = 1, \quad (9)$$

$$\sum_{\mathcal{P}=1}^{\mathbb{N}-1} T_{\mathcal{P},k} = \sum_{\mathcal{P}'=2}^{\mathbb{N}} T_{k,\mathcal{P}'} \leq 1; \forall\, k = 2, ..., \mathbb{N}-1, \quad (10)$$

$$2 \leq L_{\mathcal{P}'} \leq \mathbb{N}; \forall\, \mathcal{P}' = 2, ..., \mathbb{N}, \quad (11)$$

$$L_{\mathcal{P}} - L_{\mathcal{P}'} + 1 \leq (\mathbb{N}-1)(1 - T_{\mathcal{P},\mathcal{P}'}) \forall\, \mathcal{P}, \mathcal{P}' = 2, ..., \mathbb{N}, \quad (12)$$

$$|cost(x)| \leq \mathbb{B}. \quad (13)$$

In Eqn. 8, the multi-objective issue is solved by increased visitor interest and popularity, weather interest and a decreased expense. The limitation set out in Eqn. 9 means that the proposed plan should be started from the first POI and the last POI can be completed. The limitation provided in Eqn. 10 shows that there is no POI viewed multiple times.

The restrictions imposed in Eqn. 11 and 12 argue that another response would not include a sub-tour based on the issue of the traveler with the sub-tour eliminating problem 13. Section 15 guarantees that the overall gap for the kit is provided by budget $\mathbb{B}$. $L_{i'}$ represents the i'-th itinerary herein.

The issue is an NP-hard problem since it relies on the cost function $Cost\ (\mathcal{P}_1 ... \mathcal{P}_{\dot{n}})$. This is also affected by the multiple POIs selected from a wide variety of variants. To address these problems, we are proposing the wPOIapproach is dependent on Monte-Carlo Tree Search (MCTS) and is described herein.

3.9 Monte Carlo Tree Search Algorithm

The Monte Carlo Tree Search (MCTS) method is used in board games including Othello, Chess, and Go [5, 28]. The MCTS algorithms are based on the tree search idea. All the boards in the board graph are referred to as the node and the game's result score is considered the leaf node. The gameplay can take multiple runs to hit the endpoint based on the MCTS formula.

Any execution starts with a set of randomized nodes and reports the results. The following steps are performed to get the winning score. A set of trials have been conducted in MCTS (e.g. 100 trials) and it is repeated for a specific duration (e.g. 10 seconds). The below are the basic core tasks of MCTS:

1. **Selection**: Let θ be root and spread into a randomized selection of the child node t with defined criteria to reach the end/leaf node. Likewise, θ be the initial/ root for the board, the t child's node, and the present condition for the board.

2. **Expansion**: Any child node can be expanded to a leaf node by using a randomized collection of the unexplored child node.

3. **Simulation**: At certain instances up to the end of the game the first and second moves are replicated.

4. **Back-propagation**: Phases 1-4 lead to one MCTS run when crossing the root of the leaf node. Also, every crossed node is labeled with a win / lose (1/0), on every run (back-propagation). The procedure is repeated over a certain amount of cycles.

MCTS solution is used for various networking problems, such as the issue of travel salesmen [18] or car navigation [9]. This issue is fixed based on two main factors by the use of the MCTS approach [5].

1. Rather than finding the whole tree which reduces operating time, MCTS often recognizes specific areas with the best probability of the remedy.

2. It could be configured for practical uses with a specific iteration.

Due to the below reasons – MCTS should not be directly implemented:

1. The expense of the decisions on a tour depends on the length of the tourist traveled and the spending time on every board game find, and the varying cost of it. 1.

2. The bonus score is in the win/loss state in the board game, either 1 or 0. Similarly, the arrangement of the award is quite difficult due to various traveling costs the popularity of the tour, and the degree of interest to visitors for the proposed POIs in the case of the routing advisory scheme.

The Upper Confidence Bound (UCT) is used to navigate the POI $\mathcal{P}_{\dot{n}}$, which maximizes Eqn. 14:

$$UCT^{original}_{\mathcal{P}_\jmath} = \frac{\mathbb{T}^{Reward}_{\mathcal{P}_\jmath}}{\mathbb{V}^{Count}_{\mathcal{P}_\jmath}} + 2\mathbb{C}\sqrt{\frac{2ln\ \mathbb{V}^{Count}_{\mathcal{P}_{\jmath'}}}{\mathbb{V}^{Count}_{\mathcal{P}_\jmath}}}. \quad (14)$$

The initial UCT (Eqn. 14) is the improvement of our suggested technique where a probabilistic selection is made for the succeeding POI and is described in Eqn. 15.

$$UCT^{wPOI}_{\mathcal{P}_\jmath} = \left(\frac{\overline{Int}(\mathcal{P}) + \overline{pop}(\mathcal{P})}{\Gamma^{cost}(x)}\right) + \frac{\mathbb{T}^{Reward}_{\mathcal{P}_\jmath}}{\mathbb{V}^{Count}_{\mathcal{P}_\jmath}} + 2\mathbb{C}\sqrt{\frac{2ln\ \mathbb{V}^{Count}_{\mathcal{P}_{\jmath'}}}{\mathbb{V}^{Count}_{\mathcal{P}_\jmath}}}, \quad (15)$$

where $\mathbb{V}^{Count}$ denotes is the number of visits of viewed nodes and $\mathbb{T}^{Reward}$ Reward is the cumulative reward from proposed POIs.

3.10 Simulation and Back-Propagation

Inside the MCTS, the test started at the root node, evaluating the reward as 1 (win) and 0 (loss). For binary 1 and 0 numbers, the reward for some POIs is not fully defined. The reward depending, on various parameters including tourist interest, tour popularity, and travel expenses, and is described as:

$$Reward = \frac{\left(\overline{Int}(\mathcal{P}) + \overline{pop}(\mathcal{P})\right)}{\Gamma^{cost}(\dot{x})}. \quad (16)$$

For each loop, the reward score is computed by Eqn. 16. If the itinerary is successful, the reward score will be back-propagated to all viewed nodes Furthermore, the number of trips is replicated and then raised by one.

4 Experimental Methodology

4.1 Dataset

In this analysis, we utilized the data provided in [12]. The dataset contains images and videos by Yahoo! Flickr Creative Commons 100M (YFCC100M) [25]. Furthermore, the YFCC100M data set provided in [12] was used and geo-tagged images from different areas of the globe have been obtained. The data set comprises the photo's meta-data. It includes visiting dates and times. The dataset also contains data from the

Geo-coordinate to identify the length among POIs. The data sets utilized in this research could be accessed[1] freely.

4.2 Baseline Algorithms

Based on the work [12] we have taken into account all the benchmark algorithms beginning at one POI and then choosing the next following POI before the budget is achieved. We utilize the tour series by the tourist to suggest multiple POIs.

— **Greedy Nearest (GNEAR)**: We utilize this algorithm for our next unexplored POI by selecting the three closest attractions [15].

— **Greedy Most Popular (GPOP)**: By picking the three most popular attractions, we select an unvisited POI [15].

— **Tour Recommendation With Interest Category (TOURINT)**: This compulsory group is described as the most frequently viewed group in several tourist visits [11]. This shows the issue with a suggested tour with a compulsory group that the visitor can explore at least once on the proposed itinerary.

— **Trip Builder (TRIPBUILD)**: This builds a personalized tourist itinerary according to the attraction's interest and popularity. An interest in a POI will be calculated as the number of the POI visits in a certain group compared with his/her overall visit [4].

4.3 Real-life Evaluation

Only visitors who have completed at least two travel sequences and two groups are assessed. The method is applied to both local and global datasets [24], as well as visitors who are comparable. We compare similar visitors in this study by looking at the top 10 associated visitors from global data sets. To equate different baselines with our method, we chose the preceding formulas. For our experiments, categories of real traveling series are chosen based on the history of associated visitors in a given area.

[1] https://sites.google.com/site/limkwanhui/datacode?authuser=0

— **Tour Recall (TourRec(I))**: The $Tour\ Recall$ is identified as the section of the actual tourist's series still portion of the suggested POI C_{rec} is supposed to be a list of recommended groups. C_{real} presents in its real-life tourism series a set of categories visited by a tourist. Eqn. 17 describes the $Tour\ Recall$:

$$TourRec(I) = \frac{|C_{rec} \cap C_{real}|}{|C_{real}|}. \tag{17}$$

— **Tour Precision (TourPre(I))**: The $Tour\ Precision$ is defined in the I itinerary as the proportion of proposed categories still part of the tourist's actual life. C_{rec} is assumed to include a list of categories suggested. C_{real} is a list of categories seen in his traveling sequence by a traveler. As displayed in Eqn. 18, $Tour\ Precision$ has been represented:

$$TourPre(I) = \frac{|C_{rec} \cap C_{real}|}{|C_{rec}|}. \tag{18}$$

— **Tour F1 (TourF1(I))**: the mean harmonic value of $Precision$ and $Recall$ for the proposed itinerary I is termed $Tour\ F1-Score$ available in Eqn. 19:

$$TourF1(I) = \frac{2 \times TourPre(I) \times TourRec(I)}{TourPre(I) + TourRec(I)}. \tag{19}$$

4.4 Comparison of $Precision$, $Recall$ and $F1$

The performance of the $wPOI$ algorithm is higher than other baseline algorithms such as GPOP TOURINT and GNEAR. $wPOI$ is more effective than those baseline approaches like GPOP TOURINT and GNEAR. The results are more efficient. Tables 1, 2 and 3 indicate the $Precision$, $Recall$ and $F1$-$Score$ measurements to represent the variations among $wPOI$ and other baseline approaches.

The results show that the $Precision$, $Recall$ and $F1$-$Score$ metrics are more significant for $wPOI$ than the baseline approaches. The $Recall$ value changes for $wPOI$ approach range from 3.4%-22.6% compared to other baseline

Table 1. Comparison of $Precision$ between our proposed approach and other baseline methods

Algorithms	wPOI	TOURINT	GPOP	GNEAR	RAND
Delhi- Edinburgh	0.404±0.037	0.353±0.038	0.321±0.029	0.294±0.024	0.265±0.035
Osaka-Edinburgh	0.389±0.014	0.34±0.038	0.314±0.03	0.286±0.023	0.26±0.013
Vienna-Edinburgh	0.39±0.038	0.359±0.022	0.325±0.017	0.293±0.048	0.275±0.047
Delhi-Osaka	0.71±0.019	0.56±0.025	0.536±0.038	0.614±0.014	0.421±0.026
Glasgow-Edinburgh	0.404±0.037	0.356±0.019	0.341±0.029	0.286±0.044	0.261±0.027

Table 2. Comparison of $Recall$ between our proposed approach and other baseline methods

Algorithms	wPOI	TOURINT	GPOP	GNEAR	RAND
Delhi- Edinburgh	0.362±0.023	0.31±0.05	0.293±0.043	0.259±0.014	0.224±0.019
Osaka-Edinburgh	0.382±0.039	0.327±0.022	0.291±0.032	0.255±0.036	0.236±0.017
Vienna-Edinburgh	0.372±0.033	0.326±0.024	0.302±0.015	0.279±0.031	0.256±0.043
Delhi-Osaka	0.396±0.009	0.333±0.018	0.292±0.042	0.271±0.027	0.229±0.035
Glasgow-Edinburgh	0.365±0.023	0.308±0.034	0.288±0.05	0.269±0.016	0.231±0.039

Table 3. Comparison of $F1-Score$ between our proposed approach and other baseline methods

Algorithms	wPOI	TOURINT	GPOP	GNEAR	RAND
Delhi- Edinburgh	0.382±0.04	0.33±0.049	0.306±0.011	0.275±0.025	0.243±0.016
Osaka-Edinburgh	0.385±0.018	0.333±0.045	0.302±0.021	0.269±0.015	0.248±0.016
Vienna-Edinburgh	0.381±0.016	0.341±0.041	0.313±0.026	0.286±0.034	0.265±0.02
Delhi-Osaka	0.388±0.049	0.34±0.034	0.304±0.045	0.283±0.048	0.247±0.043
Glasgow-Edinburgh	0.384±0.028	0.33±0.011	0.313±0.021	0.277±0.017	0.245±0.018

approaches (see 2). $Recall$ measurements depending upon $|C_v|$ and $|C_{rec} \cap C_{real}|$ as per in Eqn. 17.

Here the values of $|C_{rec} \cap C_{real}|$ is better compared to the various baseline approaches which can be computed utilizing the $wPOI$ algorithm. Typically, the suggested $wPOI$ algorithm is based on two datasets, local and global, and ultimately suggests many POIs, resulting in better $Recall$ scores for various baseline approaches.

Taking into consideration the tour popularity or interest of visitors, the various baseline approaches such as GPOP, TOURINT and GNEAR do not assist weather interest. In contrast with other baseline approaches, the increase in $Precision$ scores for the $wPOI$ algorithm suggested is 3.4%-22.6%. For the $wPOI$ algorithm, the $Precision$ scores are more because they are dependent on $|C_{rec}|$ and $|C_{rec} \cap C_{real}|$ as per in Eqn. 18.

We found that C_{rec} scores vary for various baseline approaches during the analysis. The values of $|C_{rec} \cap C_{real}|$ are higher for the suggested $wPOI$ algorithm. The $F1$-$Score$ increase in the suggested wPOI algorithm based

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on $Precision$ and $Recall$, from 3.4%-22.6% compared to other baseline approaches.

5 Conclusion and Future Work

In this research, we have offered a method $wPOI$ that contributes to maximise the tourist interest, popularity,weather interest and reduced costs. Geo-tagged photos are used by $wPOI$ to show the tourists' actual travel patterns. Tourist interest, tour popularity, weather interest and traveling costs are calculated effectively for training the $wPOI$ algorithm.

The suggested method is dependent on the selection of many POIs by taking into account the POI time visiting factor. $wPOI$ will not depend on the traveling history of a certain individual in new locations.

The case in which a visitor wants to visit new places is therefore taken into consideration. b) tourist has many POIs (c) the weather interest is calculated . Given the Flickr data in several cities, we matched $wPOI$ with various baselines that take multiple criteria such as $Precision$, $Recall$, and F1-Score.

The findings of the study demonstrate that the suggested $wPOI$ algorithm in most situations surpasses baseline approaches. We wish to enhance this research in the future to several travelers who intend to be staying in a new location over many days.

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