Utility Mining-based Point-of-Interest Paths Recommendation Using SNS Posts in Pervasive Social Environments

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Abstract

In this paper, we propose a point-of-interest (POI) paths recommendation method for SNS-savvy travelers, called a Utility Mining-based POI Path Recommendation (UMPOIR) framework. To recommend the best POI paths depending on the traveler's context, UMPOIR framework considers the popularity and the personal preferences for the POIs. Furthermore, it reflects not only the current context of the traveler, but also the experience of the publishers who visited there. So, it calculates the utility of the candidate POIs and their paths. After this, the utility is refined by the popularity of the POIs, the traveler's personal preferences, and the temporal factors. To evaluate the performance, we conducted experiments to measure the adequacy and the degree of satisfaction. We proved that UMPOIR framework can improve the recommendations' adequacy and the degree of satisfaction with the recommendations.

Keywords: Photo-centric SNS, POI path recommendation, Utility calculation, Context, Pervasive social computing

1 Introduction

Social Network Services (SNSs) are catching on as a primary tool to collect travel information [2, 14, 24, 31]. This phenomenon is especially popping up with the N-generation (born between 1977 and 1997) as well as the Y-generation (born in the late 1970s) [23]. They are very accustomed to sharing and collecting information like travel experiences, postscripts, hotel ratings, and/or packages [11]. This phenomenon will become more and more widespread with the advances in Internet-of-Things (IoT) technologies and the increasing popularity of handheld smart devices with high performance [33]. This allows the travelers to collect, filter, and use information anytime, anywhere, and in any context from popular SNSs. Furthermore, the travelers can get personalized travel information based on their context and someone's posted data on the SNSs [10].

However, it is not easy to collect information about the must-visit tourist spots from travelers' SNS posts, which are usually written in a non-standard language with an informal and erratic style [1]. To overcome the problem, some researchers are trying to recommend travel information by using the photographs posted on the SNSs like Instagram, Flicker, and/or Pinterest [15, 31]. But the research has had limitations, as follows. First, it has focused on the travelers' own posts and the SNS users with friendships [31]. It may cause problems for the coverage of recommendations. Second, the traditional recommendation methods rely on the user-item rating matrix [12] even though it is not easy to collect the ratings data for the travel destinations or particular POIs. Finally, knowledge-based recommendation uses the travelers' requirements to recommend the POIs or travel destinations. But it is not easy to apply the method because the travelers' requirements may change dynamically depending on their context.

To overcome the limitations, we propose a Utility Mining-based POI Path Recommendation (UMPOIR) framework. It recommends the best POIs depending on the traveler's context. At this time, it reflects the experiences of all SNS users who have visited the traveler's current place more than once. (Hereafter, "publisher" means an SNS publisher who has posted messages or photographs on the SNSs about the traveler's current place more than once). The novelties of UMPOIR framework are summarized as follows.

— Devise of a semantic social distance: In order to reflect the behavioral characteristics of the SNS-savvy travelers, we devise a calculation measure, named the semantic social distance between the travelers and the publishers. The distances are derived by social relationships on SNSs and annotations of the posts (a set of hashtags).
— Devise of a path utility: The utility of the particular POI can be determined by the traveler's personal preferences and the popularity of the POI. Furthermore, the preferences are indirectly extracted by the number of shared POIs on the POI trajectory.
— Proposition of a utility mining: For all visiting

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trajectories of the publishers, the framework calculates the path utilities that are considered the traveler's own personal preferences and the popularity of the POIs. It selects the best POI path with maximum utility. The best POI path is adjusted by top-k POIs and is recommended to the traveler.

This paper is organized as follows. In Section 2, we describe related works on the SNS-based recommendation methods. Section 3 describes UMPOIR framework. Section 4 performs experiments and evaluation of the framework. Finally, Section 5 puts forth the conclusions.

2 Literature Review

SNS-based recommendation is expected to be a candidate to overcome the limitations of traditional recommendation methods. The traditional methods used the item-user rating matrix as input data for recommendations. However, it can be untrustworthy because of data sparsity, cold starts, rating value, etc., among the already familiar problems [5, 9, 16]. If SNS is applied to recommendation systems, it can mitigate the problem of data sparsity by using friends' information within the social network instead of searching many unspecified users. The cold-start problem can also be solved by using friends' experiences within the social network instead of one's own experience [9]. Finally, it is possible to solve fake and/or noisy rating problems by using the friends' evaluations within the social networks.

Research about performing SNS-based recommendations has been carried out by many researchers as summarized Table 1.

Table 1. Summary of SNS-based recommendation studies

Method	Recom. Targets	Applied SNS data	Description	Related research
Collaborative filtering (CF)	Item	Relation among users	User rating prediction from SNS	[9]
	Item	Relation among users	User-item community clustering for a pre-processing of CF	[18]
	Tag	Relation among users, response of related users, Tags	Tags recommendation based of frequency and SNS user behavior	[7]
	Service	Relation among users	Trustful service recommendation using SNS friends relations	[5]
Content-based (CN)	Item	Relation among users, tags, products	Recommendation based on combination with tags and users	[8]
	Social media	Relation among users, user profile, social action	Social media recommend using various social actions on SNS	[29]
	Contents	Relation among users	Contents recommendation with frequency of friends view	[32]
	Contents	Relation among users	Contents recommendation using social activity	[26]
Hybrid (CF + CN)	Item	Relation among users, user profile	User preference inference	[19]
	Contents/ item	Relation among users, tags, rating activities	Integrated and personalized SNS service using multiple SNSs	[34]

Due to the rapid development of pervasive technologies and the exponential growth in use of handheld devices, there are growing expectations among users who want to get personalized context-aware recommendation services at any time, any place, and in any context [27]. To meet these requirements, the recommendation methods depending on the context are being extensively developed. Furthermore, the research has been enriched by adopting social-network information. A great deal of research has been performed on SNS-based context-aware recommendations as in Table 2.

As Table 2 shows, the SNS data used in SNS-based context-aware recommendations are users' profiles and their relationships. Some research applied context data extracted from hashtags, POIs, and SNS posts. Lately, the recommendation systems use photographs on SNS posts to improve the reliability of recommendations. At this time, context data usually used are location and time. Additionally, weather, mood, and road conditions are applied to improve the satisfaction with the recommendations.

Given the proliferation of digital cameras and the growth of online photo-sharing social network sites, many researchers have been interested in photographs and context data on SNSs [20]. However, Majid (2013) did not consider social relations that affect the user's decision making; he used only geotags, time, and locations that are included in photographs. Ye (2010) only recommended travel destinations using photographs on the posts of SNS users in friendship. To recommend the next stop, Kurashima (2010) constructs travel histories based on the photographs posted on traveler's SNSs. Due to data sparsity and/or cold starts, it may be difficult to the recommendation that satisfies the travelers.

Table 2. Summary of SNS-based context-aware recommendation studies

Method	Recom. Target	Applied SNS data	Applied context	Semantic factors	Related research
Collaborative filtering	Service	Tags, POIs	Location, time, weather	Manipulation of tags	[2]
	Mobile service	Relation among users, user rating	Location, time	-	[28]
	Mobile service	Relation among users	Location, time	-	[25]
	POIs	POIs, user profile	Location, time	Categorization of POIs topic	[17]
	Item	Relation among users	Location, mood, demographic data	-	[21]
Content-based	Social media	Time, user rating, user profile	Time, public's attention at that time	-	[32]
	Social relation	Relation among users	Time	-	[30]
Hybrid approach	Travel service	User profile	Location, time, weather	-	[22]
	Place	User profile, Relation among users	Location, time, road traffic	-	[13]

To overcome the difficulty, we proposed UMPOIR framework that use integrated relations on SNSs, context data, and photographs on SNS posts.

3 Procedural Architecture

The procedural architecture of UMPOIR framework is depicted in Figure 1. It is composed of three modules: the Context-based SNS Posts Collection Module (CPCM), the SNS Posts Alignment Module (SPAM), and the Best POI Path Recommendation Module (BPRM). In Figure 1, each module consists of a set of functional units that perform their own tasks.

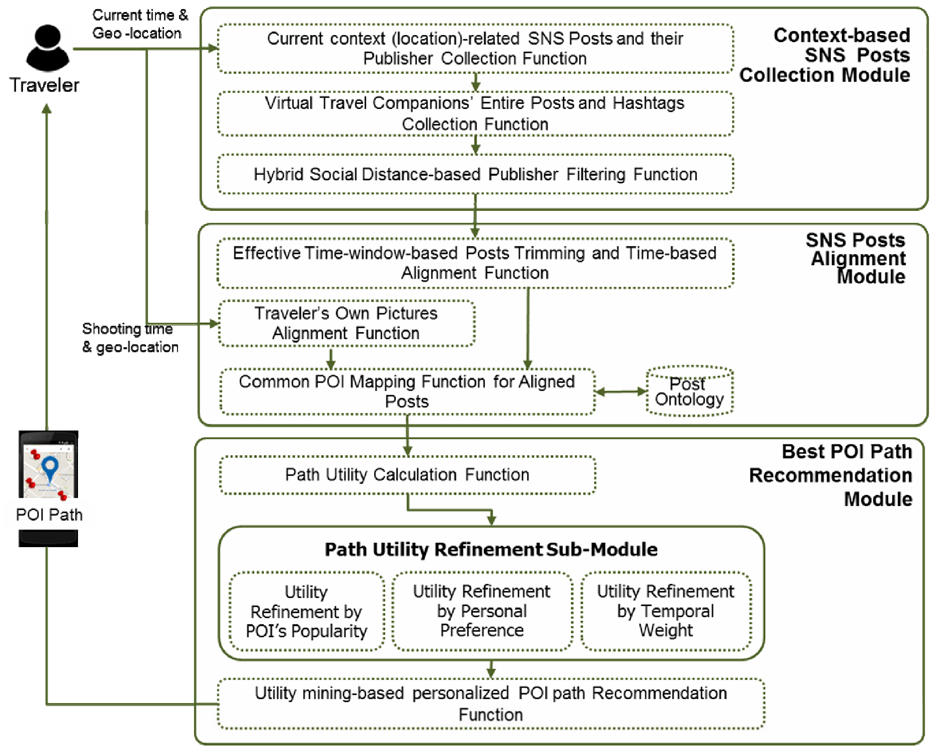

Figure 1. Overall architecture of UMPOIR framework

CPCM collects the SNS posts that have about visits to the traveler's current place or around the place. At the same time, it collects the profiles of the posts' publishers. From now on, the posts' publishers are called as "the virtual travel companions."

SPAM organizes the posts according to the shooting time of the photographs by the virtual travel companions. It also collects and organizes the photographs that are related to this tour from the traveler's smart device.

BPRM calculates the utility for the POIs and the paths. To do so, we consider the popularity of the POIs and the traveler's personal preferences. Furthermore, we refine the utility of the paths by temporal factors. Finally, the module performs utility mining to find the best POI path.

3.1 Context-Based SNS Posts Collection Module

In order to recommend the POI paths depending on the traveler's context, the framework collects the SNS posts with photographs from the virtual travel companions. Whether they visited the same place is judged by comparing the traveler's current location with the shooting coordinates of the photographs in the SNS posts. The shooting coordinates can be easily identified from the posted photographs [20]. The SNS post and the neighbor SNS post are represented as follow.

Definition 1 SNS post (p_i) p_i is represented as

$$p_i = [< ts_i, l_i > | ts_i, l_i \ni (l_i^{lat}, l_i^{long}, l_i^{name})] \quad \textbf{(1)}$$

where ts_i is timestamp of p_i and is represented by epoch time. l_i is geo-location of p_i composed of coordinates with longitude l_i^{long}, latitude l_i^{lat}, and name of the place l_i^{name}. l_i^{name} is written by the publishers.

Definition 2 Neighbor Post (np_j) np_j is represented as

$$p_j = [< ts'_j, l'_j > | ts'_j, l'_j \ni (l_j^{lat'}, l_j^{long'}, l_j^{name'})] \quad \textbf{(2)}$$

where np_j as a subset of p_i is filtered within $\sqrt{(l_t^{lat} - l_i^{lat})^2 + (l_t^{long} - l_i^{long})^2} \le r$ for all $i (j \le i)$. l_t^{lat} and l_t^{long} are the SNS-savvy traveler's geo-location and r is a threshold.

It is very easy to find the publisher's profile for np_j if s/he agrees to disclose his/her personal information. Using the publisher's profile, UMPOIR framework collects all posts with hashtags on the SNS. The collected profiles and hashtags are used to find relevant publishers using hybrid social distance. It is defined as follow.

Definition 3 Hybrid social distance ($hd(t, s_k)$) $hd(t, s_k)$ is calculated by a combination of two kinds of distance on SNS.

$$hd(t, s_k) = \frac{W_{st}(t, s_k) \cdot st(t, s_k) + w_{sm}(t, s_k) \cdot sm(t, s_k)}{st(t, s_k) + sm(t, s_k)} \forall \quad \textbf{(3)}$$

where $st(t, s_k)$ and $sm(t, s_k)$ are structural and semantic distance, respectively. $w_{st}(t, s_k)$ and $w_{sm}(t, s_k)$ are weights of $st(t, s_k)$ and $sm(t, s_k)$. It is calculated as $w_{st}(t, s_k) = \frac{\min\max(sm(t, s_k)}{\min\max(sm(t, s_k)}$, and $w_{sm}(t, s_k) = 1 / w_{st}(t, s_k)$.

$st(t, s_k)$ is calculated by the number of direct and indirect links between t and s_k on the SNS. We define the direct link as one that explicitly connects from the traveler to the publishers in a social network, and the indirect links as being multiple hops away from each other. According to Kwak (2010) and Yang (2014), more than 95% of information diffusion in Twitter is less than two hops from the origin; so we can restrict the number of hops of the indirect link to 2.

Definition 4 Structural distance ($st(t, s_k)$) $st(t, s_k)$ is represented as

$$st(t, s_k) = \frac{1}{(n_{(t, s_k)}^{(0)}) \cdot \log(n_{(t, s_k)}^{(1)} + 1)} \quad \textbf{(4)}$$

where $n_{(t, s_k)}^{(0)}$ and $n_{(t, s_k)}^{(1)}$ are the numbers of direct and indirect links ($n_{(t, s_k)}^{(0)} = 0$ or $n_{(t, s_k)}^{(1)} \ge 0$).

To refine the structural distance, we adopt the semantic distance that is a proportion of the semantically overlapped annotations (hashtags) on the posts [3]. The semantic distance is calculated by the revised TF-IDF. It adopts the frequency of the hashtags on the posts. Furthermore, it refines the hashtags by using ontology to resolve the semantic inconsistency, such as synonyms, hypernyms, or hyponyms. As a result, we develop the model to calculate the semantic distance.

Definition 5 Semantic distance ($sm(t, s_k)$) $sm(t, s_k)$ between t and s_k is represented as

$$sm(t, s_k) = \frac{1}{\sum_r (tf_{(t, s_k)}^{(h_r)} \times idf_{(t, s)}^{(h_r)})} \quad \textbf{(5)}$$

where $tf_{(t, s_k)}^{(h_r)}$ is frequency of r^{th} semantically matched hashtags (h_r) between t and s_k. $idf_{(t, s)}^{(h_r)}$ is a measure how important a semantically matched hashtag is. That is, if a semantically matched hashtag appears in many posts, it leads to less importance $tf_{(t, s_k)}^{(h_r)} = 1 + \log(f_{(t, s_k)}^{(h_r)})$ and $idf_{(t, s)}^{(h_r)} = \log \frac{N}{|1 + n(h_r, s)|}$; $f_{(t, s_k)}^{(h_r)}$ is the raw frequency of h_r, N is a number of s_k, S is a set of an entire post of s_k, and $n(h_r, s)$ is the number of s_k where h_r appears.

Using $hd(t_r, s_k)$, the publishers who are relatively far from the traveler on the SNS can be filtered out.

3.2 SNS Posts Alignment Module

Given a set of posts of the virtual travel companions, the framework has to sort all posts according to the shooting time by the virtual travel companions. It aims to find the virtual travel companions' travel routes around the traveler's current location. Before sort the posts, the framework trims the posts with an effective time window (ET) that is defined as a time interval to judge whether the traveler can be accessible by walking or car. For the current context of the traveler, sorting is performed on the posts (photographs) within the time window $t_0 \pm ET$. The sorted posts of the virtual travel companion are represented as follows.

Definition 6 Sorted posts of the virtual travel companion Assume that s_k has a set of posts with time stamp ts_k . So, the posts can be arranged sequentially such as $np_j^{ts_{-ET}} \leftarrow np_j^{ts_{-ET+1}} \leftarrow \cdots \leftarrow np_j^{ts_0} \leftarrow \cdots \leftarrow np_j^{ts_{ET-1}} \leftarrow np_j^{ts_{ET}}$ where $np_j^{t_0}$ is the post about current place. This sequence is transformed into a sequence of the POIs through a mapping with POI ontology.

As a next step, the framework organizes the travel path of the traveler itself. To do so, it collects the photographs from the traveler's smart devices and sorts them with time. The target of sorting is restricted to the photographs that are taken for the current travel. At this time, the publisher's photographs are sorted by coordinates as traveler's current context. By equation (2), the individual post as a component of sorted posts is composed of a longitude, latitude, and a name of the place on the coordinates. The name of the place can be an arbitrarily words or a set of word that is named the virtual travel companions. This might cause conflicts with the name for similar coordinates. To overcome the problem, it adopts the ontology. Using the ontology, the coordinates of the aligned posts can be mapped into common POIs. It shows the popularity and preference of each POI which are described in Section 3.3.

3.3 Best POI Path Recommendation Module

UMPOIR framework generates the optimal POI paths (a sequence of the POIs) depending on the traveler's current context. To do so, the framework calculates the path utilities of the virtual travel companions. The utility of the POI path of $u(p_{s_k})$ is defined as follow.

$$u(p_{s_k}) = \sum_{poi\sigma_{s_k}^l \in p_{s_k}} u(p_{s_k}^{(l)}) \qquad \textbf{(6)}$$

where p_{s_k} is the path of the POI for s_k , which composed of $\{poi_{s_k}^{(1)}, poi_{s_k}^{(2)}, ...\}$ and $u(poi_{s_k}^{(l)})$ is the utility of l^{th} POI in the path p_{s_k} $(l \geq 1)$.

The utility of the POIs is based on the popularity and the traveler's preference of the POIs. The popularity is derived from the number of posts associated with the POIs and the traveler's preferences are inferred by the degree of overlapping of the POIs that the traveler and the virtual travel companions have been visited. The utility of l^{th} POI of $s_k(u(poi_{s_k}^{(l)}))$ is calculated as follow.

$$u(poi_{s_k}^{(l)}) = \frac{w_{s_k}^{po_l} \cdot po(poi_{s_k}^{(l)}) + w_{s_k}^{pr_l} \cdot po(poi_{s_k}^{(l)})}{po(poi_{s_k}^{(l)}) + pr(poi_{s_k}^{(l)})} \qquad \textbf{(7)}$$

where $w_{s_k}^{po_l}$ and $w_{s_k}^{pr_l}$ are weights of the popularity and the personal preference of l^{th} POI of s_k .

3.3.1 Popularity of POI

The popularity is calculated by the number of the virtual travel companions who have put up posts related to the POI. The more visiting travelers have put up posts related to the POI, the greater the popularity. To calculate the popularity, the framework uses the time and geo-location of the photography. As a result, it can eliminate the possibility of controversy over whether they have actually visited. Furthermore, the risk of a failing recommendation resulting from lack of information can be eliminated because the POI recommendation is based on the SNS users' experiences which are the visited place more than once. So, the popularity of l^{th} POI is calculated by as follow.

$$po(poi^{(l)}) = \sum n(s_k, poi^{(l)}) \qquad \textbf{(8)}$$

where $n(s_k, poi^{(l)}) = \begin{cases} 1, \text{ if } s_k \text{ visits } poi^{(l)} \\ 0, \qquad\qquad o/w \end{cases}$. $po(poi^{(l)})$ is the total number of the virtual travel companions who have visited the $poi^{(l)}$.

3.3.2 Personal Preference of POI

It is difficult to grasp the traveler's personal preferences for the POI using only the travelers' current context. To overcome the problem, UMPOIR framework compares the traveler's visiting route to the virtual travel companions' it. If the traveler's visiting route is similar to their routes, then it is likely to visit the similar POI as a next stop. Based on the assertion, the framework calculates the degree to which POIs overlap between the traveler and the virtual travel companions.

Definition 7 Degree of POI Overlapping ($deg_{(t,s_k)}^{(se)}$) ($deg_{(t,s_k)}^{(se)}$ between t and s_k is represented as

$$deg_{(t,s_k)}^{(se)} = \frac{n(p_t \cap p_{s_k})}{n(p_t)} \qquad \textbf{(9)}$$

where $n(p_t)$ is the number of POI on the traveler's route $(n(p_t) \geq 1)$. $n(p_t \cap p_{s_k})$ is the number of overlapped POIs between t and s_k ($0 < deg_{(t,s_k)}^{(se)} \leq 1$).

Using $deg_{(t,s_k)}^{(se)}$, the personal preference of l_{th} POI is defined as follows.

$$pr(poi^{(l)}) = \frac{\sum_{p=1}^{m} deg_{(t,s_p)}^{(se)}}{m} \qquad \textbf{(10)}$$

where m is the number of the virtual travel companions ($m \geq 1$).

Through the processes, the popularity of the POIs and the utility of the paths under consideration for the traveler's preference are derived.

3.3.3 Temporal Weight to the Path Utility

It is possible to improve the satisfaction and acceptance rate by adjusting the path utility using the seasonal factors, calendar days, or climate changes [4]. Intuitively, it is general for a traveler's visiting schedule to be affected by seasons or weather. For example, the outdoor POIs might be more preferred in spring and fall than in summer or winter. The POI utility is adjusted by this kind of temporal factors. The adjusted utility $U(\widetilde{p_{s_k}})$ is defined by

$$U(\widetilde{p_{s_k}}) = U(p_{s_k}) \times w_t \quad \textbf{(11)}$$

where w_t is a weight of t^{tj} season or calendar day and is represented

$$w_t = \begin{cases} 1.0, \text{if } t \text{ and } s_k \text{ vist it in the same season} \\ \dfrac{1}{1+\log|td|}, o/w \end{cases}$$

(td is a temporal distance between t and s_k).

3.3.4 Utility Mining-based Personalized POI Path Recommendation

UMPOIR framework calculates the path utilities for the virtual travel companions' visiting routes and the utility of individual POIs. Especially, the utility for individual POIs compares the traveler's visiting route with the virtual travel companions for consideration of the personal preferences as well as popularity of the POIs. Through the process, the top-k POIs with high utility can be mined, and the mining output can generate a personalized POI path to get back the highest utility to a traveler. In this paper, we mined the top-k POIs with high utility, and then used utility mining is a recommendation process to introduce a personalized path with high utility.

To recommend a personalized POI path to the traveler, it is necessary to find a path (p_{s_k}) with the highest utility-by Equation (12).

$$\max \sum_{\widetilde{pol^l_{s_k}} \in p_{s_k}} u(\widetilde{pol^{(l)}_{s_k}}) \quad \textbf{(12)}$$

At this time, the first constraint states that t and s_k should share one or more POIs. The second constraint states that it recommends a place except for the previously a traveler's visited POI from p_{s_k}. Finally, the path with maximum utility ($\widetilde{p_{s_k}}$) is once more adjusted in a view point of the top-k POIs that are identified by the popularities and the preferences. To resolve the constraints, the framework implements the top-k POI-based path alignment algorithm (Figure 2)

In summary, the traveler receives the best POI path that considers the virtual travel companions' opinion, and the top-k POIs to reflect the context of the traveler and the virtual travel companions. The best POI path will be regenerated anytime and anywhere when the traveler's context is changed.

4 Performance Evaluations

We conducted several experiments to evaluate the efficiency and effectiveness of the framework. To do so, we collected photographs from the online mobile photo- and video-sharing social networking site, Instagram. The photographs are gathered from 986 Instagram users who visited to London, England, where the traveler is. After the pre-processing to the photographs, we identified 389 Instagram users who have POI paths.

Experiment 1: We performed an experiment to show the conformity of the POI paths that are recommended by the UMPOIR framework. To do so, we selected ten users as test data. The experiment was performed to prove the adequacy of the recommendations. In other words, the POI path with maximum utility is recommended to the traveler. The experimental results have been assessed using two metrics, namely, recall and precision [21]. Furthermore, a widely used combination metric called F1 score [6] that gives equal weight to both recall and precision was employed for our evaluation. The experiments are summarized in Figure 3.

According to the experiments, the adequacies of the recommendations are 69% (recall), 54% (precision), and 59% (F1 score). The adequacies are converged around 60%. Unfortunately, there is no similar research to recommend POI path, so it is not difficult to compare with performances of other research. However, in real world, users visited about 70% of the recommended POIs. It shows UMPOIR framework was successfully worked to deliver the good results.

Experiment 2: To identify the degree of the satisfaction to the traveler's preference, we compared the POIs on the POI path by the traveler with the POI path with maximum utility. Furthermore, additional experiments were performed to show the effectiveness of the path alignment with the top-k POIs. Top-k POIs have a utility value in the top-k. Comparison results are summarized in Figure 4.

Input: a set of top-K POI, $\mathrm{POI}^{(K)} = (poi_1^{(K)}, poi_2^{(K)}, ..., poi_k^{(K)})$
A maximum utility path $PH^{(\max)} = (poi_1^{(\max)}, poi_2^{(\max)}, ..., poi_k^{(\max)}, ...)$
Other path $PH^{(t)} = (poi_1^{(t)}, poi_2^{(t)}, ...)$ where $U(PH^{(t)}) < U(PH^{(\max)})$ forallt
output: an aligned path with top-K POIs

foreach top-K poi $poi_p^{(K)} \in POI^{(K)}$ **do** /* $l = 1, 2, ...$ */
  If $poi_p^{(K)} \notin PH^{(\max')}$ **then**
    foreach poi in $poi_l^{(\max)} \in PH^{(\max)}$ **do** /* $l = 1, 2, ...$ */
      call ***partialLink*** ($poi_p^{(K)}, poi_l^{(\max)}$)
      extend $poi_l^{(\max)}$ to $(poi_l^{(\max)}, i, poi_l^{(K)})$ /* i is intermediate POI_S $i \geq 0$ */
    End for
  End if
End for
Function ***partialLink*** $(poi_p^{(K)}, poi_l^{(\max)})$
  $linkUtility_{max} \leftarrow 0.0$
  foreach t **do** /* $t = 1, 2, ...,$ and $t \neq \max$ */
    find $PH^{(v)}$ such that $\{poi_m^{(\max)}, poi_p^{(K)}\} \in PH^{(v)}$ and $v \subseteq t$
    foreach v **do**
      extract link (s, i, d) where $s = poi_m^{(\max)}, d = poi_p^{(K)},$ & i is intermediate $POI_s, i \geq 0$)
      $linkUtility_{(s,i,d)} = u(s) + u(d) + \sum_i u(i)$
    End for
    $linkUtility_{\max} = \max(linkUtility_{(s,i,d)})$
Return link (s, i, d)
End for
EndFunction

Figure 2. Top-k POI-based path alignment algorithm

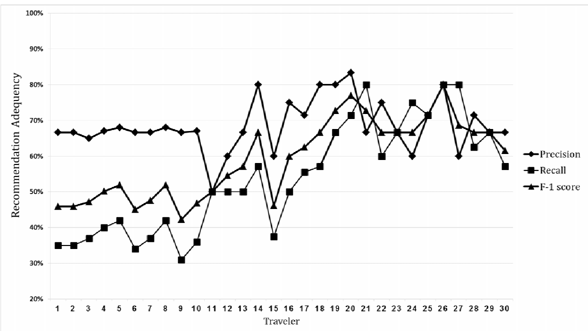

Figure 3. Recall, precision, and F1 score of recommendation results

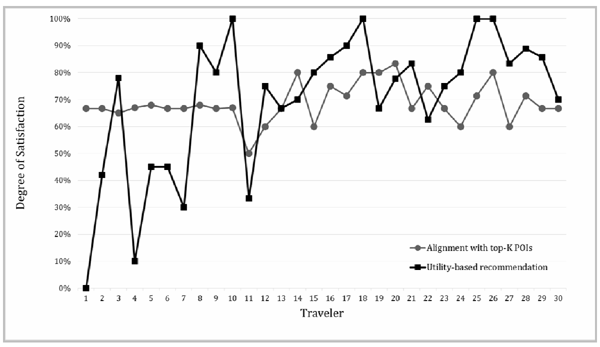

Figure 4. Degree of POI consistency between the traveler's POI path and the POI path with maximum utility

Traveler 1 had no POI data except for the current location, because s/he was just beginning travel. So, UMPOIR framework cannot calculate the POI utility for her/him. For travelers 10, 18, 27, and 28, we know that they have complete confidence in the POI recommendations. All the travelers accepted the POI recommendations at around 70 percent. The degree of satisfaction to the POI recommendations was increased by alignments with the top-K POIs.

Experiment 3: To show the superiority of the UMPOIR framework, we conducted the comparison with the previous research [20]. However, there are no researchers who have ever performed the recommendation of the POI paths. So, we compared performance of the framework with [20]. It was measured by hit ratio by each traveler as follow.

$$Hit\ ratio = \frac{Number\ of\ visted\ POI_s}{Total\ number\ of\ recommened\ POI_s} \quad \textbf{(13)}$$

To calculate the hit ratio, we filtered the travelers who had been visited too few POIs. The comparison results are summarized in Figure5.

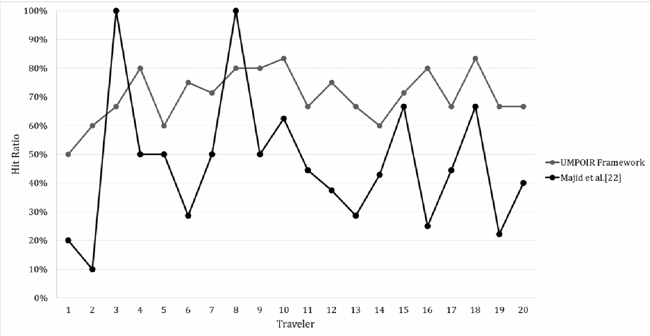

Figure 5. Comparison of Hit ratio between UMPOIIR framework and Majid et al. [21]

Through the experiments, the hit ratio is around 70 percent. It is higher than Majid's 47 percent. From judging these experimentations, the excellence of the framework has been proved.

5 Conclusion

In this paper, we propose a Utility Mining-based POI Path Recommendation (UMPOIR) framework which recommends the best POIs depending on the traveler's context. It includes three modules: Context-based SNS Posts Collection Module, SNS Posts Alignment Module, and Best POI path Recommendation Module. Finally, it recommends the best POI path by means of the utility mining on the POI paths of the publishers. In the experiments, it was shown that the framework is appropriate for the POI path recommendations in terms of precision, recall, and F1 score.

The contributions of this study are summarized as follows. First, we apply the various context embedded into the posted photographs on the SNSs to recommend the best POI path for the traveler. Second, we devised a new utility calculation mechanism for the POIs that use explicit popularity to the POIs, and adopt implicit personal preferences and temporal factors for the POIs. Finally, we build the model to mine the utility of the POI paths.

This research can be extended in several directions. We need to implement the utility mining engine develop the framework to search the SNSs and automatically collect the implicit data embedded in the posted photographs on the SNSs. Finally, we can perform in-depth experiments with many publishers and POIs to evaluate the performance of the recommendations based on utility mining.

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